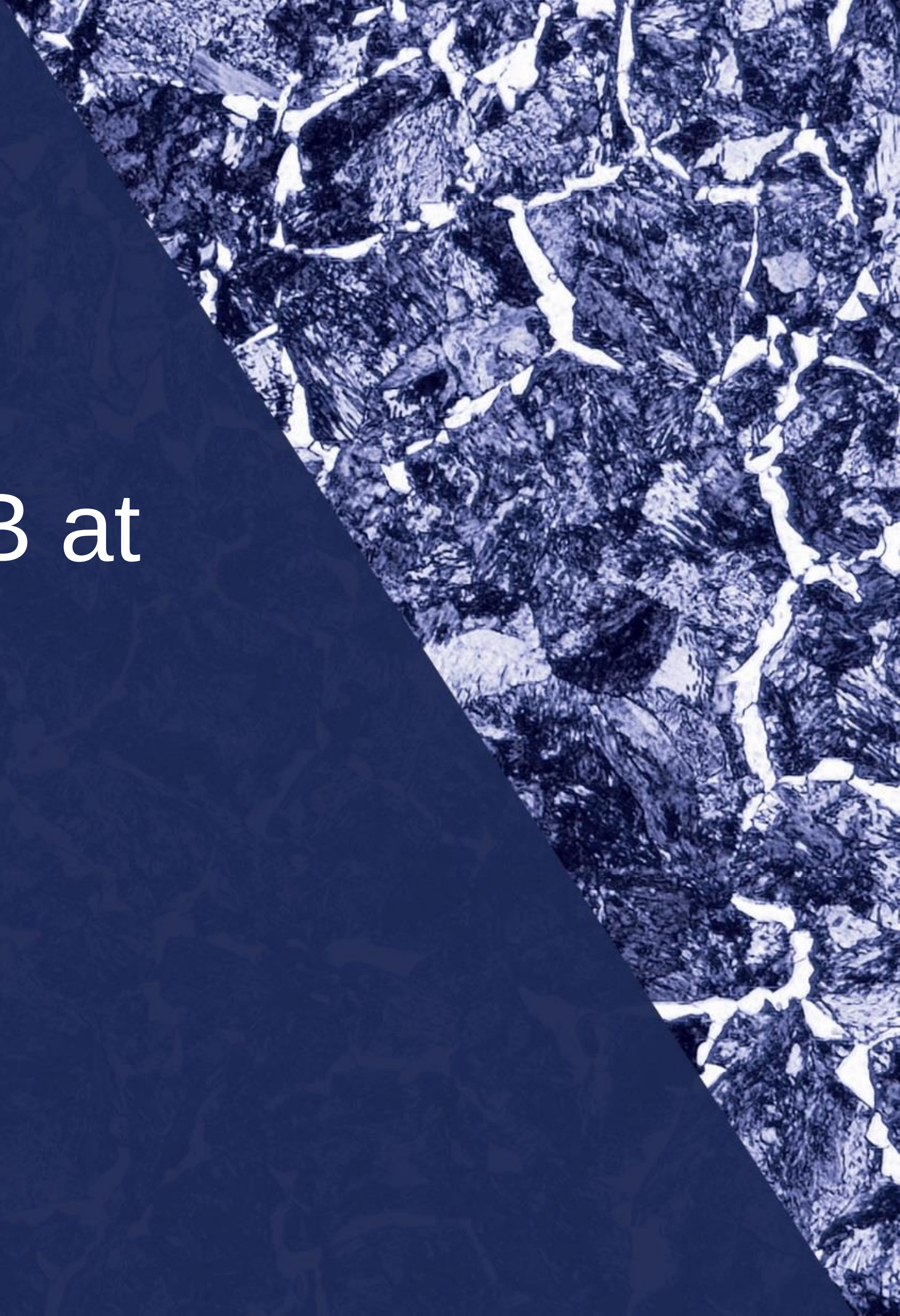
Machine Learning with MATLAB at TimkenSteel

-Marc Harris



TimkenSteel

TimkenSteel Background

- Manufacturing as a whole is moving towards “Industry 4.0”
  - Data science driven predictions / decisions / automation facilitated by machine learning and optimization algorithms
- Steel industry adoption of machine learning solutions is spreading fast
- TimkenSteel adoption company-wide is focused on low capital cost fast deployment systems for:
  - Image based steel inspection facilitated by machine learning
  - Big data interpretation for process performance optimization
    - Reducing defects
    - Maximizing throughput
  - Increased automation
    - Reduced man-hours per ton
  - Capability improvements
    - New alloy development
    - Tighter process control

TimkenSteel Image Processing Projects

- Non-metallic inclusion image interpretation
  - Human-level image interpretation
  - Automation of analysis
    - Faster throughput
    - Reduction in man-hours per analysis
    - Consistency
- Pin Stamp Reader
  - Automation of ID check process
  - Reduction in man-hours per ton of steel
- MATLAB Toolboxes Used
  - Image Processing Toolbox
  - Parallel Computing Toolbox
  - Deep Learning Toolbox
  - Computer Vision Toolbox

