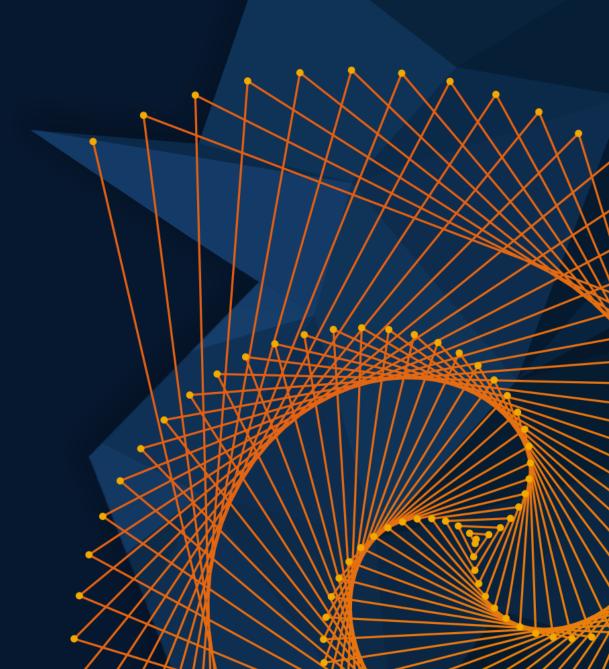
WATLAB EXPO UNITED KINGDOM

# Automating Fault Detection Using Visual Inspection

Elre Oldewage, MathWorks





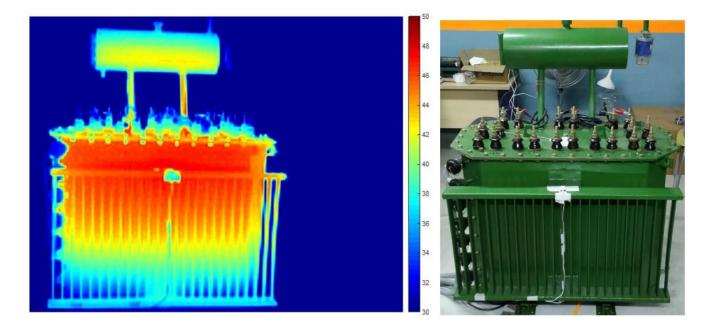


#### Siemens Develops Health Monitoring System for Distribution Transformers



#### Results

- Retrofittable solution with non-invasive temperature sensors
- User-friendly commissioning
- Online learning for algorithm



**User Story** 

# Korea Institute of Energy Research Develops AI-Based Predictive Maintenance Models for Offshore Wind Power





#### Results

- Development time cut in half
- 90%+ prediction accuracy achieved
- Aggressive deadline met

# Mondi Implements Statistics-Based Health Monitoring and Predictive Maintenance for Manufacturing Processes with Machine Learning



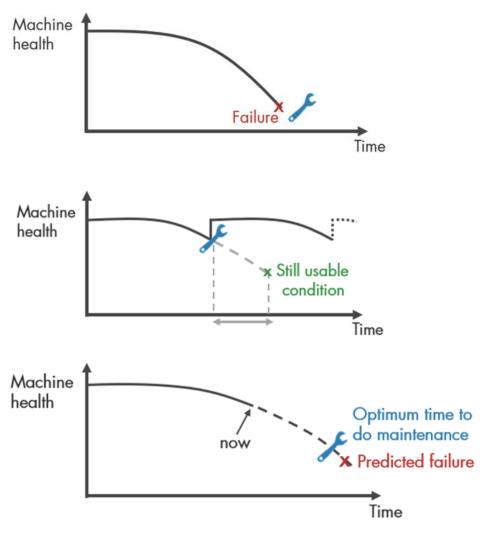
#### Results

- More than 50,000 euros saved per year
- Prototype completed in six months
- Production software run 24/7

<u>User Story</u>

#### How best to do maintenance?

- Reactive Do maintenance once there's a problem
  - Problem: unexpected failures can be expensive and potentially dangerous
- Scheduled Do maintenance at a regular rate
  - Problem: unnecessary maintenance can be wasteful; may not eliminate all failures
- Predictive Forecast when problems will arise
  - Problem: difficult to make accurate forecasts for complex equipment



### Why perform predictive maintenance?

- Prevent loss or damage of expensive equipment
- Failures can be dangerous
- Maintenance also costly and possibly dangerous
- Reduced downtime
- Improved operating efficiency





What is visual inspection?

"Automated visual inspection is the **image-based inspection** of parts or equipment where a camera scans the device under test for both **failures** and **quality defects**"

# Automated Defect Detection

Computer VisionOptical InspectionAutomated InspectionImage ProcessingMachine Learning

