Leading the Charge in Steel Industry Applications of Artificial Intelligence and Machine Learning:

ArcelorMittal

ArcelorMittal Use-Case Examples

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Presentation at the Machine Learning for Industry Forum 2021 (ML_4I 2021)
August 10-12, 2021

ML_4I

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Presentation Outline

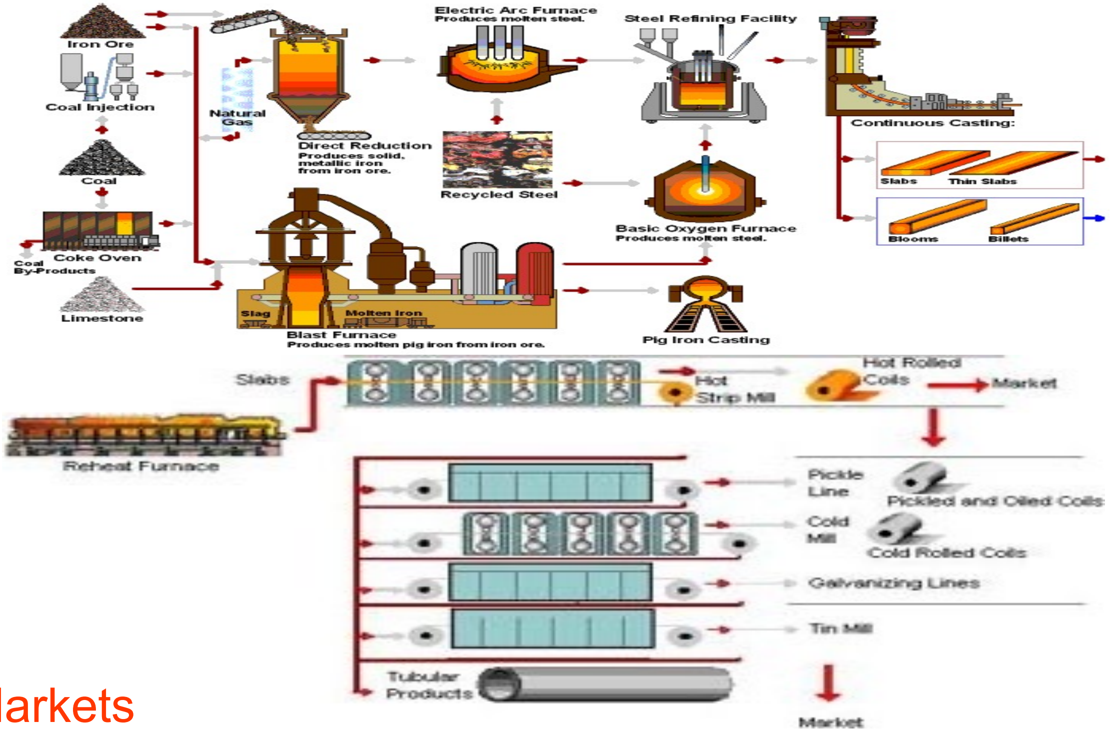
- ArcelorMittal Introduction
- Digital Transformation
- Recent ML use-case examples at ArcelorMittal
- Specific ML use-case examples:
  - Clogging prediction in steel continuous casting
  - Calvert #1HDGL Primetals Automated Surface Inspection System (ASIS) Deployment
- Summary/Conclusions

ArcelorMittal Introduction

World's leading steel and mining company (>190K employees with presence in more than 60 countries, industrial footprint in 18 countries and steel products shipment of 84.5 million tons in 2019)

- A leader in a wide range of steel manufacturing processes from raw materials processing to finishing lines
- Supplier of high-quality products for all major markets (automotive, construction, appliances, packaging, energy etc)
- Guided by a philosophy to produce safe, sustainable steel with commitment to carbon-neutrality by 2050

Processes



Markets

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ArcelorMittal Digital Transformation

Fully committed to a total digital transformation:

- Global platforms (Big Data, IIoT, Deep Learning developments);
- Manufacturing digitalization (Safety, Production, Quality and Maintenance);
- Business digitalization (Procurement, Commercial, Supply Chain, Strategy, Finance) and
- Digital-ready workforce development
- External partnerships (collaborations with vendors, universities, consortia, private and government agencies)

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ML use-case examples at ArcelorMittal

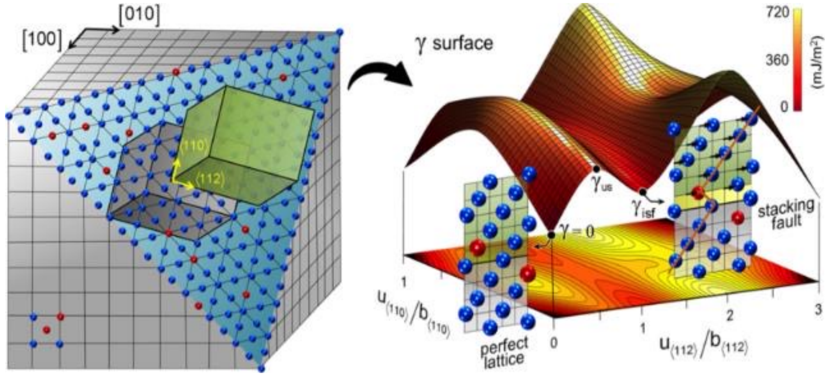
Accelerated Product Development of Next Gen AHSS

Goal: Establish a rational methodology for rapid product development of lightweight 3G AHSS via the application of High-Performance Computing (HPC) for physics-based simulations, combined with data-driven AI/machine learning techniques.

Description: This project would specifically focus on a comparative study of a promising 3G AHSS alloy family: The Fe-Mn-Al based alloy system

Technology: A combination of physics-based modeling and ML. The physics-based part utilizes both a Monte-Carlo Density Functional Theory (MC-DFT) to quantify the compositional dependency on the Generalized Stacking Fault (GSF) energy and Dislocation Dynamics (DD) to predict the bulk mechanical behavior of these AHSS steels. Machine learning is applied to the MC-DFT process to expedite the time-consuming calculations and cover a wider range of chemistry.

Results: Project is ongoing. When completed, this project would be the first end-to-end industrial implementation of any HPC & AI-driven product development workflow for the metal industry



Example of GSF surface by Choudhury et al. [J. Engg. Mat. Tech., Apr 2018, p. 020801]

Ongoing collaboration with LLNL, ANL, PNW and ArcelorMittal. Budget: $300,000 Total, $75000 ArcelorMittal Cost Share. Co-PIs: Brian Lin (ArcelorMittal R&D), Dr. Amit Samanta (LLNL), Dr. Sylvie Aubry (LLNL), Dr. Prasanna Balaprakash (Argonne National Laboratory). Start and end dates – March 2021 to 2022:

ML4I HPC4 ENERGY INNOVATION Lawrence Livermore National Laboratory Argonne NATIONAL LABORATORY ArcelorMittal

ML use-case examples at ArcelorMittal

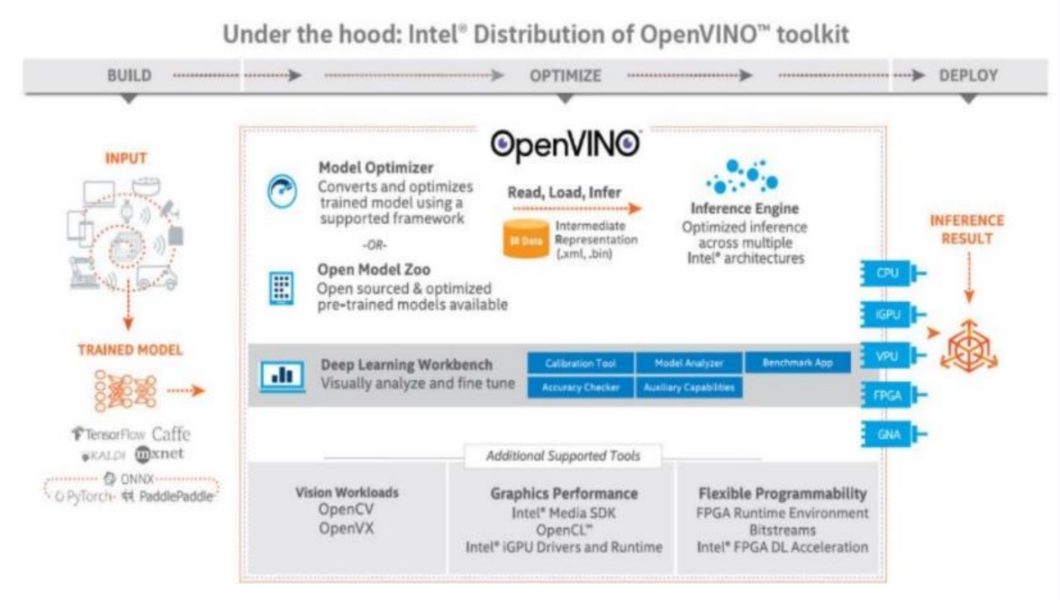
AI-Enhanced Railway Transportation

Goal: Leverage computer vision, deep learning, and near-real-time processing on the identification and recognition of railway cars throughout ArcelorMittal Poland in order to improve logistics efficiency

Description: Existing logistics used video technology to categorize and tag incoming cars, which was a time-consuming and tedious process. For example, there are several checkpoints located throughout the site where railway cars are weighed. Operators must be available 24/7 to tag the cars, which adds up to a large number of work hours.