Automated Inclusion Classification

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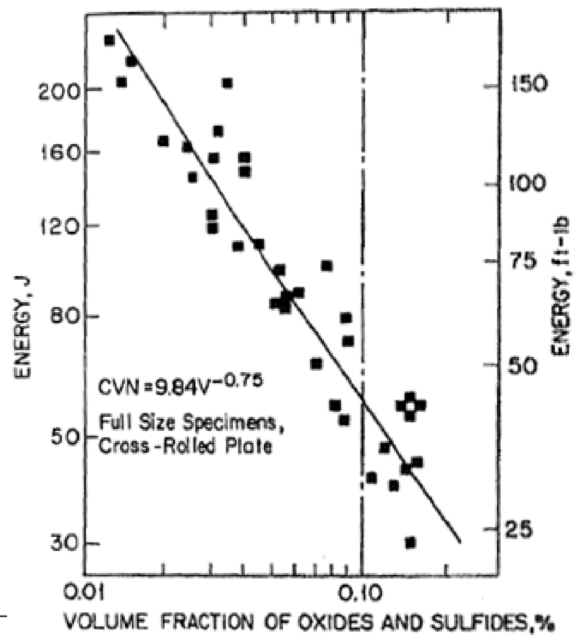
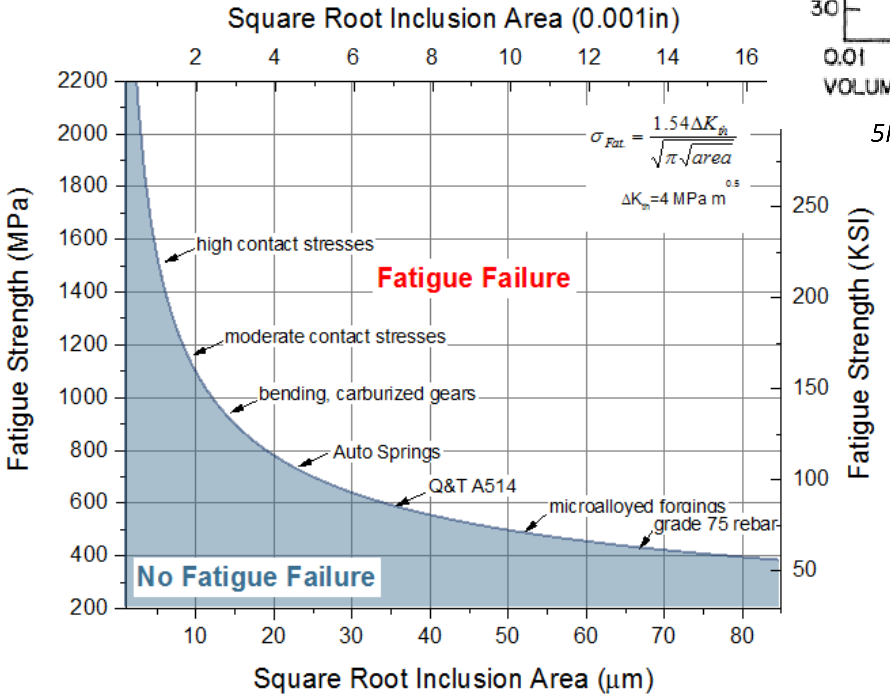
Steel Cleanness Background

- What is steel cleanness?
  - Presence of <u>non-metallic inclusions</u> formed thermodynamically in steel melt or through physical entrapment during melt processing
  - Size, shape, quantity, location, and chemistry are all aspects of “cleanness”
- Why do we care about steel cleanness?
  - Performance and quality are driven in large part by inclusion population
    - Cleaner steel = lighter weight for given load or more horsepower for given design
  - TimkenSteel specializes in producing extremely clean air melted steel
    - Requires focused measurement of cleanness and complete evaluation



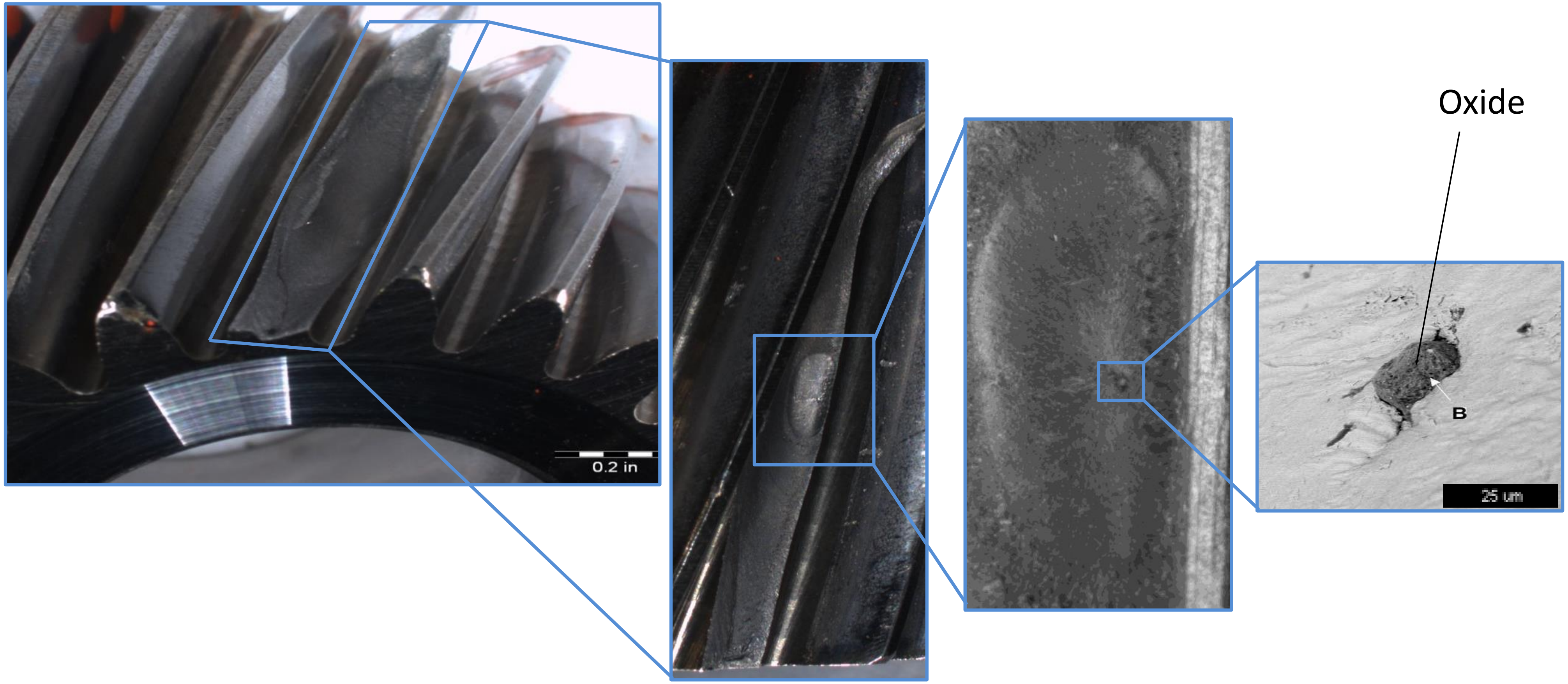
5Ni-Cr-Mo-V Q&T Steel, Leslie, 1982



Damm– The effects of Non-Metallic Inclusions on Mechanical Properties and Performance of Steel