#### Classical image processing Detecting defective pills for quality control

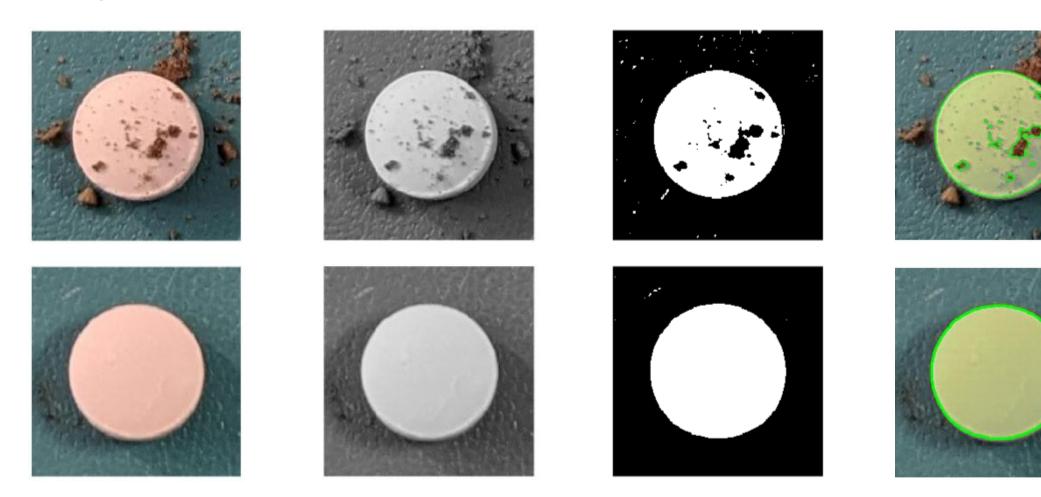


#### **Documentation example**

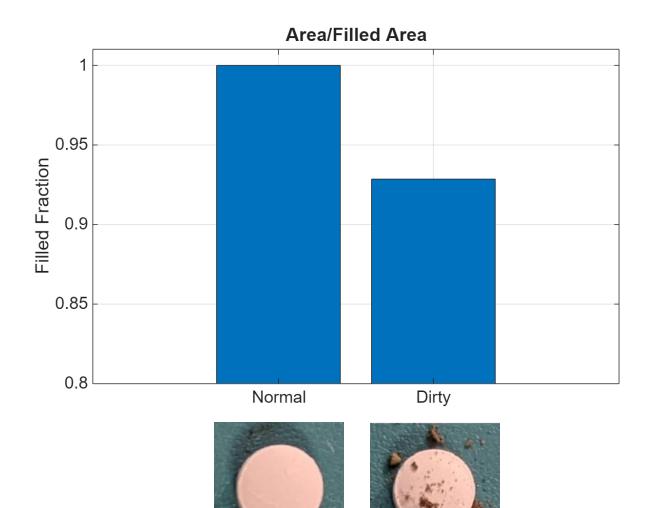


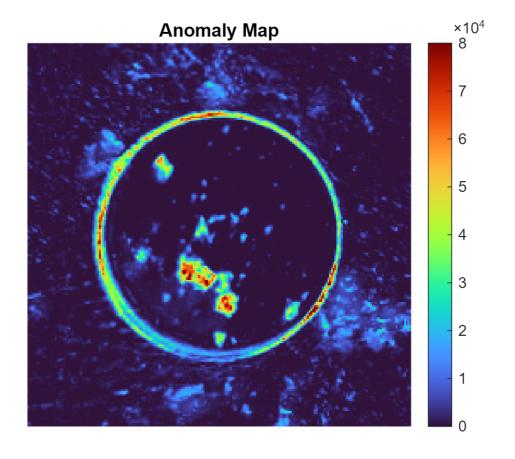
#### Normal Dirty Chipped

#### Classical image processing Detecting defective pills for quality control



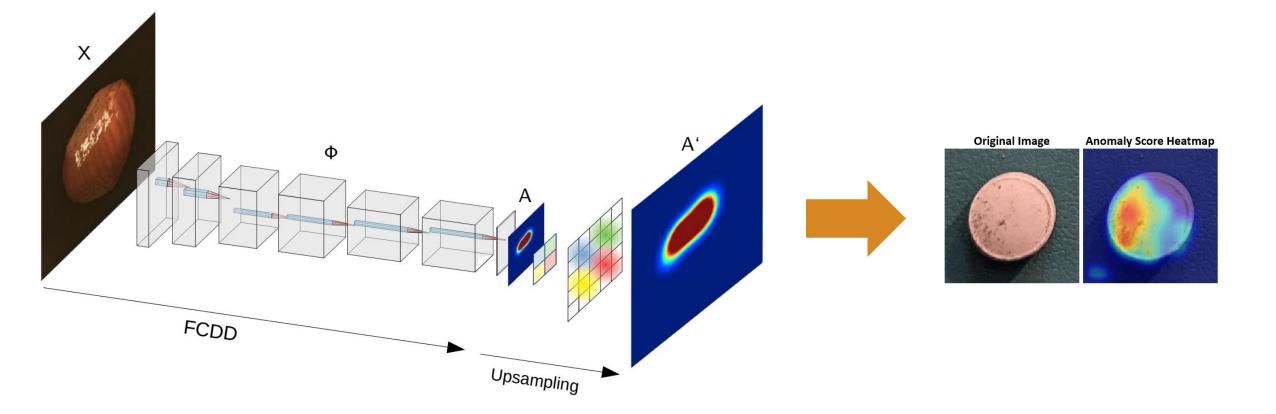
#### Classical image processing Detecting defective pills for quality control





normDiff = sum( (double(normal) - double(dirty)).^2 , 3 );