Technology: Includes two cameras per checkpoint with the capacity to log critical pieces of data quickly and accurately and the ML algorithm, which is included in the Intel® Distribution of OpenVINO™ toolkit.

Results: Using the new technology frees up operators to focus on other important tasks.



Source: https://www.intel.com/content/www/us/en/customer-spotlight/stories/arcelormittal-customer-story.html

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ML use-case examples at ArcelorMittal

Ants Colony Optimization of Production Scheduling

Goal: Optimize production line-ups in ArcelorMittal plants ensuring maximum productivity and lowest cost

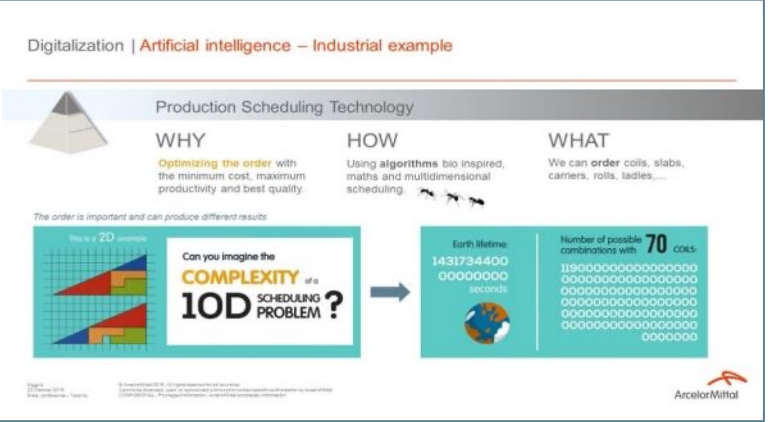
Description: Production scheduling in a steel plant is a complex multi-dimensional process that must consider customer orders, inventory, equipment availability, logistics and everything in between. Existing Production Scheduling systems have been inadequate in handling the multiplicity of parameters involved in production scheduling decisions making it necessary to develop a more robust generic algorithm for the steel plant.

Technology: ArcelorMittal Global R&D Asturias center adapted for industrial use, the Ant Colony Optimization algorithm concept (ACO), originally proposed by the Université Libre de Bruxelles (ULB) in an academic environment.

Results: New capability to produce an optimal production schedule in just a few minutes and achieving superior performance in energy and material intensity due to improved quality and higher productivity without significant investment

Features and Benefits:

- Currently deployed in multiple plants
- Easy to deploy
- Little effort from the plant side.
- Light and flexible, open to many different integration options.
- Suitable for any production line: CC, HSM, PIC, CAL, HDG, OC…
- Powerful search engine for a really difficult problem: billions of possible solutions even for a small sequence.



Source: https://corporate.arcelormittal.com/media/case-studies/artificial-intelligence-gleaned-from-ants-radically-improves-production-scheduling-1

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ML use-case examples at ArcelorMittal

IoT Condition Monitoring for Predictive Maintenance

Goal: Predict failure of HSM motors in order to perform predictive maintenance and avoid unplanned turnarounds

Description: Conventional method of vibration analysis to predict motor failure is unreliable as the sensors frequently fail due to hash working environment. Gent plant needed a more reliable method to accurately predict motor failures at the HSM.

Technology: Semiotic Lab's SAM4 AI-based predictive maintenance solution analyzes electrical waveforms from inside the electrical control cabinet far away from the motors.

Results: Detects over 90% of failures 5 months in advance. Prevents unplanned downtime, increases productivity, improves equipment reliability, reduces energy consumption

About SAM4

SAM4 is the Smart Condition Monitoring solution for AC induction motors and rotating equipment. SAM4 monitors equipment 24 / 7 and detects upcoming failures up to months in advance.

SAM4 consists of sensors, analytics and an online dashboard that offers real-time insights into the health, performance and energy consumption of connected assets.

SAM4 is provided as a Condition Monitoring service, based on a monthly subscription fee.

Source: https://www.youtube.com/watch?v=oS_PpyQWB90

ML use-case examples at ArcelorMittal

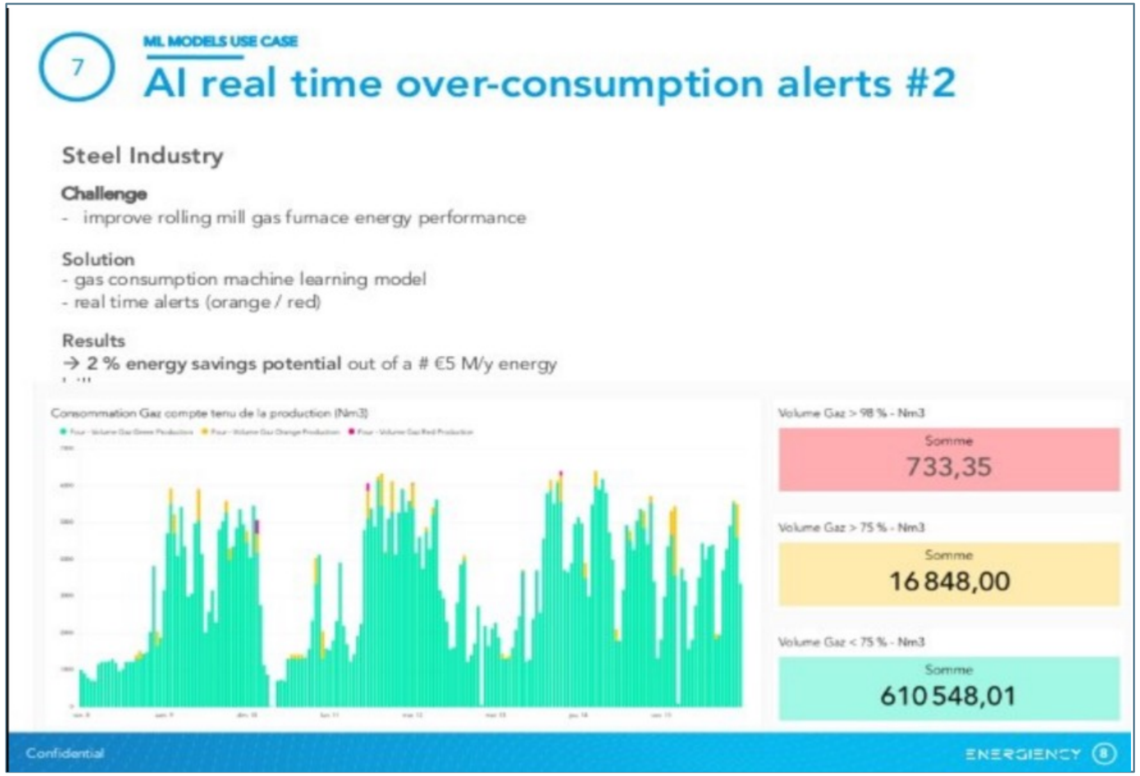
ML of HSM Gas Consumption

Goal: Improve the energy performance of the Rolling Mill Furnace at ArcelorMittal Belval plant

Description: This was a test case to see if machine learning could be used to model gas consumption based on different production parameters including the used material, layout, type, length, etc. The gas consumption accounted for €5M and needed to be reduced by applying ML methods.

