The Value and Science Behind MDS Pro Assessment Techniques

Adrian Belanger, Dane Burden, Ron Lundstrom, Miguel Maldonado
T.D. Williamson

PPIM 2025
PIPELINE PIGGING & INTEGRITY MANAGEMENT
JANUARY 27-31 • HOUSTON

Organized by
CLARION
TECHNICAL CONFERENCES

https://doi.org/10.52202/078572-0038

https://doi.org/10.52202/078572-0038

Abstract

The evolution of in-line inspection (ILI) tools over the last six decades has provided pipeline operators with continual growth of integrity management capabilities. While the core physics of many of these systems have remained fundamentally unchanged, there has been a significant progression from single-technology solutions to sophisticated, multi-technology frameworks. The last decade has increasingly enabled the integration of multiple, high-resolution sensor systems and coupled them with advanced digital technologies such as machine learning (ML) and artificial intelligence.

This paper will explore the progression of multiple-technology ILI tools combined with the implementation of advanced computing techniques and how they have addressed complex and multifaceted problems within the pipeline integrity industry. Several case studies will be presented to illustrate the current capabilities for assessing common, complex, and unique integrity threats highlighting the value they bring to operators and the industry. Among these cases will be selective seam weld corrosion (SSWC), mechanical damage (i.e. gouging and restrained vs unrestrained dents), hard spots, stress corrosion cracking and pipe identification. Finaly, the paper will explore potential future developments, looking at emerging trends, innovative integrations, and the anticipated impact on the industry.

The Path of Advancement

Acquiring data from multiple modalities in a pipeline survey using a single tool does not seem a case that needs promoting, but the history of pipeline inspection leading up to multiple dataset tools has been a long one with painful lessons. As is the case for most technological advancements, there must be driving need to justify the cost of development and incentivize adoption.

The first smart pigs had their humble origins in cleaning pigs. In 1962 TDW patented the Kaliper tool which recorded the change in inner diameter on a single channel. In 1965 the first commercial run for a magnetic flux leakage (MFL) tool was performed by Tuboscope for Shell with a tool that could only inspect the bottom 90° of the pipe with four sensors in a single physical housing. MFL and caliper technology were the main modalities of inline inspection until 1984 when Pipetronics developed the first tool to use ultrasonic technology (UT) to measure pipe wall thickness. [1] [2]

All these tools, though, were platforms for a dedicated technology, either caliper, MFL or UT. Each of these non-destructive examination (NDE) methods have their strengths and weaknesses and if an operator wanted to leverage all their strengths, they would have to make multiple runs. Even with a single technology there are cases where multiple inspection would have to be made. For example, a hard spot survey would require two tools, one with an active high-field MFL and the another with passive or residual (RES) sensors, to measure the permeability changes caused by the elevated hardness [3].

 https://doi.org/10.52202/078572-0038

Tragedy

On June 10, 1999, a 16” diameter gasoline pipeline in Bellingham Washington ruptured releasing 236,796 gallons (896370 litres) of gasoline into Whatcom Creek which ignited, killing three people and causing 45 million USD in property damages. The ruptured resulted from a gouge associated with a dent. Two pipeline surveys were run, a MFL in 1996 and a caliper run in 1997. Both surveys were also performed by different providers. It should be noted that caliper runs prior to this incident were run primarily to detect large ID restrictions, such as buckles and very deep dents. The MFL survey detected the metal loss features, but in absence of the caliper data they were classified is mill anomalies [4]. The short comings of running different technologies in separate runs without an established system of aligning and assessing them together so a more precise threat characterization could be made, was a wakeup call for the industry.

Growth

The tragic incident at Bellingham gave birth to the development of the combo MFL-caliper tools that are run by numerous providers today, but caliper and MFL data were not the only ILI technologies developed before the turn of the century. It has been known that the axial direction of the conventional MFL tools has limited capabilities in detecting and sizing long, narrow axially oriented metal loss. Patents for magnetizing the pipe in a circumferential direction go as far back as 1969 [5] and in the 1990s research and development was done to create and test a prototype tool [6].