#### Deep learning Detecting defective pills for quality control



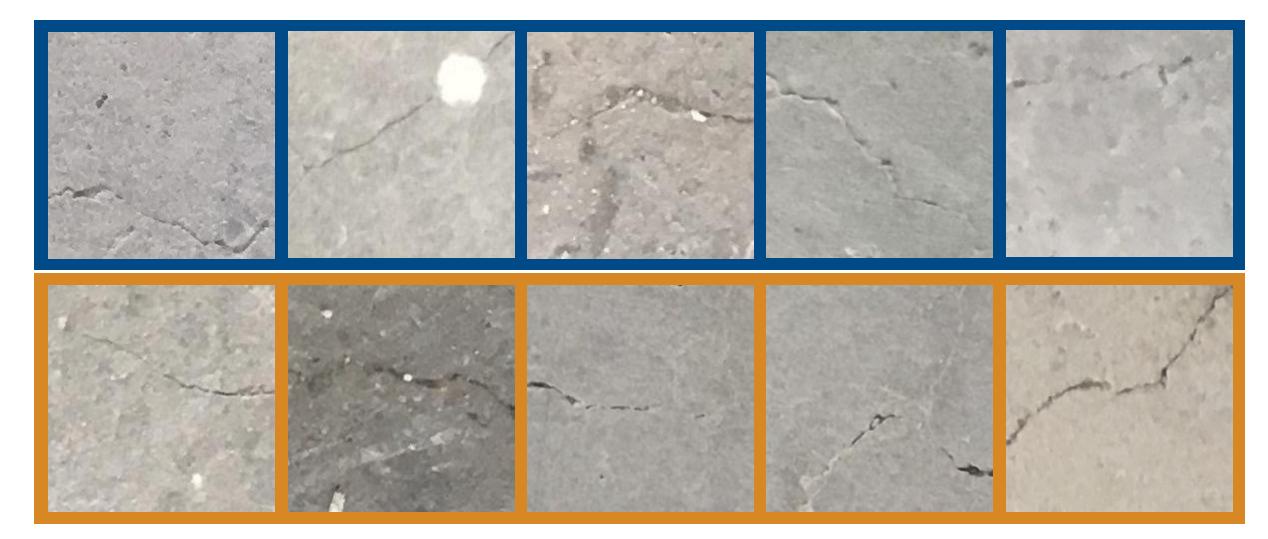
Explainable Deep One-Class Classification, Liznerski et. al (2021) https://arxiv.org/pdf/2007.01760

#### Challenge: Poor quality input data



#### Are conditions under which the data is gathered controlled?

### Challenge: Difficulty identifying anomalous inputs



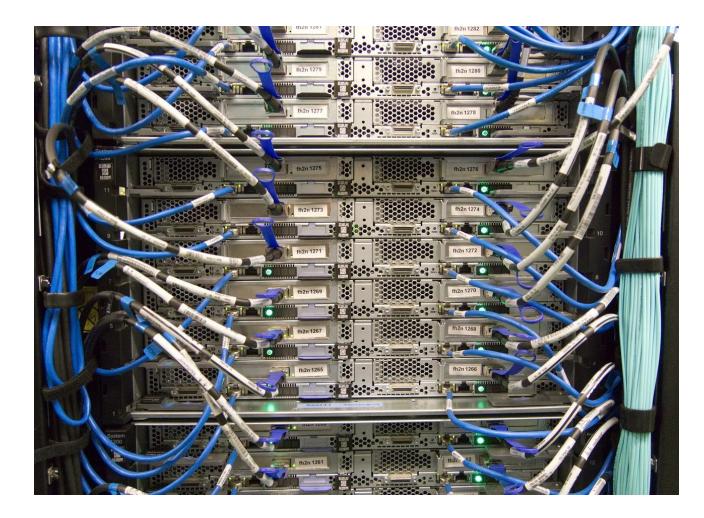
Concrete Crack Images for Classification DOI:10.17632/5y9wdsg2zt.2