Technology: ArcelorMittal partnered with Energiency to apply Big Data Analytics to process more than 1600 historical data streams from the furnace with a time step of 1 second over 1 year.

Results: The model achieved a reliability of 98% and over 3% (9 GWh) on annual energy savings, exceeding the initial objective of 2%.



Source: https://www.hannovermesse.de/apollo/hannover_messe_2021/obs/Binary/A1089178/Success%20Story%20ArcelorMittal%20Energiency%20ENG.pdf

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Clogging prediction in steel continuous casting

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Shu Yang, Andreas Rebmann and B. Wayne Bequette
For ML for Industry Forum, 10-12 August 2021

Acknowledgement: *This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Advanced Manufacturing Office Award Number DE-EE0007613.*

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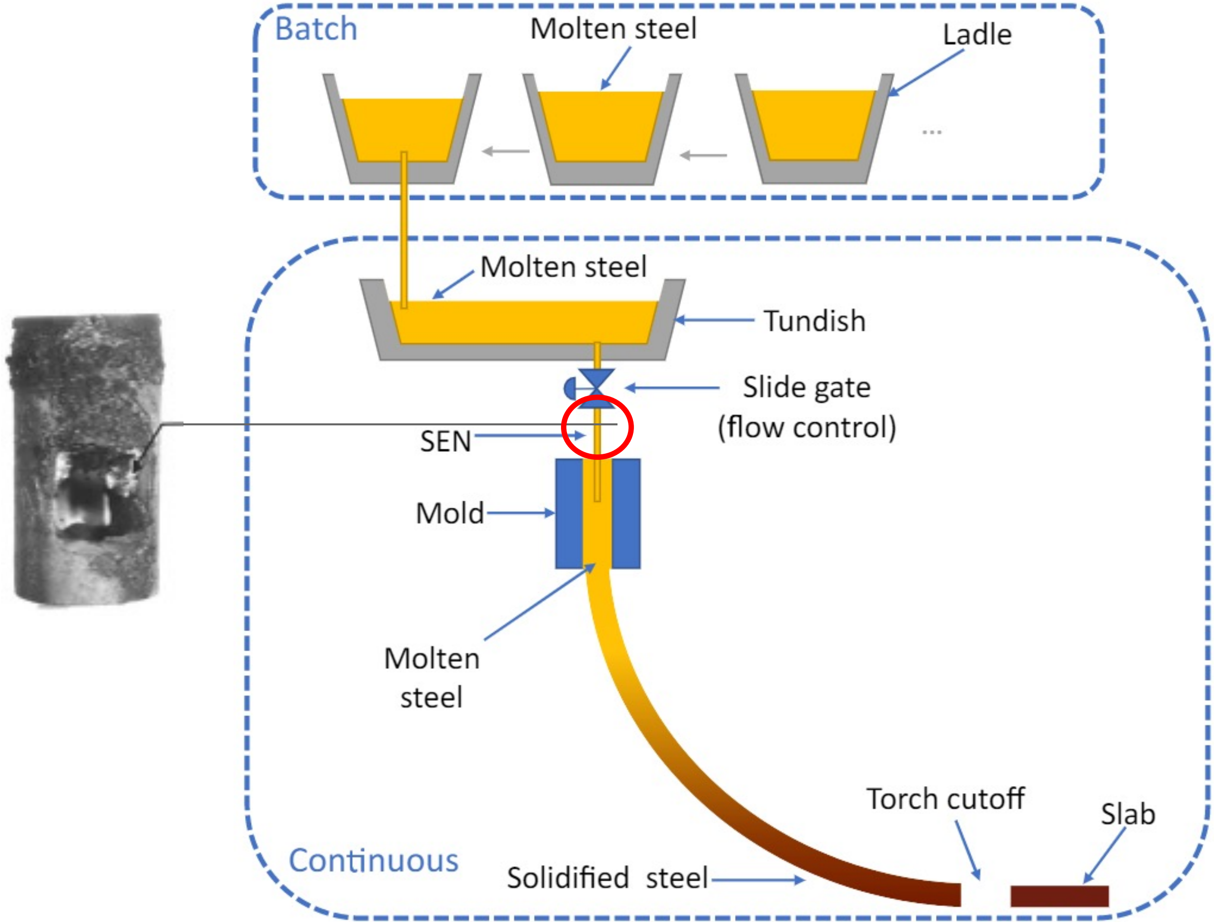
Background: Clogging

- Cause:
  - Solid particles building up in flow channel
- Consequences:
  - Unplanned downtime
  - Downstream defects
  - Safety hazard
- Objectives:
  - Predict fault (clogging) in advance (~10 min)
- Technical difficulties:
  - Harsh environment for instrumentation
  - High complexity for mechanistic modeling



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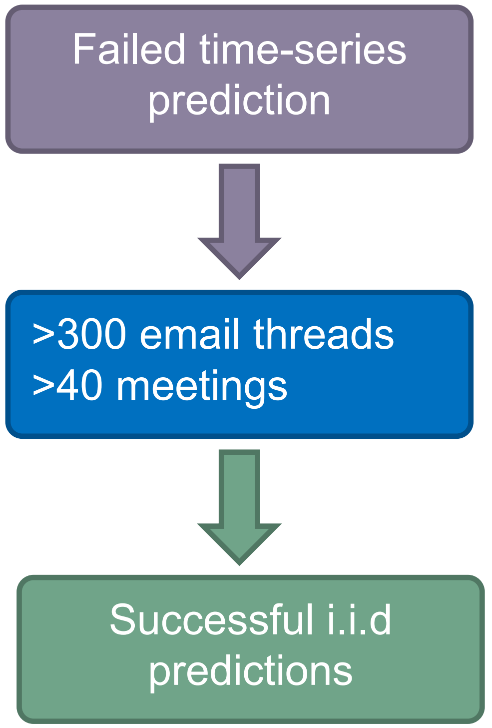
Major bottleneck: Contextualization

- Feature engineering
  - Complex physical mechanism
  - Complex production process
- Data preprocessing
  - Heterogeneous datasets
  - Unsynchronized sensor
  - Multi-modal
  - …
- Future:
  - CESMII Smart Manufacturing Innovation Platform™