Hard spots were a known integrity threat since the 1960s and as mentioned previously, a second tool was run to inspect for them using the residual magnetization left behind by the MFL tool. Hardness is not the only material effect that changes the magnetic permeability of the pipeline steel. Stress also has an effect on the MFL response [7] and research was done by Battelle [8] to determine the ability of a combination of high and low magnetizations that will identify the areas of tension and compression in an area of mechanical damage, such as a dent with a gouge.

In 2008, TDW incorporated these groundbreaking technologies into a single tool [9]. The motivation to combine all these technologies into one tool was to gather all the data to assess metal loss features, both volumetric and axial, and provide a comprehensive mechanical damage assessment. In this spirit, the circumferential magnetization was replaced with the SpirALL® MFL (SMFL) [10] which provided a magnetization in the oblique direction with greater than 360° coverage by overlapping sensor boundaries. Unlike the design of the circumferential magnetizers, which required a pair of magnetizing bodies to cover the blind spots where the brushes introduced signal into the pipe wall, the SMFL could be a single body. This new body was combined with axial MFL, low-field MFL (LFM) or residual (RES), high-resolution caliper (DEF), internal and external discrimination (IDOD), and pipeline mapping (XYZ) in a single MDS platform.

https://doi.org/10.52202/078572-0038

Adaptation

In the beginning the MDS was primarily run as a mechanical damage tool, but very quickly numerous other applications were found, including as a hard spot tool [11]. Not only were the high-field MFL and the LFM used to identify and size hardness, but the high-resolution DEF detected flattening, the IDOD, using a radially oriented field, were sensitive to permeability change. Secondary coincident features, such as hydrogen induced cracking (HIC) were detected and identified using the SMFL.

SSWC could also be detected and identified as well as discriminating coincidental metal loss from gouging in a dent [12]. These integrity threats were anticipated to be able to be addressed by the MDS tool, but other unforeseen threats that required innovative techniques were identified, such as puddle welds [13] and circumferential stress corrosion cracking (CSCC) [14].

Transformation

Incorporating the different inspection technologies into one tool is only half the battle. One of the limitations in the early days of inline inspection was the limitations in storage and data acquisition speeds. Towards the 90's, neural networks were applied to inspection data [2] but the limitation in computing power, machine learning architecture (early models had a notorious knack of forgetting old information after being trained on new information) [15] and difficulties of getting actionable data from field validations. The real breakthrough came with development of data science tools to process the information contained in the synergies between the different datasets.

This paper will show how the MDS-Pro transformed data analysis from examination a single dataset and sizing using heuristic algorithmic techniques bounded by features that can only be extracted from a single dataset to using random forests [16], extreme gradient boosting (XGB) [17] and convolutional networks [18] to process the data from multiple datasets to access several integrity threats including, but not limited to, circumferential stress corrosion cracking, mechanical damage and complex corrosion.

Applications in the Real-world

Pipeline integrity management is a critical aspect of maintaining safe and efficient energy transportation. Threats to the safe operation of this infrastructure are numerous and require a multifaceted approach to risk management. When multiple-dataset ILI tools are included in this portfolio, unique and complex integrity threats can more comprehensively be addressed. By capturing high-resolution, multidimensional data, these tools enable more accurate detection, classification, and sizing of anomalies under varied, and ever evolving, operating conditions.

Solutions to real-world problems using ILI can be further amplified by using learning models as they can process and analyze vast datasets to identify patterns, correlations, and subtle features that might be overlooked in manual reviews. However, vast datasets with known conditions derived from field

 https://doi.org/10.52202/078572-0038

investigations are difficult and costly to accumulate, and time consuming to accurately curate. As such, solving novel problems (or improving the solutions of existing ones) often requires the exploration of simpler manual processes until enough data is available. This process of starting simple to build a foundational understanding evolves over time into expansion, extension, and automation as data is gathered and experience is gained. Relevant threats to pipelines today and the ILI contribution to mitigation are examined below, each detailing parts of this developmental growth.

Circumferential Stress Corrosion Cracking [19]

Stress corrosion cracking (SCC) used to be synonymous with axially oriented SCC, primarily due to the prevalence of the features generated by circumferential hoop stress in pressurized pipelines. However, other external forces act on pipelines and when the loading from these overcomes the principal hoop stress then crack orientation diverges from axial. Circumferential SCC (CSCC) occurs when the longitudinal stress becomes the primary loading force and material fibers pull apart axially around the circumference of the pipe.