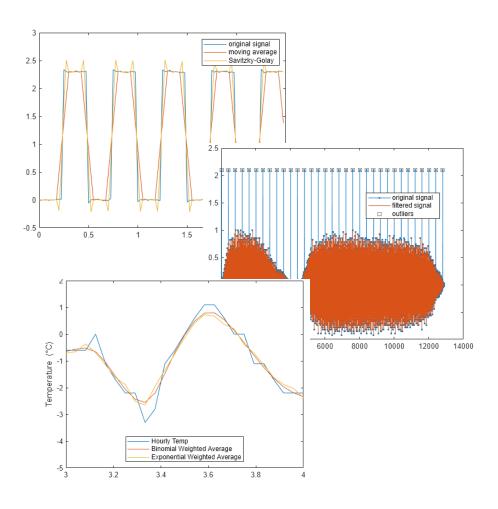
### **Challenge:** Automation



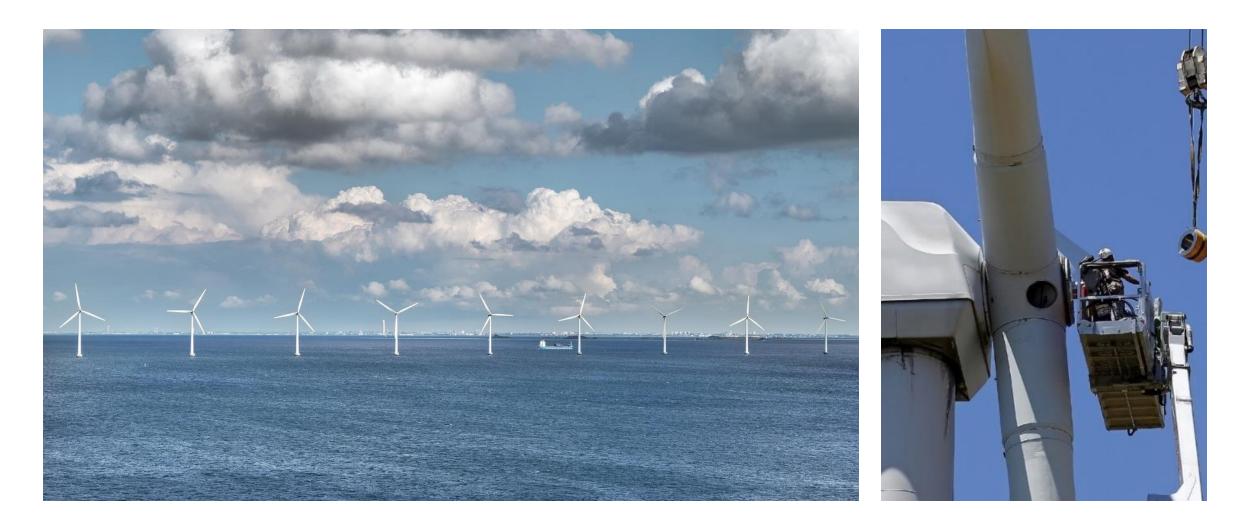


### Challenge: Scale

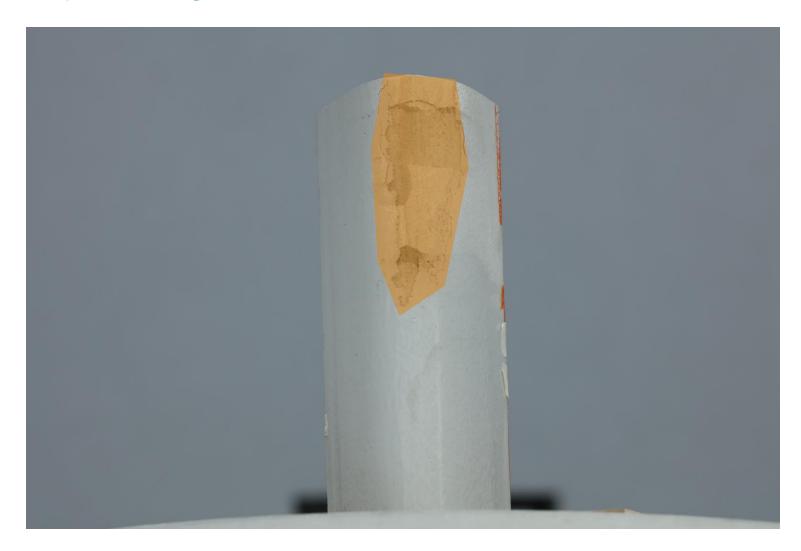




### Case study – Visual inspection for wind turbines



#### Can we identify damaged areas on wind turbine blades?



**Damaged Turbine Blade** 

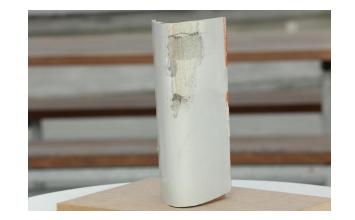
#### Visual inspection of wind turbine blades Our dataset





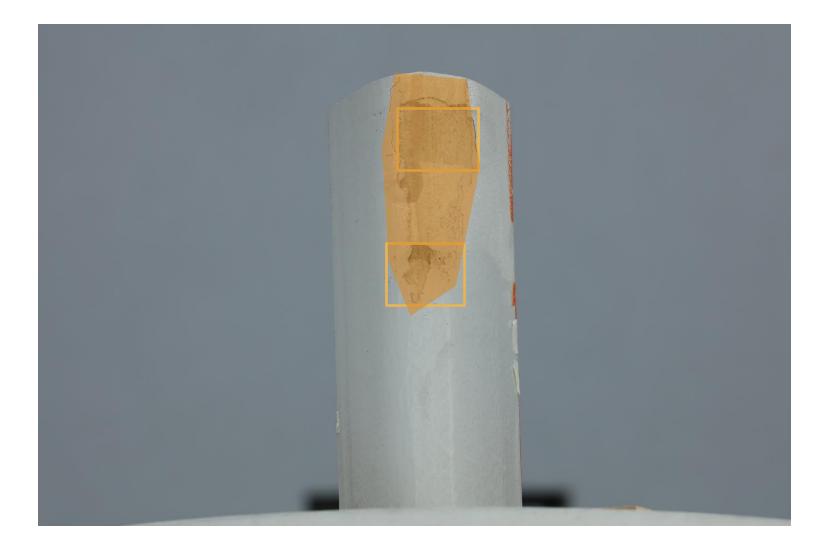


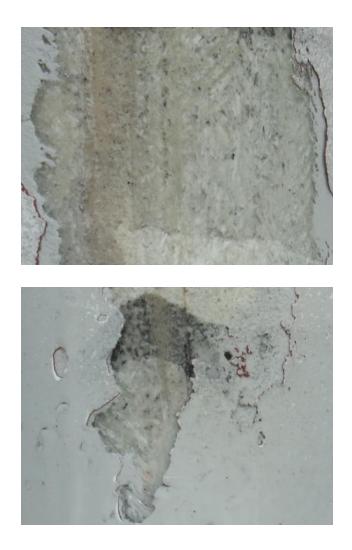






# Identifying blade damage





#### **Problem Outline**



#### **Importing Data**





#### **Crop to Blade**

Detect Damaged Area

#### Importing the data





img = imread("2C8A0207.JPG"); imshow(img)