Real World Consequences of “Dirty” Steel

- Fatigue applications such as automotive gears are highly sensitive to the inclusion content in the steel
  - Example below shows a ~20um sized inclusion causing a gear tooth failure

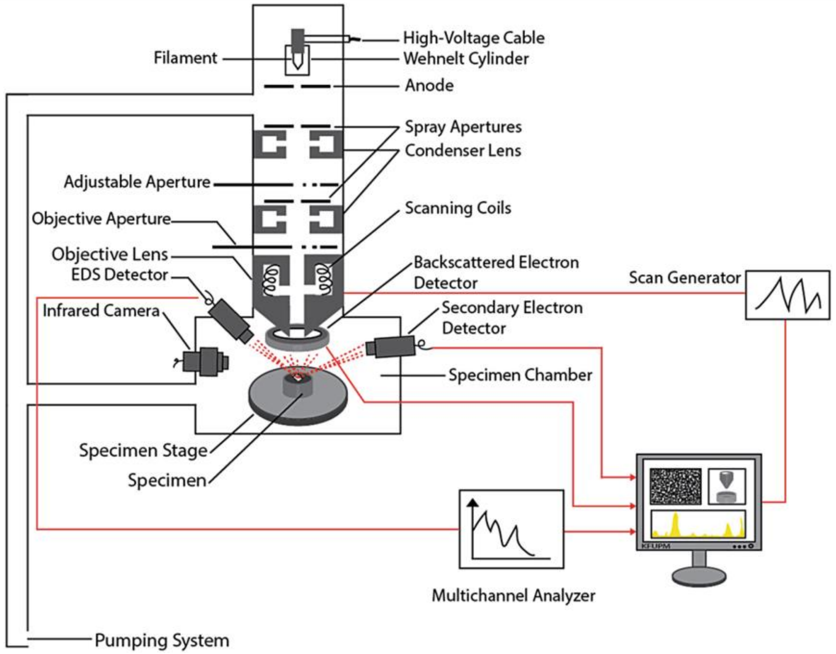


Measurement System Background

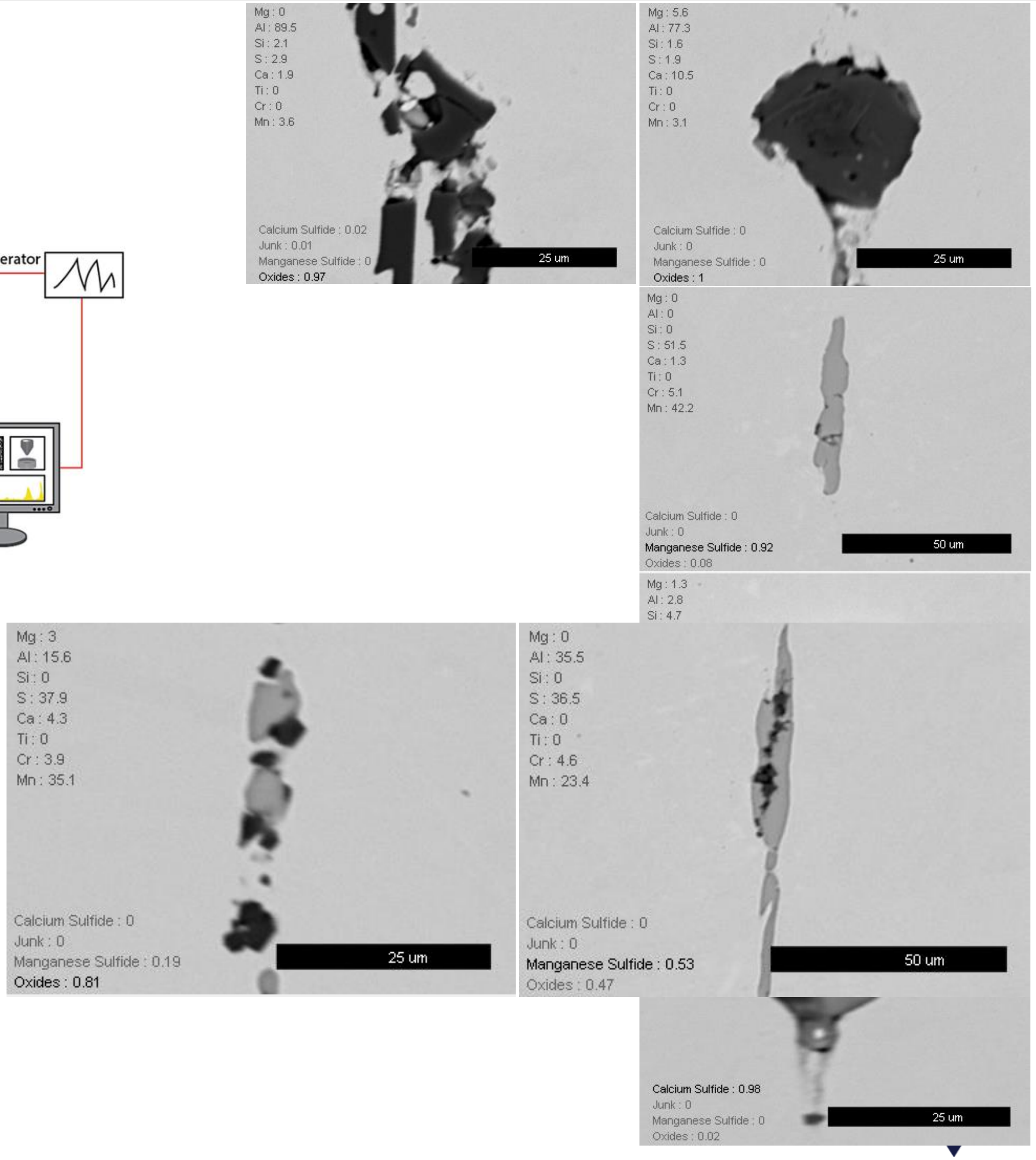
- Steel cleanness measurement system is automated, analysis is not (yet)
  - Steel is polished to 1um finish
  - Sample is placed into an automated scanning electron microscope with energy dispersive spectroscopy
  - Sample is scanned automatically for every single inclusion >1um in size and a chemistry measured
    - Additionally coordinates, shape statistics, and other details are measured
    - Images are captured of each inclusion (1 scan = 1000’s of images, one steel analysis = 32 scans)
  - Resulting dataset is evaluated using in-house software (MATLAB)
  - Engineer or trained technician has to evaluate 100’s of large sized inclusion images to confirm type and remove potential contaminants that were detected from the analysis
    - 1 analysis of a steel takes 20-40 minutes depending on how many inclusions are present
    - Very manual process and can be a judgement call in some cases