Additional loading on a pipeline can be caused by several factors, such as temperature changes, external ground forces, bending, or residual stresses. These have driven the need to expand the capabilities of traditional magnetic based technologies and push them to their peak detection and identification limits. The process for identifying and prioritizing began with a simple flow chart utilizing data from SMFL, MFL and bending strain datasets and is shown in Figure 1. As field verified data was limited, this simple approach provided a coarse low, moderate and high prioritization scheme designed to identify crucial CSCC features with known ILI data indicators [14].

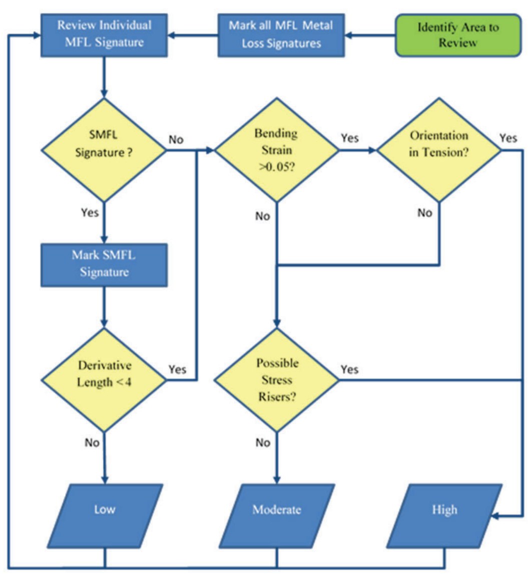

Figure 1: Initial CSCC identification and prioritization decision tree process.

As additional field and ILI data was gathered, the coarse prioritization was extended to a discrete scoring model that provided more granularity. The decision points in the initial decision tree were

https://doi.org/10.52202/078572-0038

expanded to include LFM or RES magnetic dataset signatures and their associated signal characteristics, such as amplitude, shape and relationship to the high-field responses. New features, such as feature presence in historical inspections, signal change derived from signal-to-signal matching, and association with line movement events were added to further refine identification and prioritization accuracy.

With the accumulation of CSCC data and increase in industry demand, an automated detection scanner was developed and implemented. This scanner automatically detects candidates based on the low-field signal response and the amplitude relationship to the corresponding high-field MFL feature(s). **Figure *2*** provides an example of a feature detected using this scanner, highlighted in the middle image labelled RES with a translucent red box. As can be seen, a circumferential slot feature with a disproportionate low to high-field MFL signal response was automatically detected. The lack of a signal response on the SMFL confirms the circumferential geometry of the feature and increases the likelihood of being CSCC. The current prioritization model for this feature assigned a score of 17, the number one priority feature in the line. Field investigation results for this location found a circumferential crack-like indication that was leaking. This automated approach and evolving prioritization method provides operators with an actionable CSCC analysis that can be completed in a shorter amount of time than previous methods.

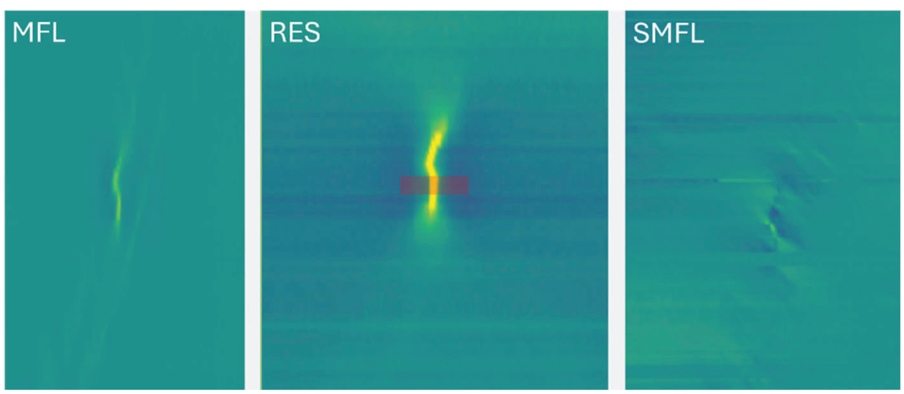

Figure 2: Candidate feature identified using an automated scanner design for CSCC detection.