#### Image read

#### Scaling this up?

#### **Problem Outline**



**Importing Data** 



**Crop to Blade** 



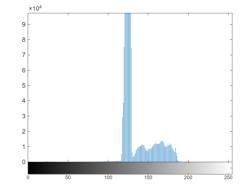
#### Detect Damaged Area

### Cropping out the background

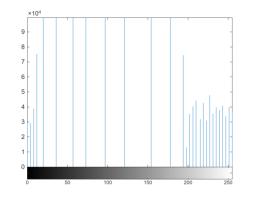
histeq

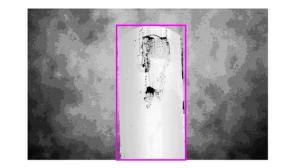














bwareafilt
regionprops



#### **Problem Outline**



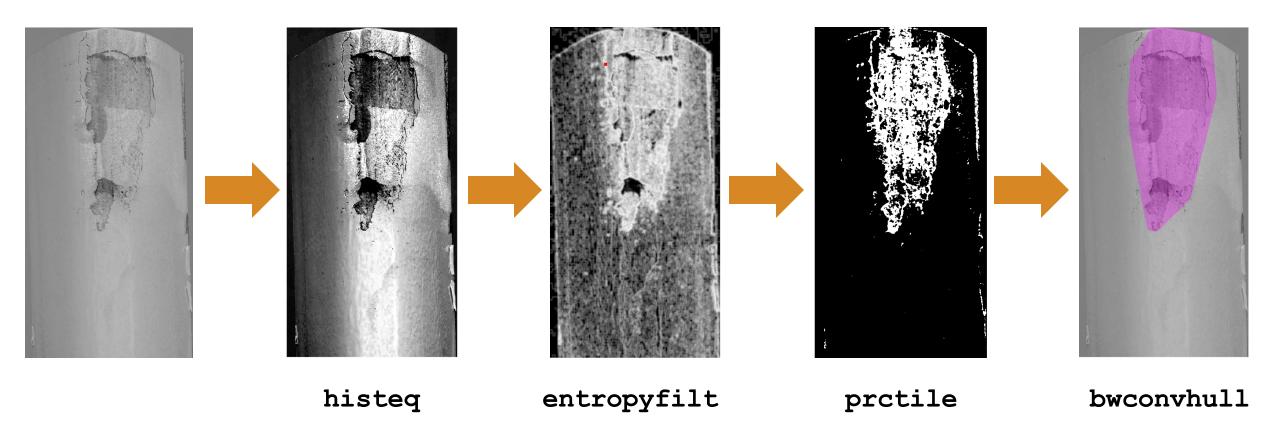




#### **Importing Data**

#### **Crop to Blade**

#### Detecting damage



#### **Problem Outline**



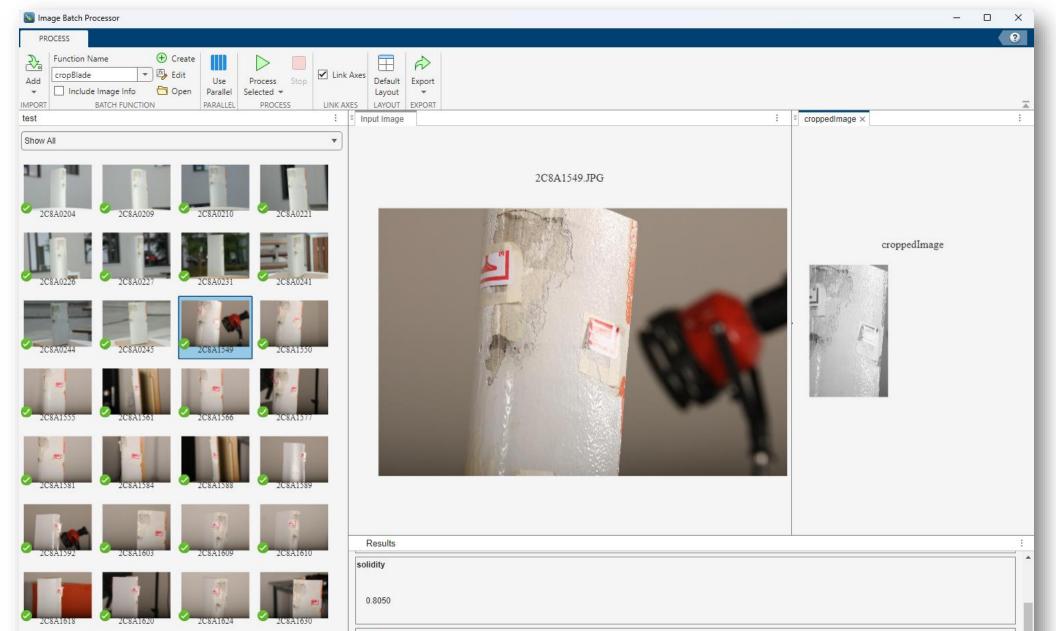




# Importing Data Crop to Blade Detect Damaged Area

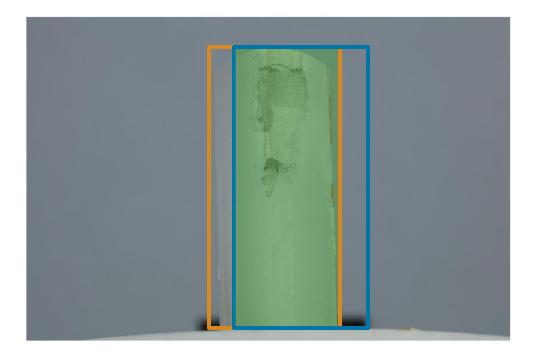
# Image Batch Processor

More about the image batch processor



#### Validation

- Compute overlap between computed bounding box and ground truth
- Map detected damage convex hull back to original image co-ordinates and compute overlap with ground truth
- This requires labeling to obtain a ground truth