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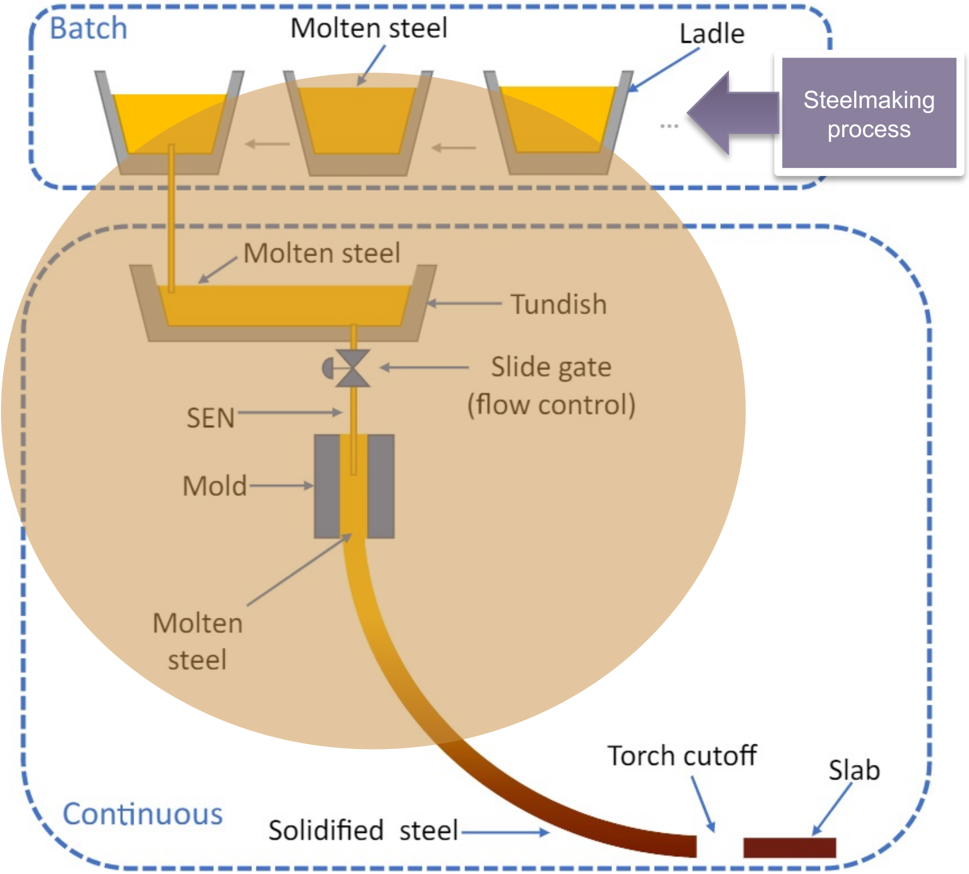
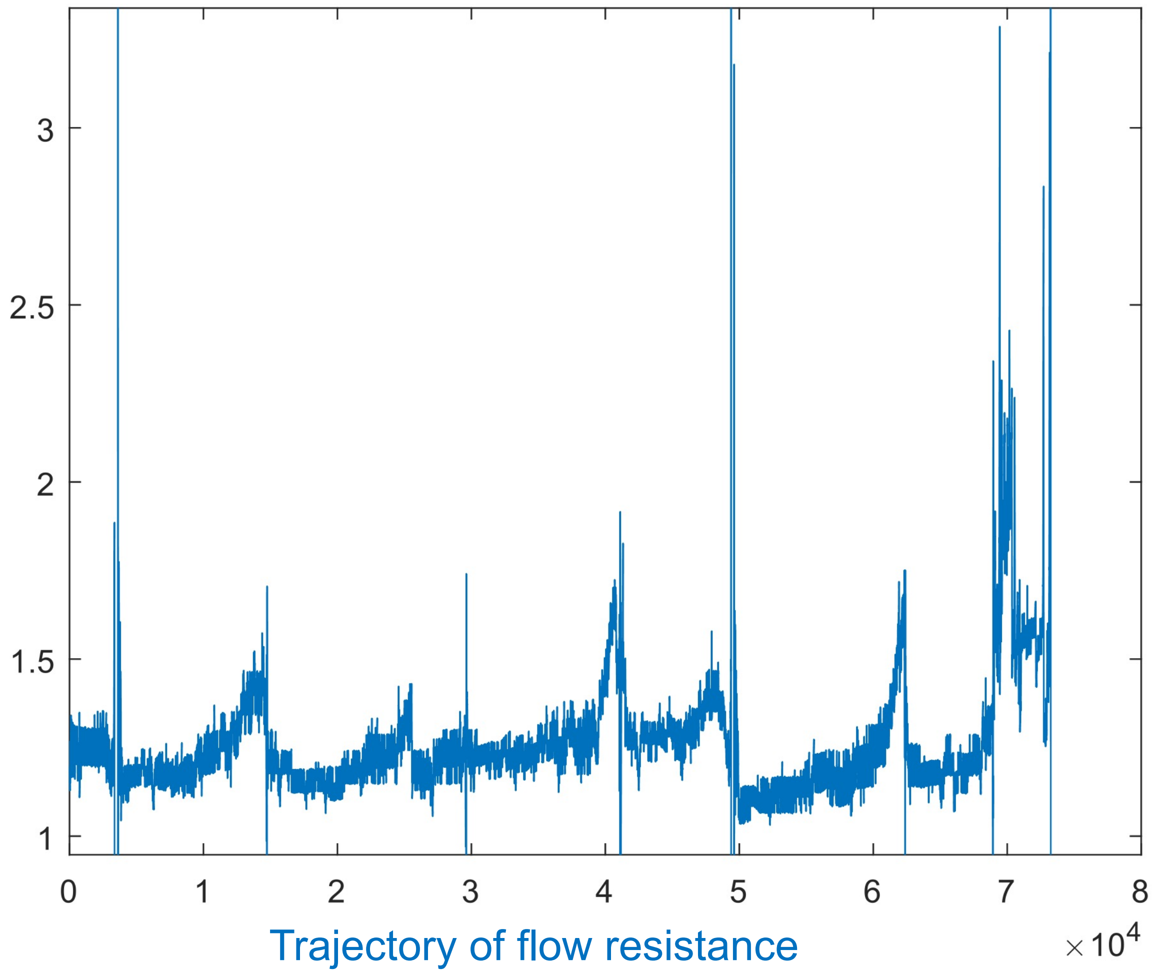
Datasets

- Steelmaking data (upstream batch process)
  - X: recipe of batch of steel .etc.
  - Y: if this batch clogged (human label)
    - I.I.D
- Casting data (continuous process)
  - X: casting process parameters (such as temperature)
    - Time series

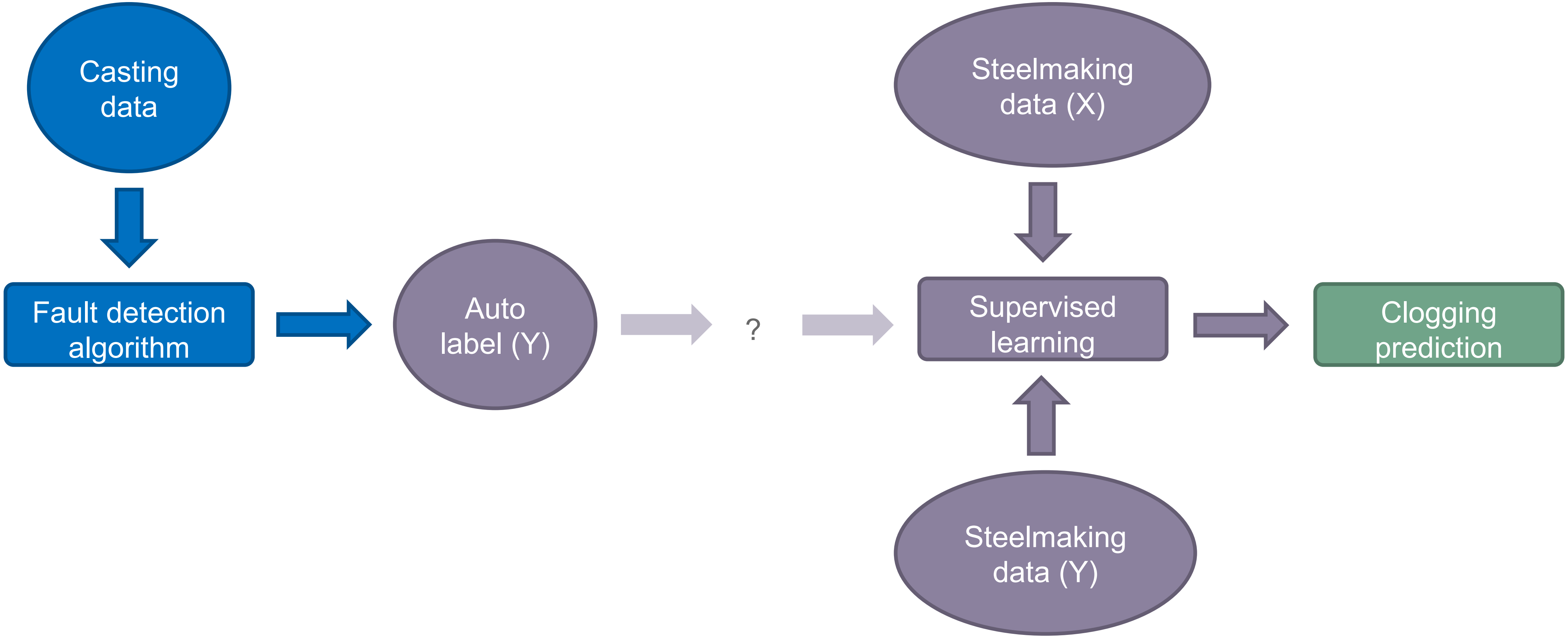


Dataset

- Casting data
  - Pros:
    - Straightforward representation
  - Cons:
    - Difficult prediction
- Steelmaking data
  - Pros:
    - Upstream to fault, allowing timely prediction
  - Cons:
    - Unbalanced dataset
    - Binary labeling (near misses)