Measurement System Background

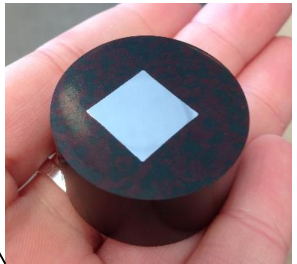
ASPEX – Automated SEM/EDS System



SEM - EDS

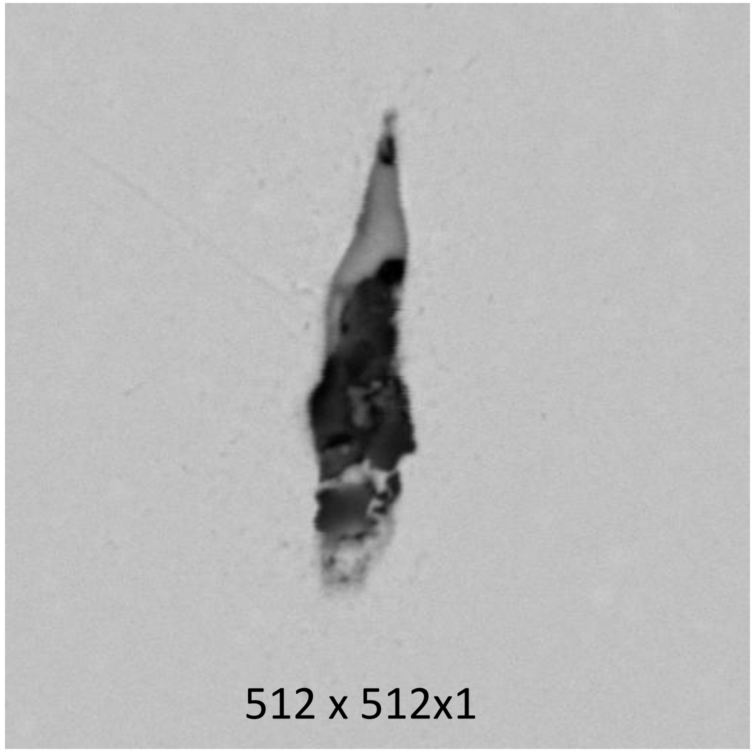


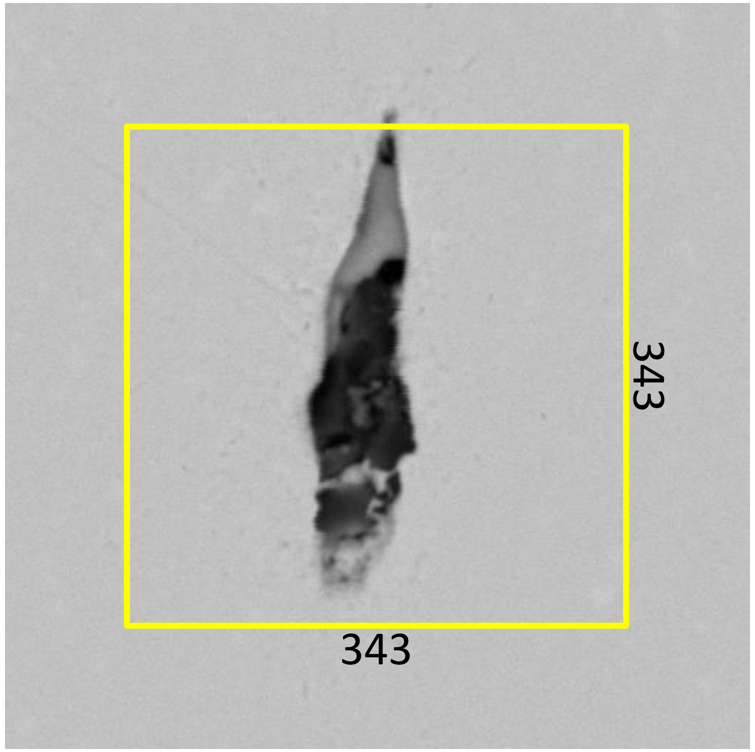
Polished Steel



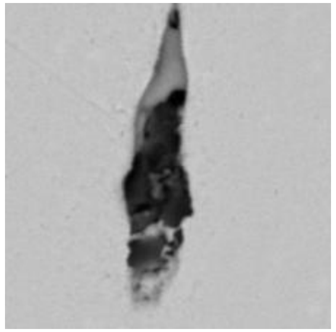
Training Process

- Raw Images resolution of 512x512 with inclusion of interest centered
  - Center crop of 2/3
  - Image resizing to 224x224
- Data augmentation
  - Random rotations from -90 to +90 degrees
  - Random brightness adjustment from -5% to +5%
  - No contrast adjustment due to calibration before each scan
- Training Method
  - Stochastic gradient descent with momentum
  - Mini-batch size of 12, 60 epochs, learning rate drop factor of 0.95 per epoch, validation set per 50 iterations