# Image Labeler

#### More about the image labeler

📣 Image Labeler - LabelingProject.prj*	– 🗆 X
IMAGE LABELER VISUALIZATION	ि रू ड <sup>े</sup> २
Import       Import	
✓ ROI Label Definitions	: View Labels, Sublabels and Attributes :
<ul> <li>▶ blade</li> <li>▶ damage</li> </ul>	Expand All Collapse All
	Label/Sub-Label         ▼ Object Labels         blade         damage
Scene Label Definitions	
To label a scene, you must first define a scene label.	
Apply to Image Remove from Image	
Image Browser	1

#### **Problem Outline**

# Can we do better using deep learning?







**Read Data** 

#### **Crop to Blade**

Detect Damaged Area

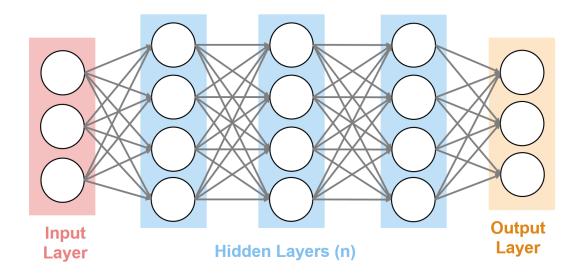
### Deep learning workflow

ACCESS AND EXPLORE DATA LABEL AND PREPROCESS DATA DEVELOP AND VALIDATE MODEL

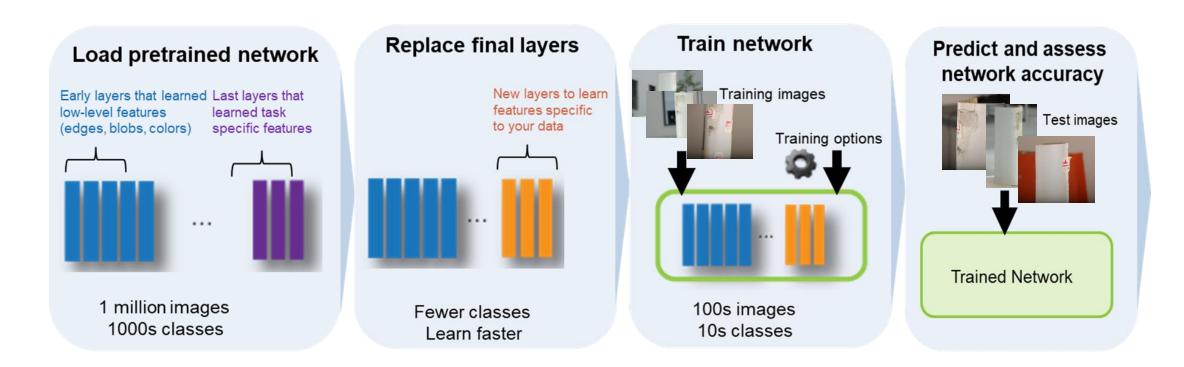
DEPLOY

# **Neural Network = Model**

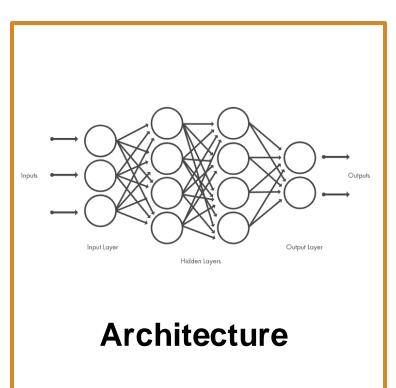
- Designing the architecture
- Training and validating the model
- Tuning training options

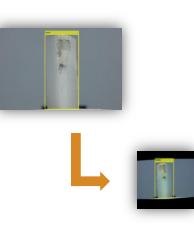


#### **Transfer learning**

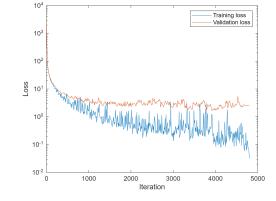


#### Solving the cropping sub-problem





Data Augmentation

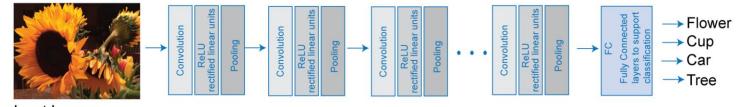


**Train & Evaluate** 

#### Architecture

**Classification** 

#### **Convolutional Neural Networks**



Input Image

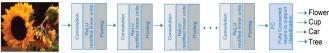
#### Architecture

**Anomaly Detection** 

#### Encoder Decoder $\bigcirc$ ENCODING 256 features $\bigcirc$ Dense $\bigcirc$ Dense Dense connections connections connections О $\bigcirc$ connections connections • connections • : . Dense Dense Dense $\bigcirc$ $\bigcirc$ $\cap$ $\bigcirc$ Hidden layer (2) $\bigcirc$ 512 neurons Hidden layer (1) 1024 neurons Input image Output (Input image reconstructed)