As more and more CSCC data is accumulated, advanced machine learning models can be tested and implemented. When applied correctly, these models have proven to provide a significant boost to prediction performance and can be adapted to detection, identification and sizing tasks. Translating the engineered features in the current prioritization scoring methodology to a supervised learning model is easy. Accumulating enough data for the model to generalize well, not overfit training data, and provide enough confidence in performance results is difficult, costly, and time consuming, but worth pursuing.

Mechanical Damage

While the CSCC process needs more data, the identification of a dent with associated gouge or corrosion (GvML) has accumulated enough data to focus on automation. Work began on the

 https://doi.org/10.52202/078572-0038

identification problem in 2014 under the DOT PHMSA project 498 Improve and Develop ILI Tools to Locate, Size, and Quantify Complex/Interacting Metal Loss Features and Dents [20]. In 2020 a validated classification performance specification was developed utilizing a random forest machine learning model [21] that built off the work completed in 2016. The results showed that classification performance could reliably achieve a recall and precision performance of 90% and 80% respectively [22].

Over the last four years, thousands of dents with interacting features have been analyzed and investigated. Currently implemented analysis methods have matured, and thousands of hours of experience have been gained. Analysis of the available data showed that the manual aspects of the analysis process contributed to increased report delivery times and inconsistent model input parameters that required subject matter expert (SME) intervention. These factors highlighted the need to fully automate the classification process and transform SME intervention to a quality control review. The process was scoped such that:

1. A qualified data analyst would merely have to review the prediction results and never be required to enter input parameters.
2. The model performance would also be at least as good as the previous performance, achieving a recall of at least 90% and precision of at least 80%.
3. Analysis time to classify dents with coincident features would decrease from the current standard.

As of today, item one has been completed, and a fully automated model classification routine has been developed that requires no manual intervention by a data analyst. **Figure *3*** provides a visual example of a multi-apex dent that was automatically analyzed and classified with the new process.

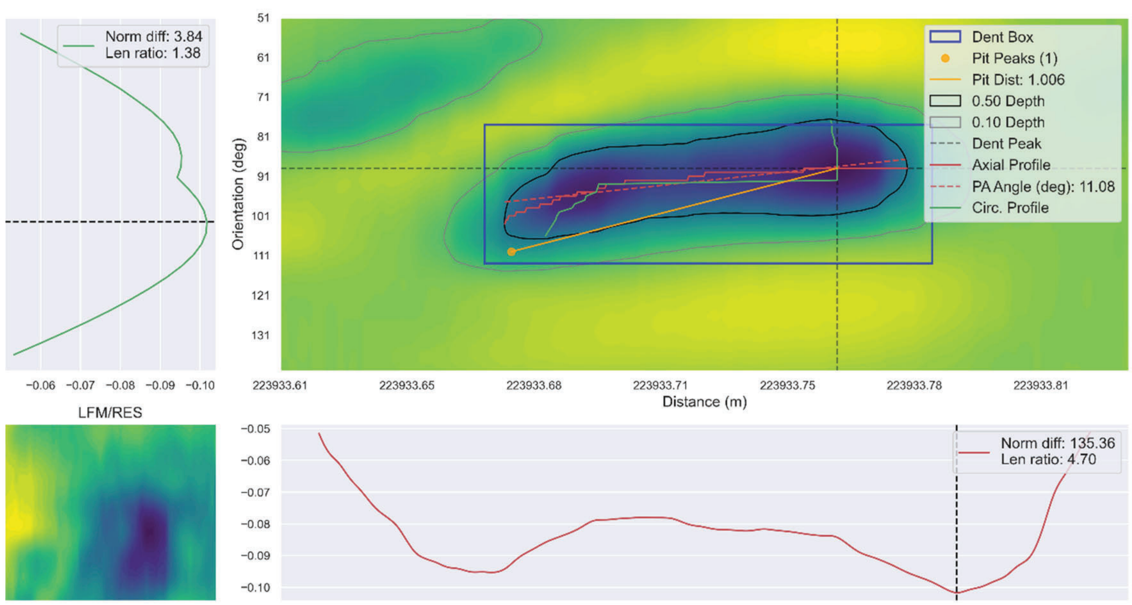

Figure 3: Visual example of a multi-apex dent automatically analyzed for gouge or corrosion association.