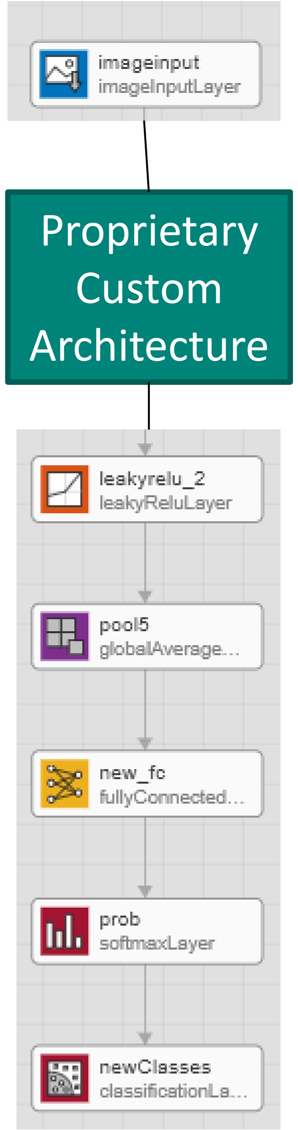




Resized using bicubic interpolation



224x224x1



Accuracy & Speed Testing Results

- Overall accuracy achieved of 93%
  - Human performance ~92-94%
    - Measured by taking repeated manual categorizing of same images randomly shuffled 1 week later
    - Vast majority of error in discerning CaS from Oxides and deciding final category for complex MnS-Oxide inclusions
  - Greatest error on easy to confuse CaS category
  - Accuracy for Oxides and MnS matches human specialist performance
  - Accuracy on discerning surface contaminants close to human but some further work to achieve 95%+ is in process
    - Human accuracy for discerning surface contaminants using randomly shuffled 1 week time lapse test was ~97%
- Speed of 0.012s / image achieved (~3-10 minutes per analysis)
  - Average technician/engineer takes ~2-3 seconds/image
  - System fully automated
  - Completely consistent (human fluctuation and variance does not impact or confound cleanness results)

<u>Training Image Count Breakdown</u>

Junk: 261
Oxides: 350
MnS: 364
CaS: 212

Training + Test Set Confusion Matrix

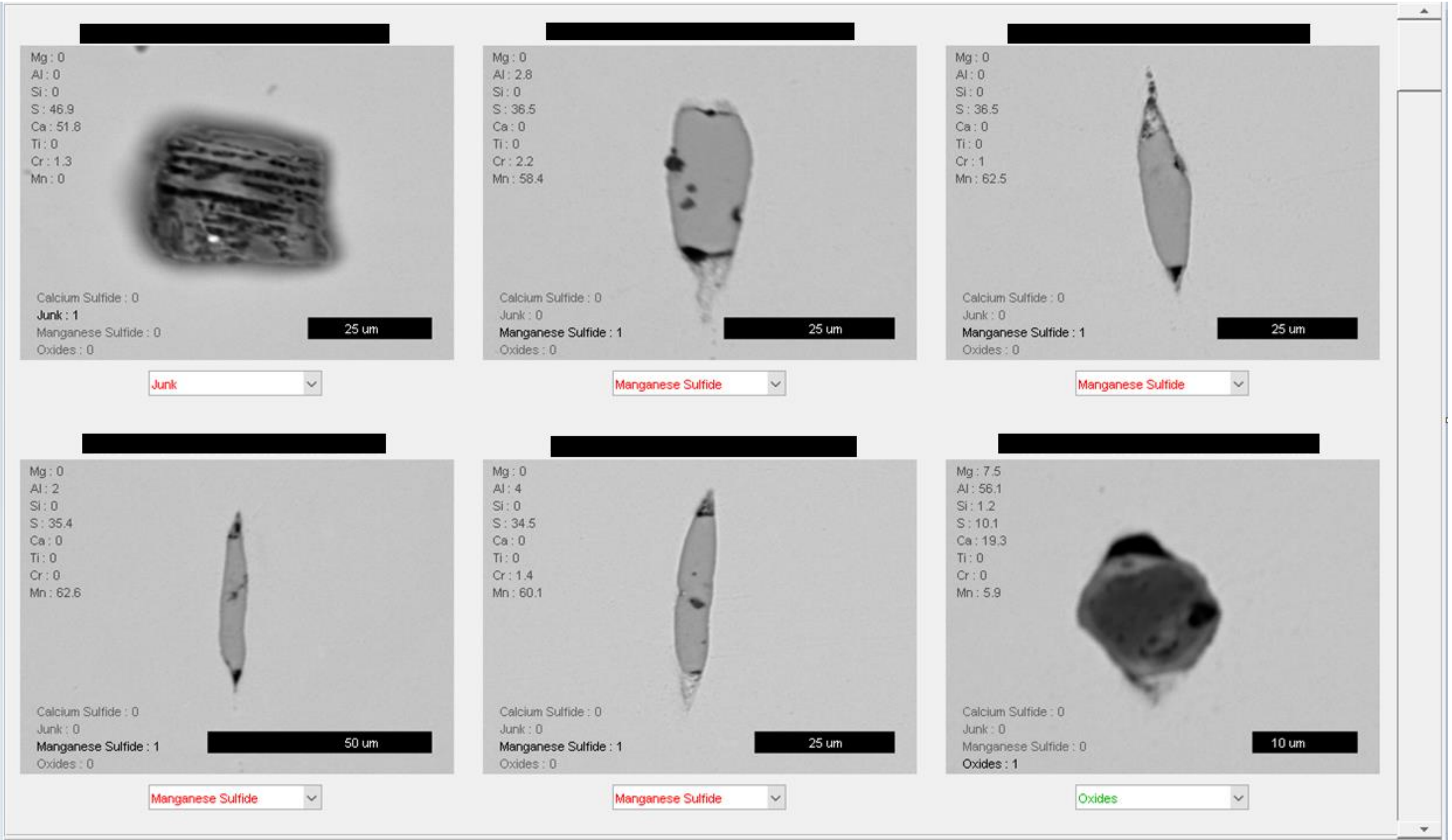
Actual \ Pred.	Junk	Oxides	Manganese Sulfide	Calcium Sulfide
Junk	273	8	6	7
Oxides	22	1700	87	53
Manganese Sulfide	7	81	2405	37
Calcium Sulfide	2	25	9	203

If Model says X, what is the probability that is true?