**Deep Autoencoder** 

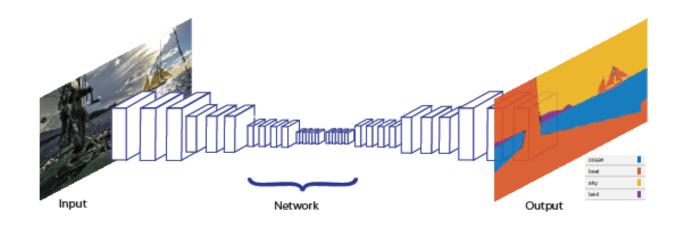
#### **Convolutional Neural Networks**



#### Architecture

**Image Segmentation** 

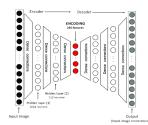
#### **Semantic Segmentation Network**



#### **Convolutional Neural Networks**



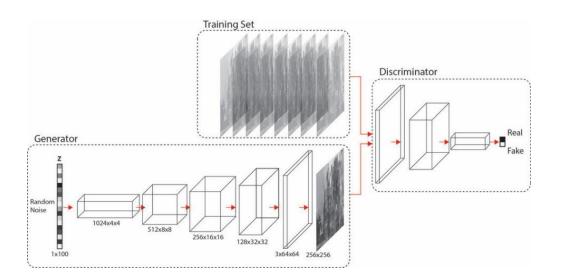
#### **Deep Autoencoder**



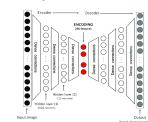
### Architecture

**Denoising, Synthetic data generation** 

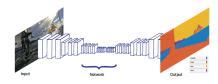
#### **Generative Adversarial Network (GAN)**



Deep Autoencoder



#### **Semantic Segmentation Network**

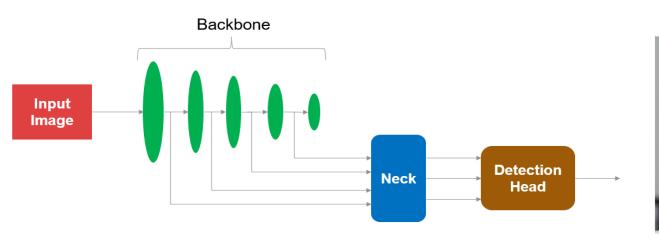


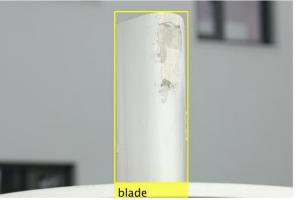
**Convolutional Neural Networks** 

#### Architecture

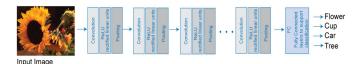
**Object Detection** 

#### YOLO – You Only Look Once

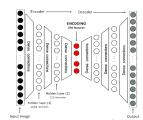




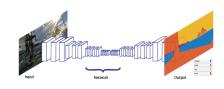
#### **Convolutional Neural Networks**



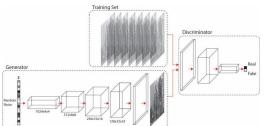
#### **Deep Autoencoder**



#### Semantic Segmentation Network

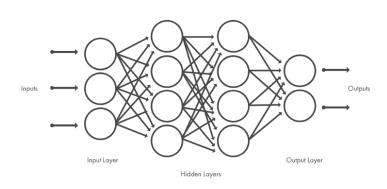


#### Generative Adversarial Network (GAN)

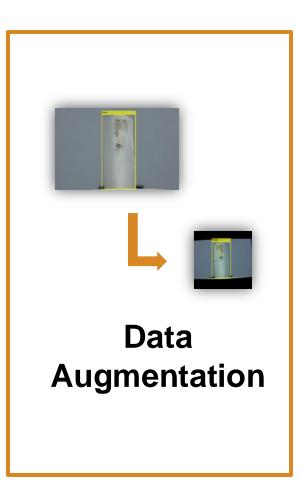


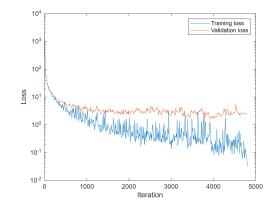
MATLAB EXPO

## Solving the cropping sub-problem



Architecture





**Train & Evaluate** 

## Importing the data





img = imread("2C8A0207.JPG"); imshow(img)

#### Image read

#### Scaling this up?

### Importing the data and data augmentation



f = figure(); img = imread("2C8A0207.JPG"); imshow(img)