Item number two has also been completed and performance, using the same evaluation methods of the previous model, is slightly better than the current model. **Figure *4*** shows the precision versus recall and receiver operating curve (ROC) performance metrics. A recall of 90% and the associated precision is shown on the precision versus recall plot (left) by green dashed lines. As can be seen, for a recall of 90% the associated precision is greater than 80%, specifically 81.9%. This shows that an automated classification process can perform as well as the manual one.

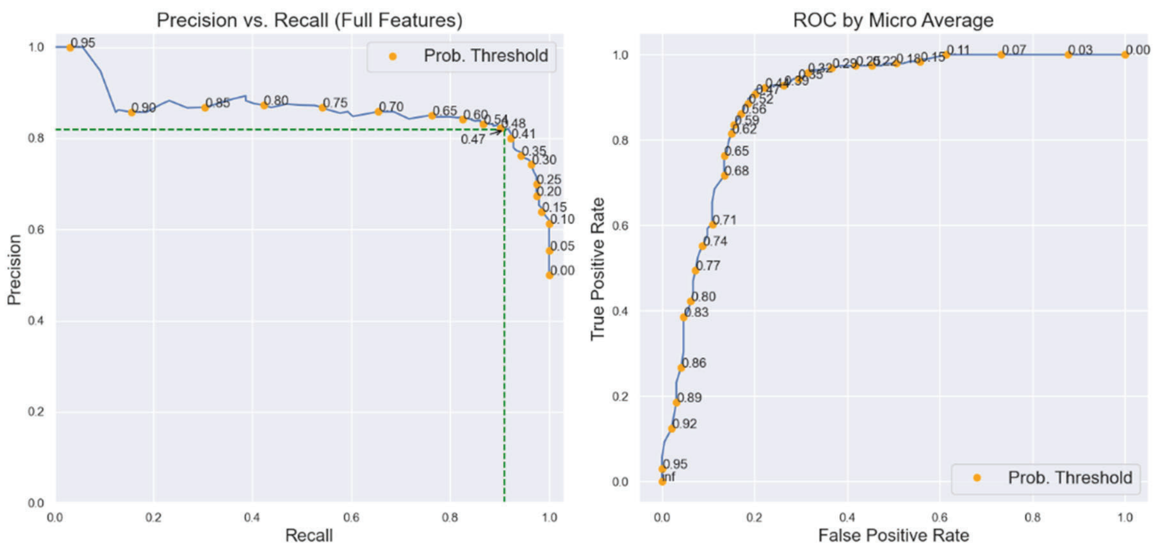

Figure 4: Precision versus recall (left) and receiver operating curve (right) performance metrics for the automated classification of dents with gouging.

Item 3 and the associated implementation into the production workflow is ongoing. Initial investigations show promising results in analysis time reduction. It is important to note, that while the classification process is automated, a manual SME review of the predictions is still completed. This is to provide a second layer of review, generally for outlier cases, and utilize the extensive knowledge of SMEs. Initial work has also shown promise in integration into other advanced dent assessment techniques, such as dent prioritization and methods outlined in the API RP 1183 screening processes [23].

Hard Spots

As mentioned previously, the implementation of high and low magnetization developed to assess mechanical damage also improved the detection of hard spots. Previous inspections were focused on A.O. Smith pipe as historically that manufacturer had the largest prevalence of hard spots in pipe produced between 1952-1960 [24]. Recently there have been failures due to hard spots from other manufacturers.

Figure *5* and **Figure *6*** show hard spots with differing metallurgical properties. **Figure *5*** is the type of hard spot detected and identified by the older technology while **Figure *6*** is typical of what is being found in pipes of different manufacturers [25].