Model Prediction	Accuracy
Junk	89.8%
Oxides	93.7%
MnS	95.9%
CaS	67.7%
Anything	93.0%

Final Result for User

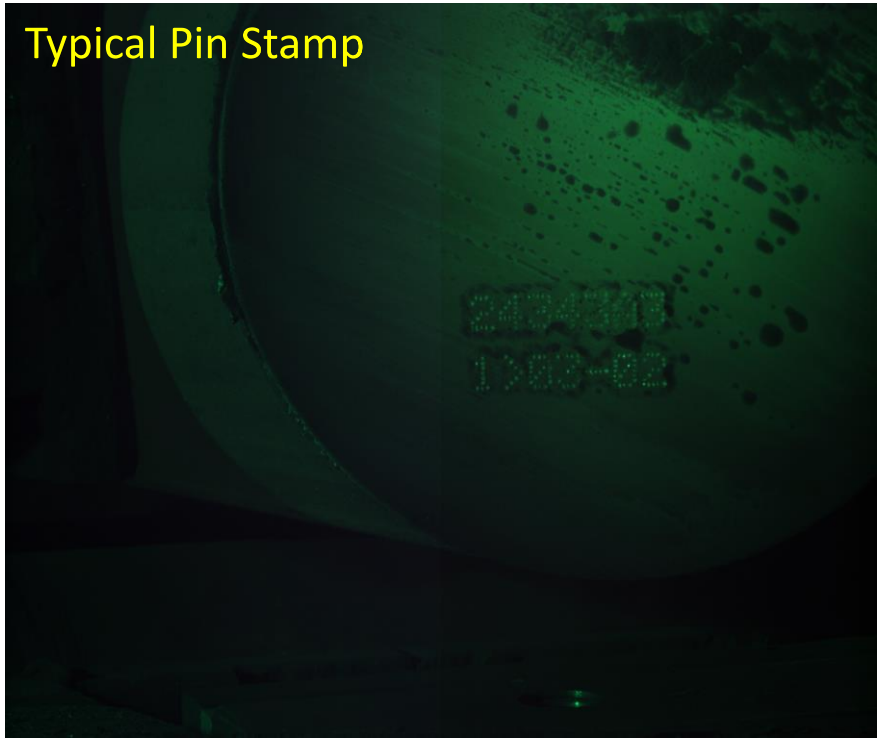
- Practically invisible to user – auto classification
  - Analysis is practically a button press
  - Human engineer/specialist accuracy



Pin Stamp Reader (in process)

Background

- All steel must be tracked + double checked to ensure no product mixes occur or can occur
  - Product mix is when a "mix up" happens causing a different steel grade/size/order to be processed incorrectly as a result
  - Rare but very costly mistake
- Current method is human double checking a pin-stamp + piece tracking software system
- Automating this process would alleviate tens of thousands of dollars in man-hours



Typical Pin Stamp

Initial Failure with Simple Crop-Scan-Classification Approach

- Initial attempt was using Resnet101 and sliding crop window
  - Crop -> Forward pass -> Crop Scan -> Forward Pass process took 15 seconds for ~50% accuracy of centering pin stamp
  - Further analysis using pre-spaced crop windows (see right) resulted in overall accuracy <20% due to crop misalignment
    - Balancing drastic speed reduction versus accuracy – must maintain <10 second pace per image
    - Reducing step size improved accuracy but drove computation time to minutes
- Determined best solution is YOLOv2 version of convolutional neural net for pre-crop system