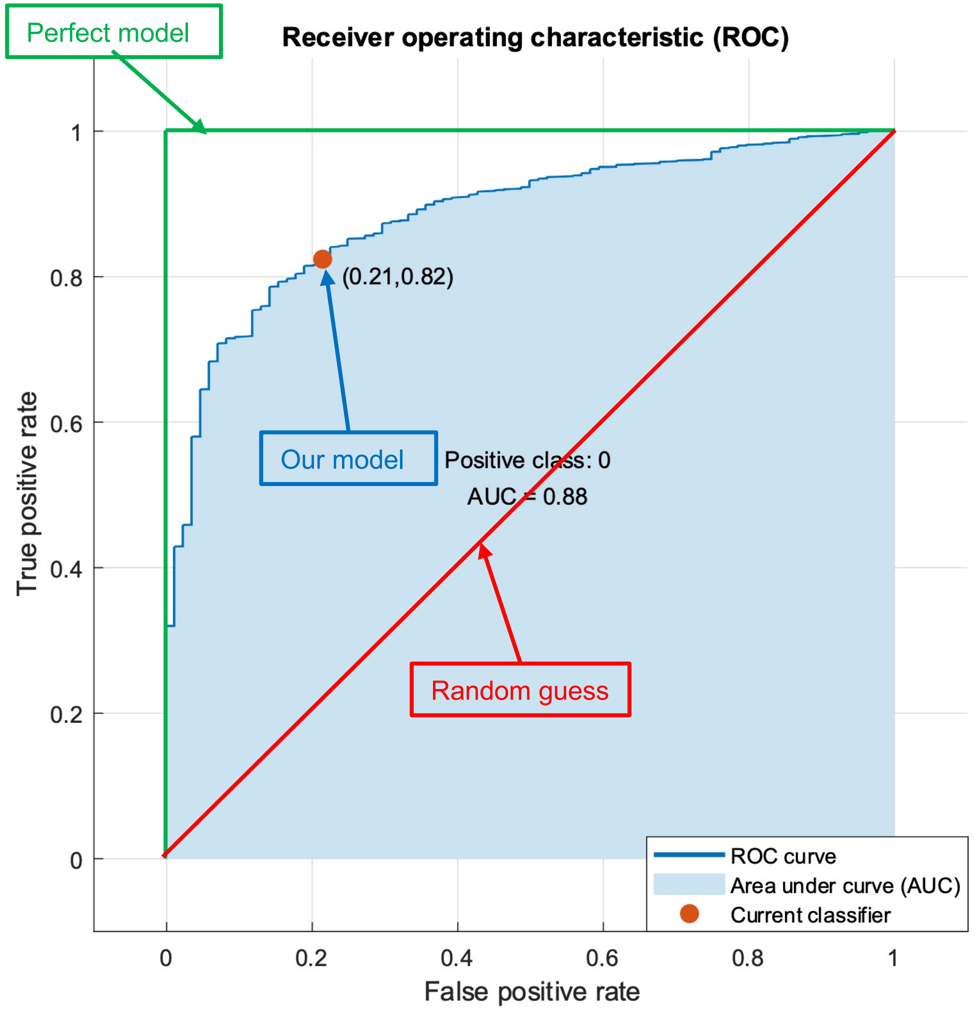
A combined approach



Supervised learning

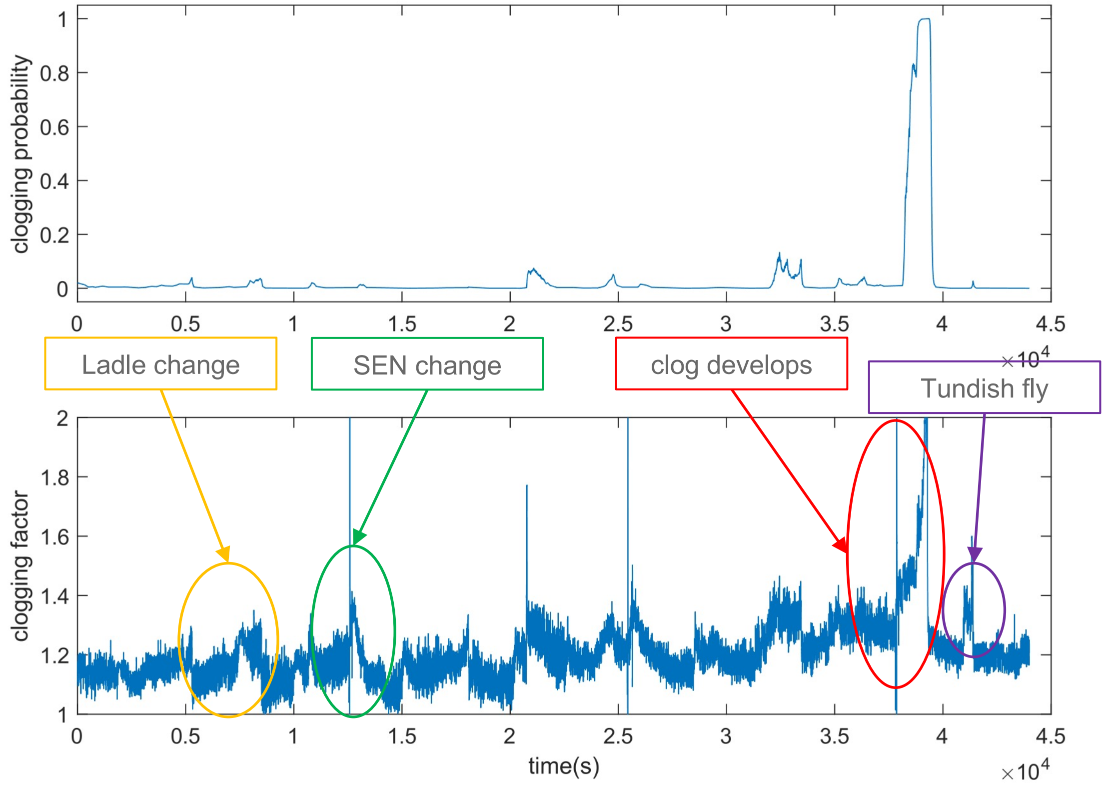
- Explored methods
  - Logistic regression
  - Linear discriminant analysis
  - Neural networks
  - Support vector machine
  - Gradient Boosted Decision Trees
- Results are reasonable
  - Gradient Boosted Decision Trees perform best
    - Good AUC (0.88)
    - Learned model agrees well with field knowledge
  - But high false positive rate
    - Unbalanced dataset
    - Steelmaking data alone is insufficient
    - Labeling can be improved

Truth \ Pred	Normal	Clog
Normal	22975	4908
Clog	18	66



Automatic labeling

- Multiple-model adaptive estimator
  - Higher resolution labeling
    - Accounting for near misses
  - Probabilistic output
    - Consistent labeling



Future work

- Predictive model improvement
  - More automatic labels
- Process improvement:
  - From associative to causal

Discussion

- Knowledge first
  - Even small help from field experts is important
  - Huge improvement in data-driven methods
- Live with uncertainty
  - Industrial datasets are tougher than machine learning benchmark datasets
- Always keep causality in mind