 https://doi.org/10.52202/078572-0038

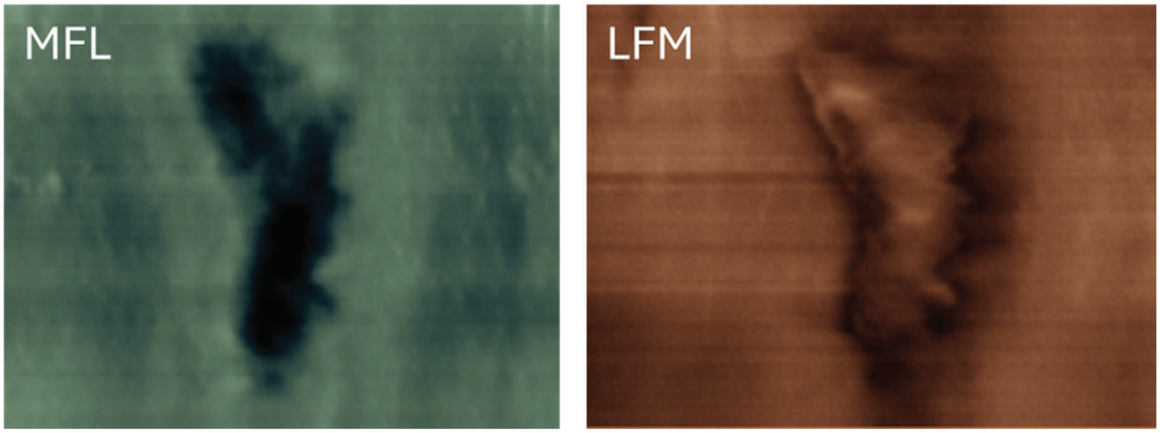

Figure 5: High (left) and low (right) MFL data contour maps of a 380 Brinell hard spot.

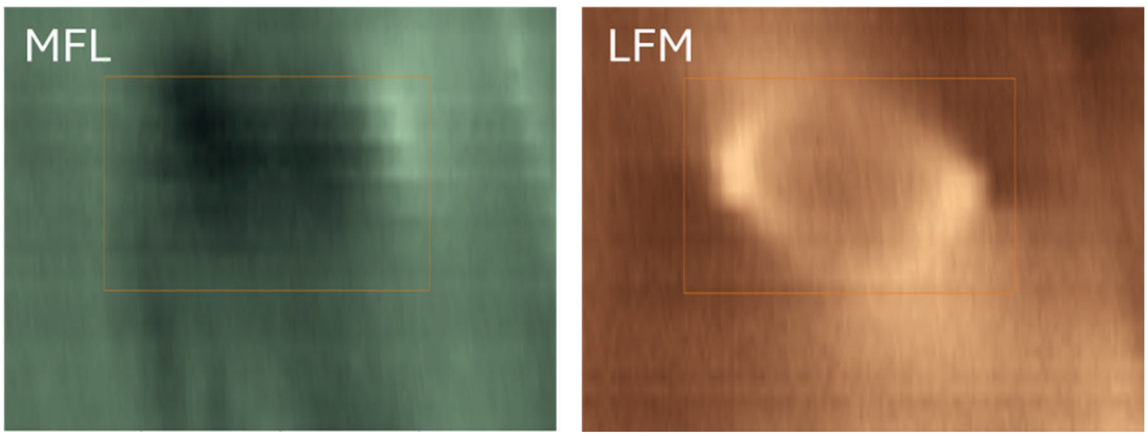

Figure 6: High (left) and low (right) MFL data contour maps of a 281 Brinell hard spot.

The optimally designed pairing of high and low field magnetizers not only improves detection but also identification and sizing of hardness.

Complex Corrosion

While CSCC and dents with coincident features are relevant threats to the pipeline energy infrastructure, corrosion remains one of the most widespread and prevalent as shown by the Pipeline and Hazardous Materials Safety Administration (PHMSA) 20-year pipeline incident trend [26]. Magnetic based inspection technologies developed over half a century ago focused on these features and advancements in ILI tools today have kept detection, identification, and sizing of these as a core competency even as system capabilities continue to expand.

The proliferation of MFL is due to the robust and ubiquitous solutions it provides in a relatively simple and cost-effective system. However, the core physical properties of the technology limit it to be an indirect measurement of pipeline features. Magnetic flux lines bend and arch smoothing out fine details when responding to changes in pipeline features. This causes measured signal responses

https://doi.org/10.52202/078572-0038

to often bloom together and at times makes two individual metal loss features appear as one. **Figure** *7* shows an example of a set of corrosion-like features developed from acid etching pipeline steel and the corresponding MFL signal data for the same area. As can be seen, the signal responses are not a one-to-one representation of the actual features. Instead, the signals resemble the smoothed out general shape and circumferential features, such as those labeled 2 and 5, blend.