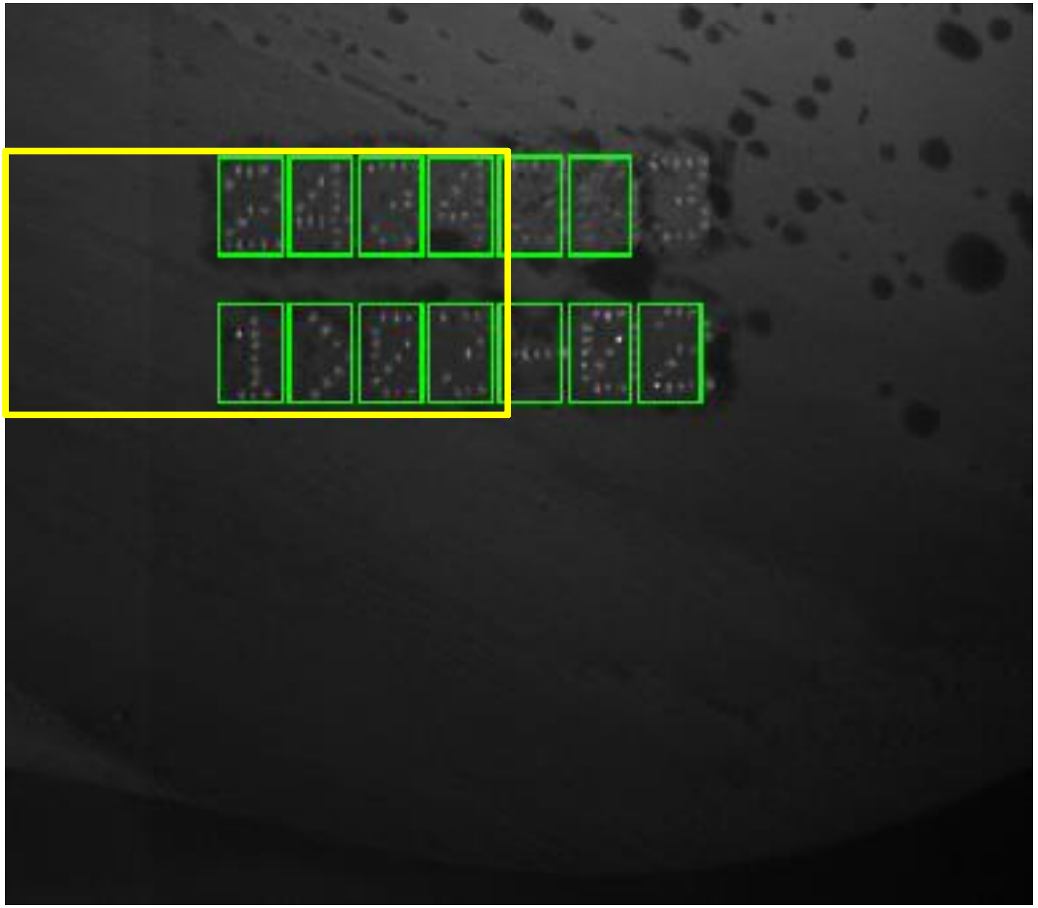
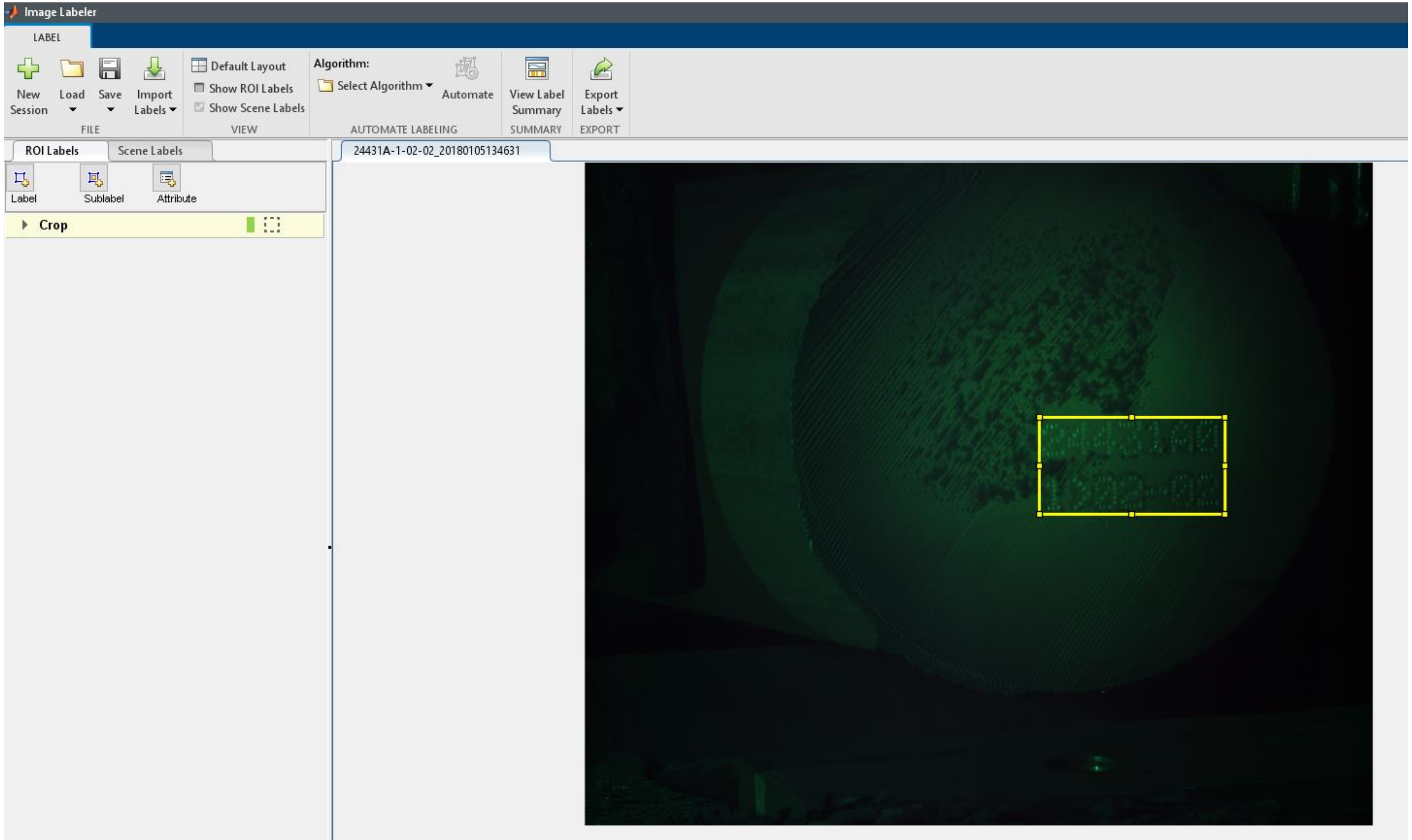


Image Labeling – YOLOv2 CNN

- Training dataset created by manually drawing bounding box of each object of interest
  - In the case of initial cropping just a centered section of the pin-stamp