Calvert #1HDGL Primetals Automated Surface Inspection System (ASIS) Deployment

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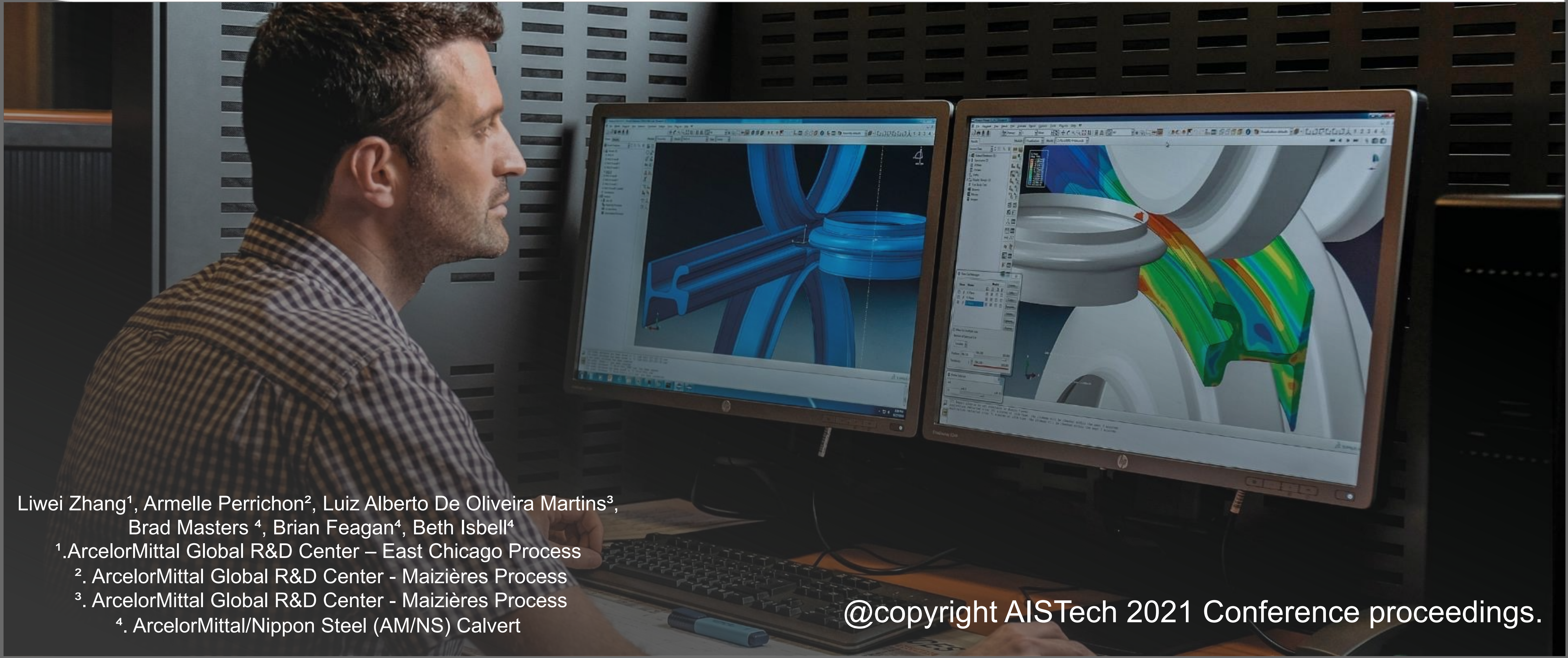


Liwei Zhang[1], Armelle Perrichon[2], Luiz Alberto De Oliveira Martins[3], Brad Masters [4], Brian Feagan[4], Beth Isbell[4]

[1].ArcelorMittal Global R&D Center – East Chicago Process

[2]. ArcelorMittal Global R&D Center - Maizières Process

[3]. ArcelorMittal Global R&D Center - Maizières Process

[4]. ArcelorMittal/Nippon Steel (AM/NS) Calvert

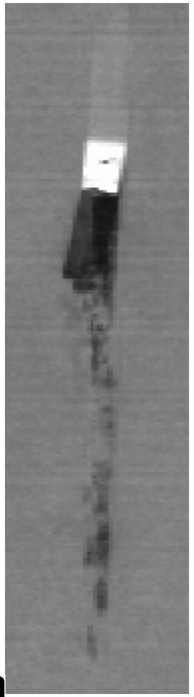
Outline

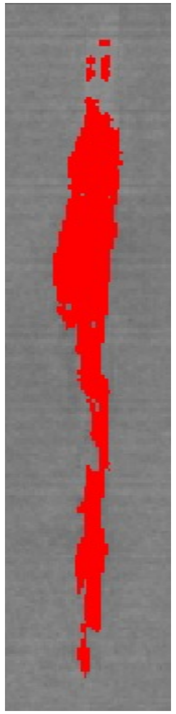
- ASIS introduction
- ASIS defect classification process and tuning
- ASIS defect classification result deployment

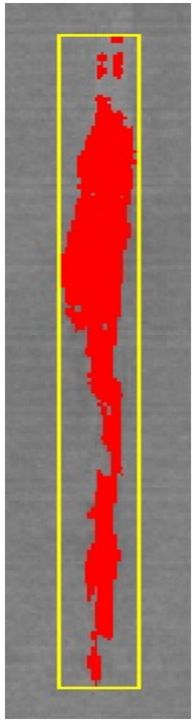
What is an Automated Surface Inspection System?

- Automated Surface Inspection System (ASIS) is a computer vision system enabling the online detection, localization and classification of surface defects while the strip is running.

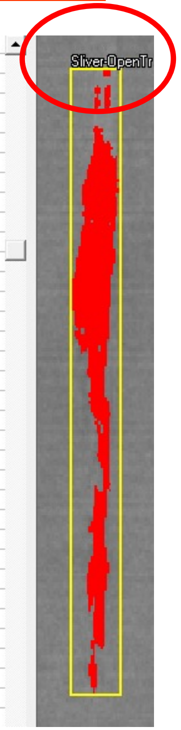
Cameras and lights for *image acquisition* → **Algorithms for *defect detection and segmentation*** → **Algorithms for *defect feature extraction and classification***







Height	177.196 mm
Width	13.425 mm
Aspect Ratio	13.198499
Defect Area	944.486078 sq mm
Box Area	2,378.939484 sq mm
Density	39.70198 %
Bright Area	214.633854 sq mm
Dark Area	729.852224 sq mm
% Bright	22.724936 %
% Dark	77.275064 %
Bright Height	164.717 mm
Bright Width	11.674 mm
Bright Aspect Ratio	14.109382
Bright Box Area	1,922.963943 sq mm
Bright Density	11.161616 %
Dark Height	149.743 mm
Dark Width	12.842 mm
Dark Aspect Ratio	11.660646
Dark Box Area	1,922.963943 sq mm
Dark Density	37.954545 %
Average Intensity	109.412339
Bright Average Intensity	186.934389
Dark Average Intensity	86.61477
Brightest Intensity	255
Darkest Intensity	21
Intensity Range	234
Defect Perimeter	428.977 mm
Box Perimeter	381.243 mm
Roundness	0.085534
Perimeter Ratio	1.125205
Repeat Period	0.000 mm
First Repeat in Series	False
Maximum Segment Width	11.091 mm
Average Segment Width	4.77 mm
Segment Width Ratio	0.430119



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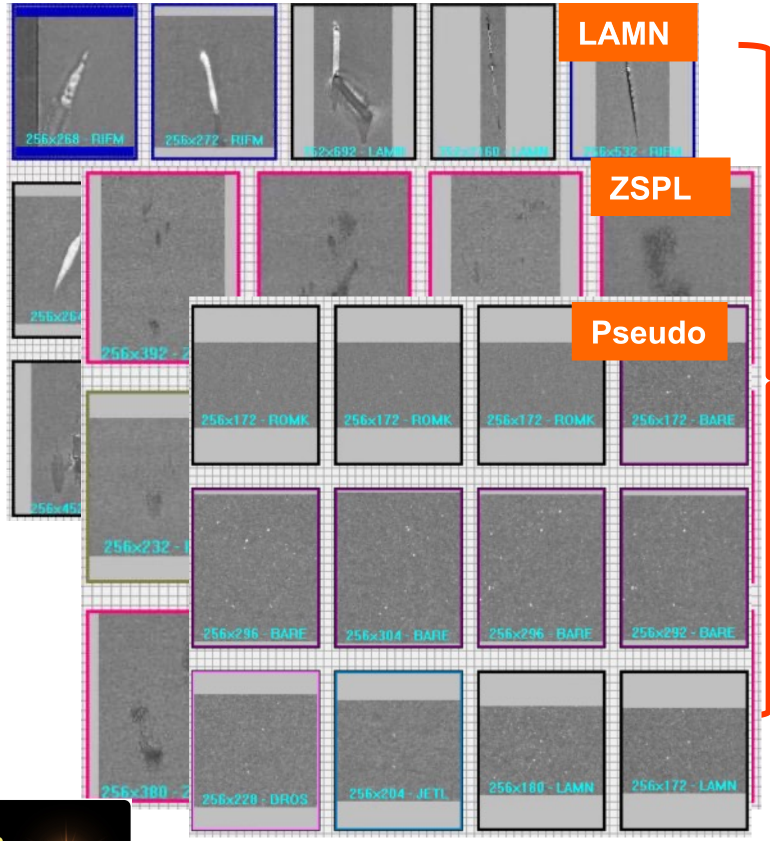
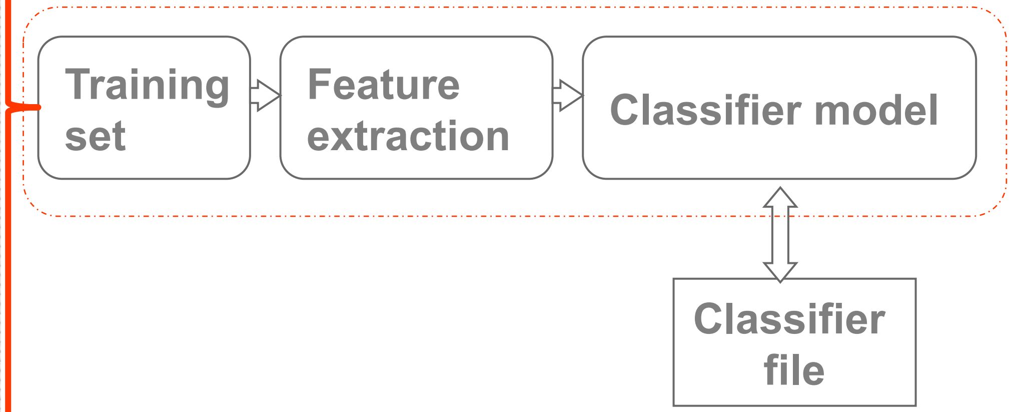
Classification tuning