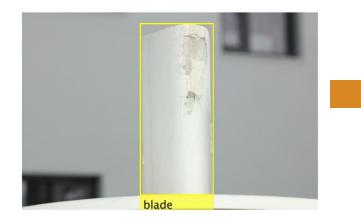
Image read

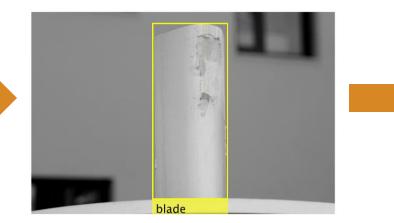




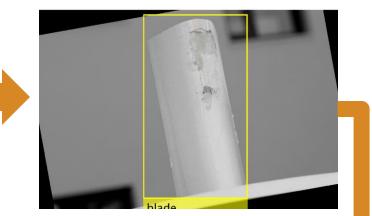
#### **Datastores**

#### Data Augmentation

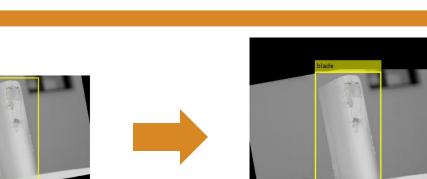




jitterColorHSV



randomAffine2d + imwarp

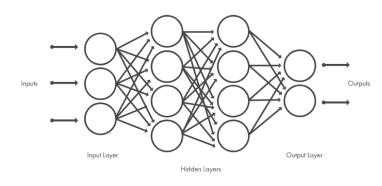




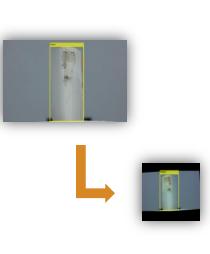
imresize

padarray

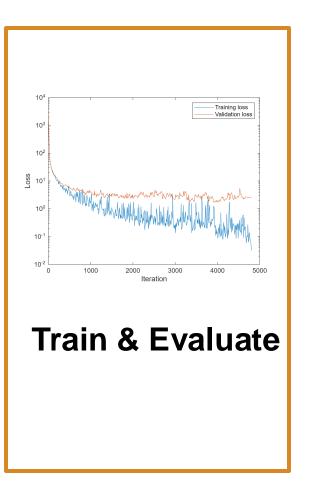
## Solving the cropping sub-problem



Architecture



Data Augmentation



# Training and evaluation

70

2

00.01.06

13	<pre>detector = yolov40bjectDetector("tiny-yolov4-coco","blade",anchorBoxes,InputSize=inputSize);</pre>							
44	options =	trainingOpt	ions("adam",					
45		tialLearnRate=0.001,						
46		MiniBatchSize=4,						
47	MaxEpochs=200,							
48								
	Shuffle="every-epoch",							
49	ValidationData=valDS);							
	Computing Input Normalization Statistics. ************************************							
	Epoch	Iteration	TimeElapsed	LearnRate	TrainingLoss	ValidationLoss		
	1	1	00:00:11	0.001	2407.7	2746		
	1	10	00:00:44	0.001	504.49	432.31		
	1	20	00:01:18	0.001	144.33	138.46		
	2	30	00:01:52	0.001	76.456	75.908		
	2	40	00:02:27	0.001	48.541	51.499		
	3	50	00:02:59	0.001	39.563	40.005		
	3	60	00:03:32	0.001	32.804	33.864		

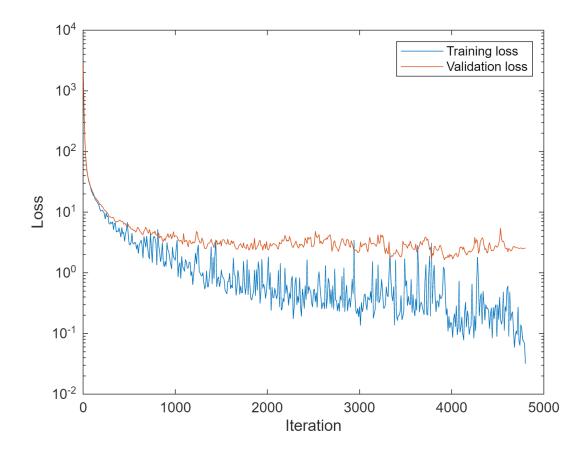
0 001

20 251

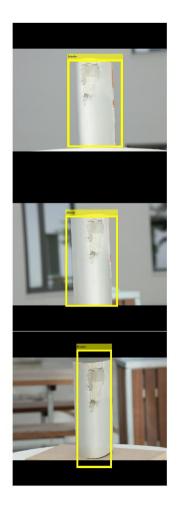
20 126

MATLAB EXPO

## Training and evaluation









# Take-Home Messages

## **Control your data gathering environment**







**Importing Data** 

**Crop to Blade** 

Detect Damaged Area

#### Classical image processing and deep learning can be complementary

	Classical Image Processing	Deep Learning	
Data Requirements	Low	High	
Data Labelling	Not required	Algorithm / workflow dependent <i>Time consuming</i>	
Algorithm Development	Potentially complex	Learnt from data	
Anomalies	Must account for manually Likely to be missed once deployed	Learnt from data Depends on algorithm	
Explainability	Complete	Low by default Tools exist to improve	
Execution Speed	High	Slow Specialized hardware can improve	

## Onramps - Learn the basics in 2 hours or less



#### Image Processing Onramp

2 hours | Languages Learn the basics of practical image processing techniques in MATLAB.



#### **Computer Vision Onramp**

1.5 hoursLanguagesLearn the basics of computer vision to design an object detector and tracker.



#### Machine Learning Onramp

2 hours Languages

Learn the basics of practical machine learning methods for classification problems.



#### **Deep Learning Onramp**

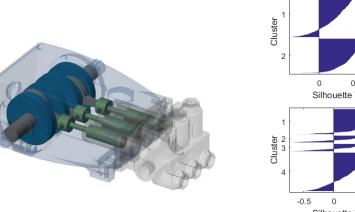
2 hours Languages Get started quickly using deep learning methods to perform image recognition.

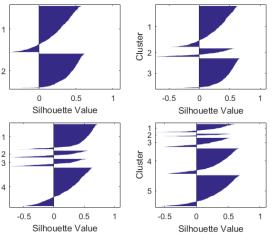
## Training Course: Predictive Maintenance with MATLAB

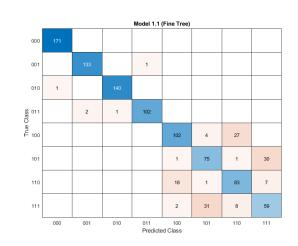
Topics included in this 2-day course:

- Importing and organizing data
- Creating custom visualizations
- Fault Detection/Classification
- Preprocessing to improve data quality, and extract time and frequency domain features
- Estimating Remaining Useful Life (RUL)
- Interactive workflows with apps











### **Achieve Results Faster with Predictive Maintenance Consulting**

Our expert consultants can help you with the entire predictive maintenance workflow: Data Preprocessing, Exploratory Analysis, Predictive Modeling, and Operational Deployment



#### Transparent Approach

You will have full access to all our work throughout your project. Your self-sufficiency is our goal.



#### Customized Engagements

We'll work with you on a customized project plan aligned to your business goals.



#### Return on Investment

Reduce development time and cost, learn faster, and improve quality and collaboration.

Request a free consultation: <u>www.mathworks.com/pmp</u>

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