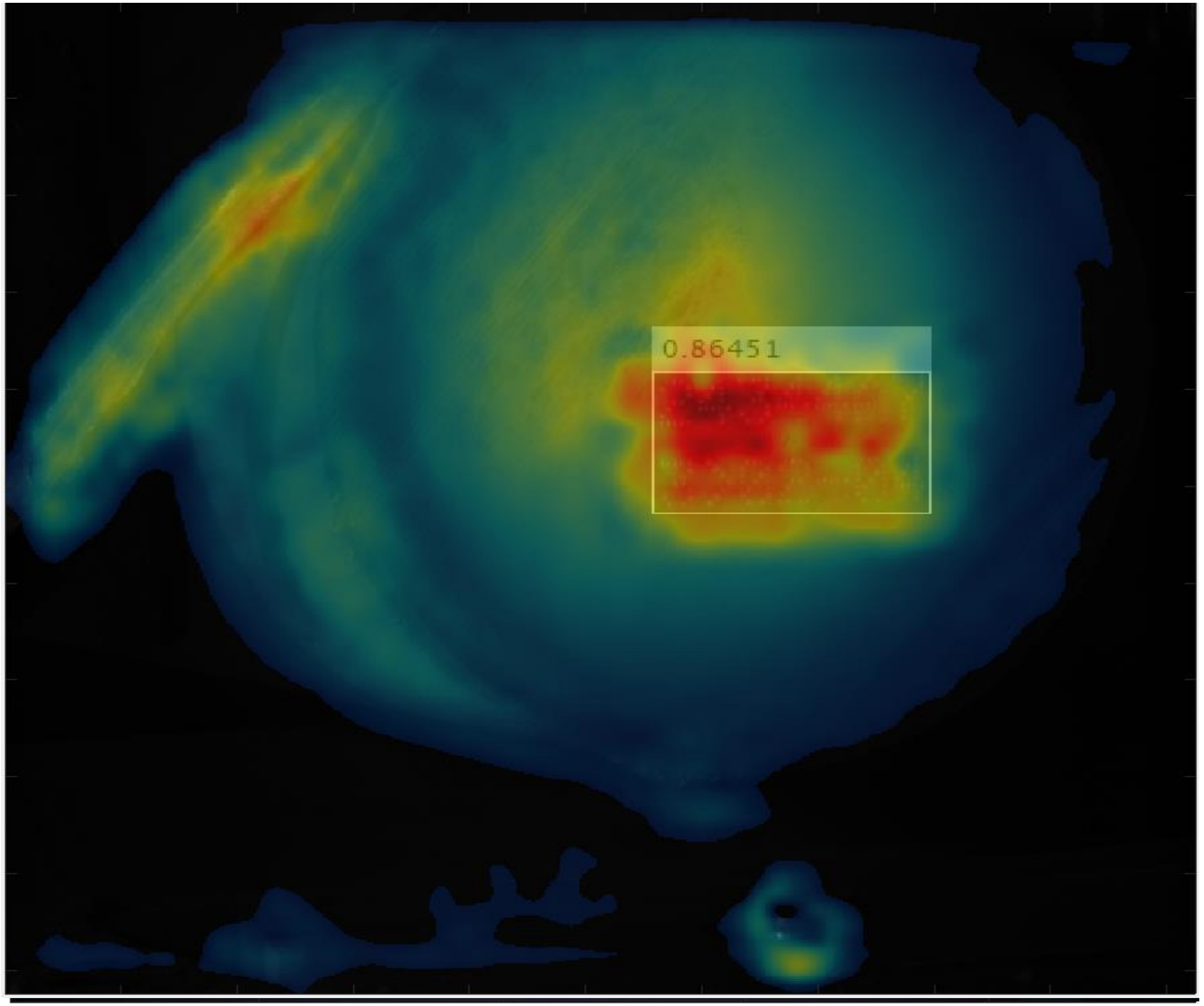


Training Process

- Training set was 168 images
  - Raw image resolution 2432x2050
  - Resized to 512x512
- CNN architecture was 25 layer YOLOv2
- Training was performed using stochastic gradient descent with piecewise learning rate reduction
- Data augmentation was used to reduce overfitting
  - Brightness +/- 40%
  - Contrast +/- 40%
  - Saturation +/- 10%
  - No reflections, +/- 10% scale, +/- 100 pixel translation in any direction, +/- 2 degree rotation

Results on Test Set

- 145/286 test images (never seen before) were *perfectly* cropped
  - 51% accuracy in 0.1-0.2 second run time
- 141/286 test images incorrectly cropped
  - 138 properly sized and existing on image
  - 70 images off by only 1-2 digits in horizontal direction
  - 30-40 images extremely noisy or vastly different from training dataset
    - No Expectation for success (not even for human)
    - To be retrained mixing in some more noisy images
  - 33 images were truly errored (11.5% error)
- Available dataset is >10,000 images
  - Future work is expanding training dataset for more variance



Future Work – Pin Stamper

- YOLOv2 system had <1 week turnaround from learning to use Matlab module to a working model & surpassed previous record performance with only 168 training images
  - Retrain using larger dataset
  - Include more variance in training set to account for noise
  - Experiment with architecture for improved accuracy/speed ratio

Deployment

Two Methods Used

- MATLAB Compile to .NET dll
  - Advantages
    - Fully contained pre-processing and model interpretation
    - Ease of deployment
  - Disadvantage
    - Memory usage / speed
    - MATLAB run time .dll requirements
    - Cross platform compatibility
- Export to ONNX (consumed in C#)
  - Advantages
    - Widely used system that is recognized in large variety of languages from c# to python
    - Model upkeep/translation in practically any common language is easy
    - Generalized deployment minimizes any code refactoring
  - Disadvantage
    - More difficult initial deployment code
      - Only a one time hit since generalized .ONNX model interpretation automatically handles variety of models types/shapes/sizes

Conclusions

- TimkenSteel has seen several benefits from adopting a machine learning approach to numerous problems
  - Rapid alloy development surpassing known mechanical properties
  - Automation of previously manual processes saving cost on man-hours
  - Faster throughput in manufacturing processes through optimization
  - “Free” steel inspection using only already-existing cameras with deep learning
- MATLAB provides a rapid-prototyping and development platform that makes deep learning/image processing simple
  - Speed of idea to finished model is magnitudes faster than the organization of the data itself
    - First deep learning system took 4 days to learn, produce, and have an accurate model
    - Subsequent systems have been more complex and expanding our capabilities with very little time needed for actually creating/training the CNN
  - Other systems not as user-friendly, slower to develop, and non-visual
    - Have looked at python, ML.net, and TensorFlow

Thank you!

Questions?

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