- **Training set:** a set of defect data to provide information about hidden state -- supervised learning.
- **Features:** describe the defect appearance by mathematical parameters (vectors). **the feature extraction** aims to create discriminative parameters good for classification.
- **Classification tuning**: set classification model from the training set. The classification algorithm is fixed by ASIS vendors.





- model can be over 25 defect classes/categories

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ASIS performance evaluation

- Classification performance evaluation
  - ✓ Defect classification accuracy rate: it defines the percentage of correctly classified defects for a category.

$$CLASS\_RATE_{accuracy} = (TP_{no})/(TP_{no}+FN_{no}) \times 100\%$$

  - ✓ Defect classification confidence rate: it defines the percentage of correctly classified defects in a category.

$$CLASS\_RATE_{confidence} = (TP_{no})/(TP_{no}+FP_{no}) \times 100\%$$

- a few ways on ASIS classification performance evaluation
  - ✓ Confusion matrix on complete training set (used at the training stage)
  - ✓ Confusion matrix by leaving 1 or 10 out sample classifier testing;
  - ✓ Confusion matrix on independent test set (confusion matrix on reference coils);
  - ✓ Confusion matrix using the on-line validated results (during the inspection)

Note:

- *True Positive Number (TPno): TPno is defined as the count of correctly classified defects for one category.*
- *False Positive Number (FPno): FPno is defined as the count of defects from other categories being falsely classified into this category.*
- *False Negative Number (FNno): FNno is defined as the count of defects for one category which are falsely classified to other categories.*

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Refer to the presentation "Surface Inspection System Performance Evaluation Methodology" by L. Zhang et al., ISIS summit 2010.

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Calvert #1HDGL ASIS classifier tuning

- Total 6 defect libraries were built and 6 classifier models were created.
- An example of ASIS classification performance
  - ✓ ASIS classification performance for GA exposed material: 10 GA coils from the latest product were selected for the classification performance evaluation

True class / Predicted class	LAMN, LAMHM, RIFM, SLIV, SRBC, SRAC	Others	Total defect number	Confidence rate
LAMN, LAMHM, RIFM, SLIV, SRBC, SRAC	69	16	85	81.2%
Others	5	94	99	93.1%
Total defect number	74	110	184	
Accuracy rate	93.2%	90%		

…tion; LAMHM: Lamination Hot Mill; RIFM: Rolled in Foreign defect; SLIV: Sliver; SRBC and …Others including other important defects like dross, zinc splash, unknown so on.

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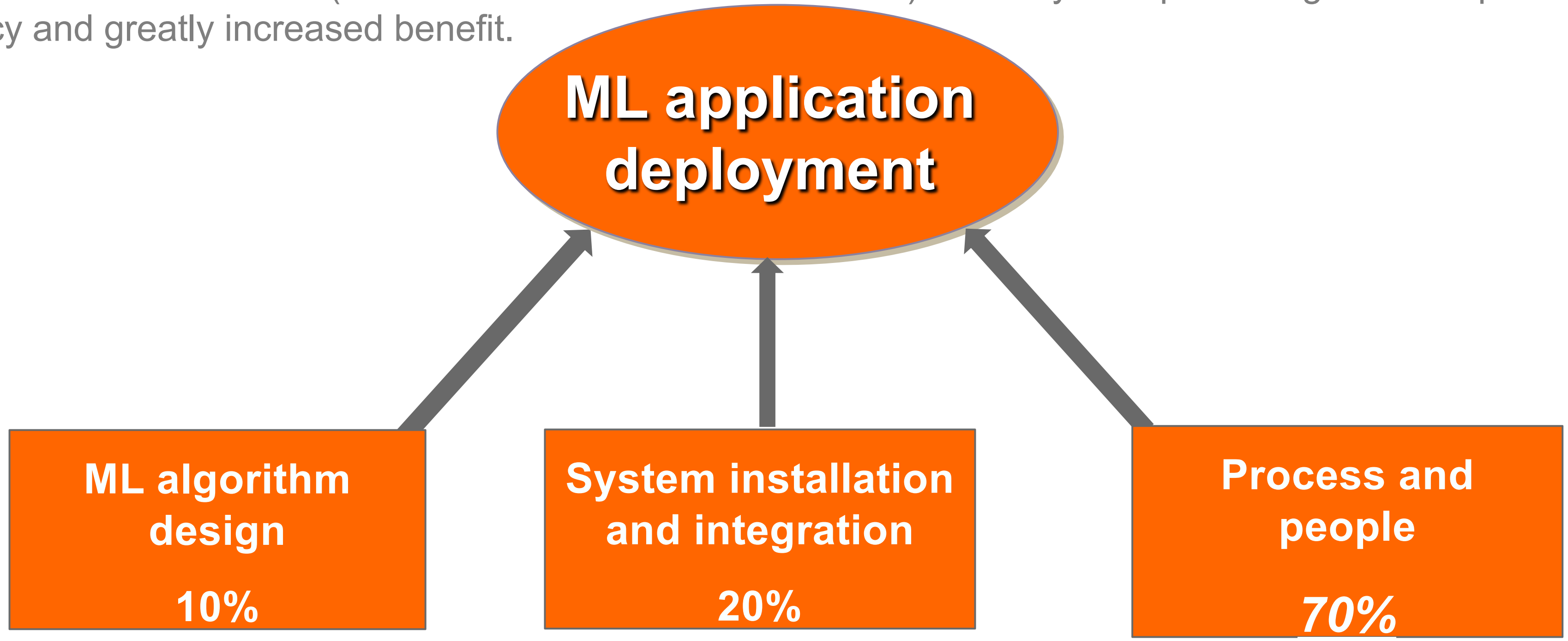
ASIS deployment -1

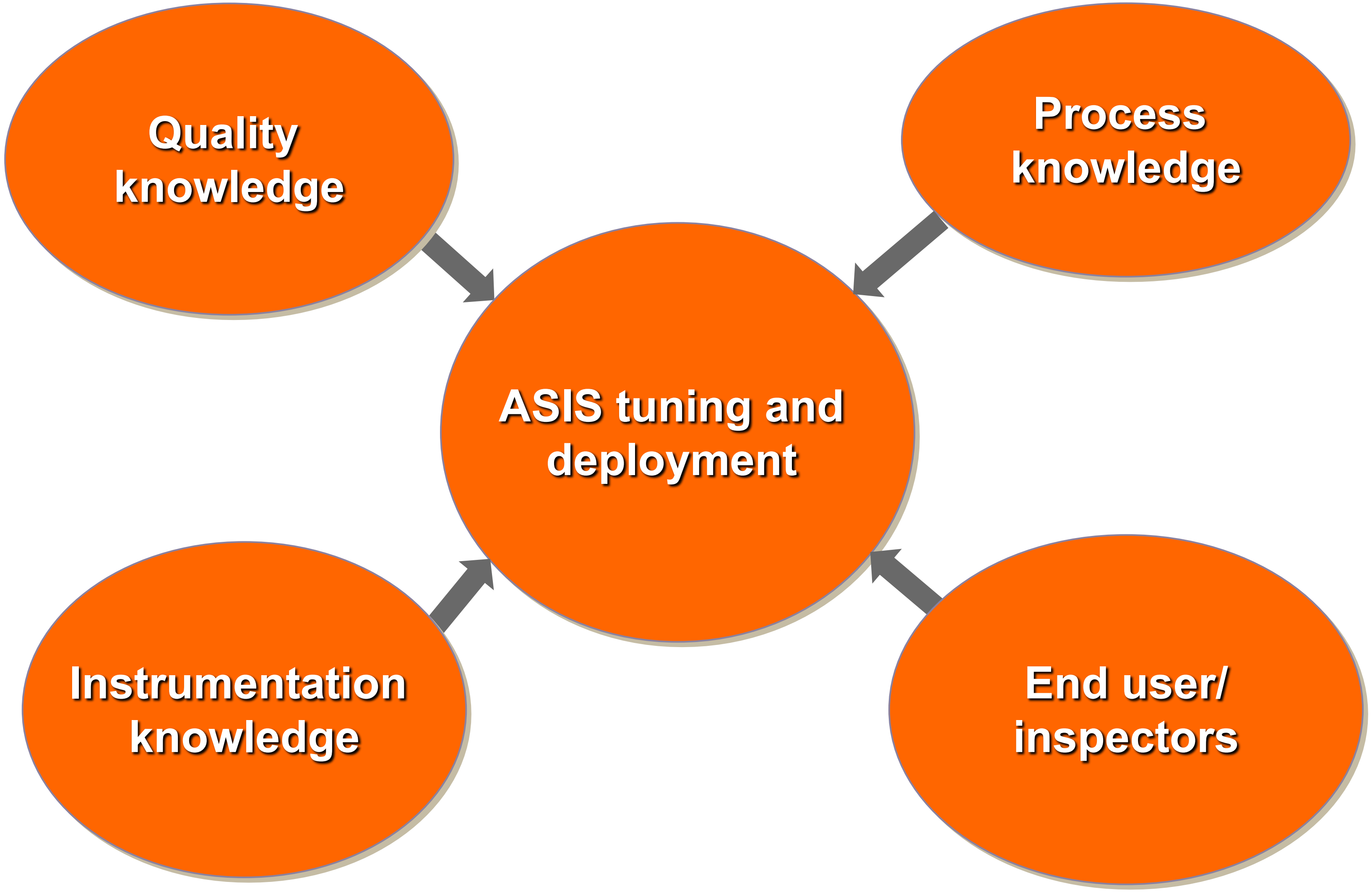
- Good practice
  - ✓ Achieve collective intelligence: “how people and computers can be connected and collaborated so that collectively they act more intelligently than any human, group, or computer has ever done before”*.
    - In the classification model tuning and deployment process, over 70% effort relies on how to manage the classification tuning and classification result use (which are business needs oriented) and may disrupt the original work practice for improved efficiency and greatly increased benefit.



References: * Superminds: The Power of People and Computers Thinking Together - MIT Technology Review;
https://www.ted.com/talks/sylvain_duranton_how_humans_and_ai_can_work_together_to_create_better_businesses/up-next

ASIS deployment - 2

- Create MS Teams Environment for collaboration of ASIS tuning and deployment (with Microsoft Excel and OneNote)



ASIS deployment - 3

ASIS and ArcelorMittal Coil Grading Surface Inspection Software (CGSIS) are deployed to the inspector station together (the system has been in use since Oct 2020)

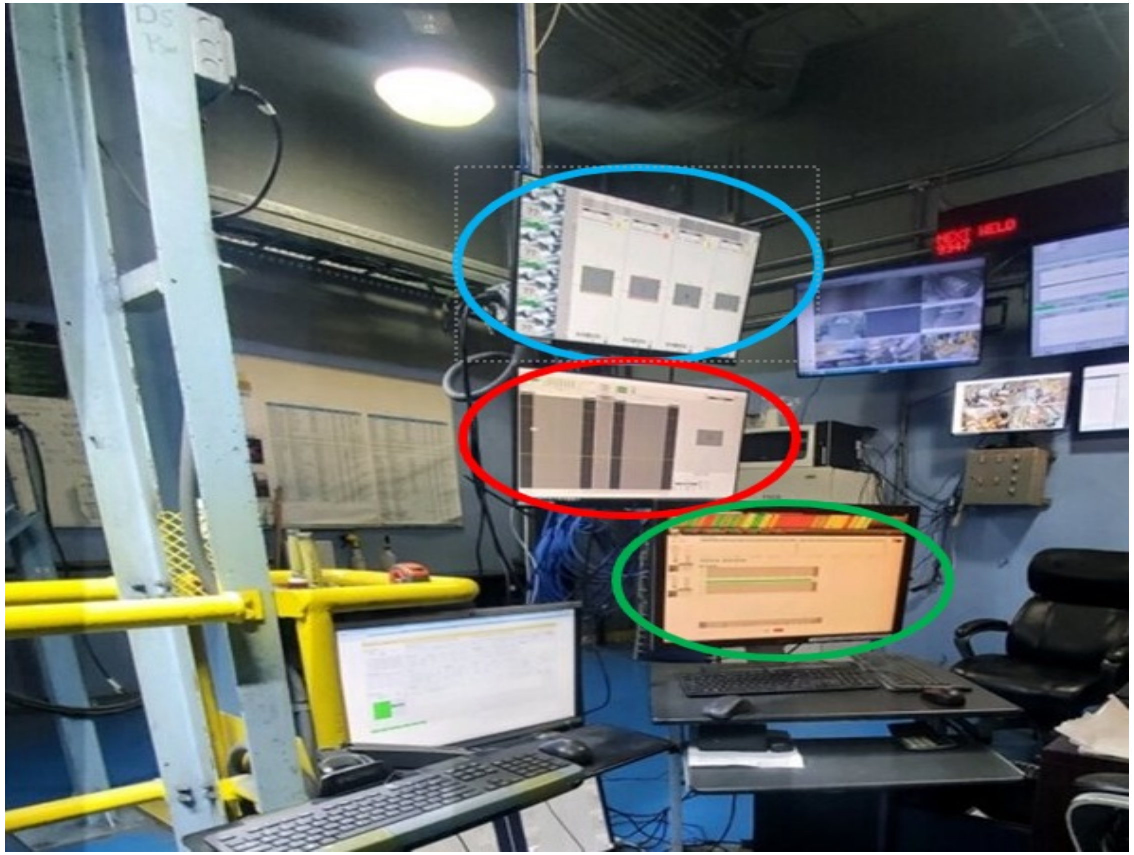


Figure. ASIS and CGSIS GUI at the inspector station (Blue circle: SIAS® multi defect screen; Red circle: SIAS® live coil map; Green circle: CGSIS GUI).

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ASIS deployment - 4

- Ways to handle false classification, incorporate human intelligence and achieve more consistency between the computers and humans
  - ✓ Review of Unknown defects before the coil is finally dispositioned
  - ✓ Inspectors have ability to correct false classification results through CGSIS results. The CGSIS will recalculate the coil grading results
  - ✓ Inspectors can input additional notes and add missing defect information (low contrast roll marks) into the CGSIS

ASIS Deployment Summary

- This industrial use case shows defect classification tuning process and how the defect classification results are put in the good use through better incorporation of computer intelligence and human intelligence.
  - ✓ The new ASIS classification results are input into the CGSIS software and then objectively quantified through coil grading algorithms in CGSIS software;
  - ✓ The CGSIS software has also expanded functionality to integrate inspectors' verification and correction of defect classification;
  - ✓ The new ASIS and CGSIS deployments not only bring new capabilities for Calvert #1HDGL to ensure surface quality for their customers and help indicate process issue for near real-time surface quality control, but also bring new capability of defect root cause analysis and defect predictive model development due to higher defect classification performance.

Conclusions

ArcelorMittal is taking bold steps toward industry 4.0 and technology leadership beyond steel manufacturing:

- Rapidly developing new advanced digital technologies to improve its business and manufacturing processes across the globe
- Collaborating with external partners to take advantage of best available digital technologies
- Welcomes new ideas and technologies applicable to steel manufacturing

Opportunities for the application of Machine Learning within the Steel Industry are vast and opportunities for a career in Data Science within the Steel Industry is brighter than ever

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