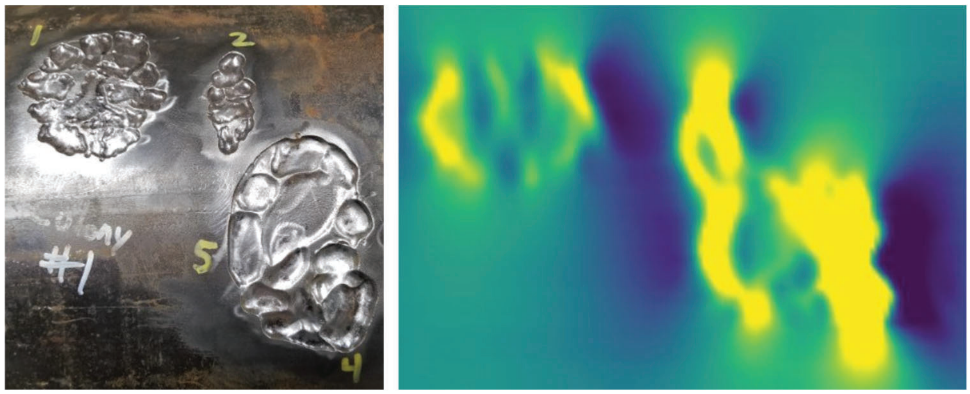

Figure 7: Example of MFL signal responses (right) for a patch of acid etched features (left).

It is important for sizing models and clustering algorithms to have the individual components of a corrosion area detected and identified. This allows for more accurate feature geometry predictions to be made which directly influence burst pressure calculations. Detection methods for individual non-interacting corrosion features are straightforward and easy to develop. However, when corrosion features begin to interact in complex ways, detection of individual components becomes difficult. To overcome this an automated segmentation method was implemented based upon the fundamentals of a flood fill algorithm [27]. **Figure** *8* shows the corrosion-like feature from **Figure** *7* on the left, the results of applying an MFL specific segmentation method in the center, and the results of a 3t-by-3t clustering algorithm. As can be seen, the results show a highly accurate parsing of individual signal responses that allow for more focused predictions from sizing and clustering algorithms.

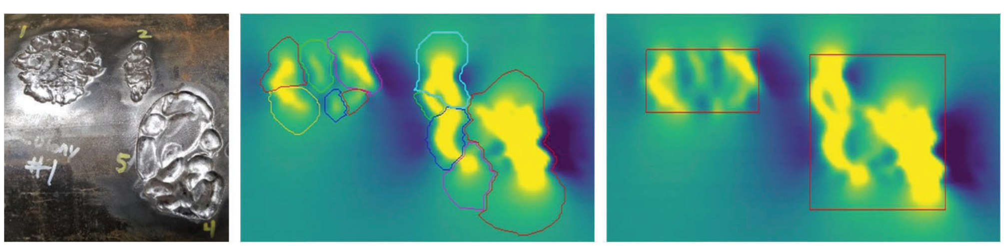

Figure 8: Corrosion cluster (left), the associated segmentation results (center), and 3t-by-3t clustering results (right).

The segmentation process and associated sizing and clustering predictions are fully automated, requiring only verification from data analyst subject matter expertise. This process significantly reduces manual annotation in areas of complex interacting corrosion while providing operators with more accurate feature predictions.

 https://doi.org/10.52202/078572-0038

Un-fogging the Future

Managing a pipeline's integrity and regulatory compliance have driven a considerable amount of growth in the ILI industry. The Bellingham Washington tragedy reactively spurred the need to develop combination caliper and MFL inspections and today's challenges have driven new combinations of high-resolution multiple dataset ILI systems. These advanced multiple dataset platforms are expanding to include ever greater sensor densities and axial sampling rates. The current development trajectory of ILI tools appears well defined; put as many sensors as possible, on as many technologies as possible in the smallest most convenient platform.

Advanced Computing's Next Cycle

The machine learning progress to date provides a foundation for next steps, which are expansion, extension, and automation. The life cycle of innovations always requires several iterations for maturity. Proven techniques, such as recent sizing model improvements, will be expanded into more datasets and detection methods will be extended to include classification and sizing. These lead to automation to ensure we have the capacity to consistently meet industry needs. Finally, techniques for data annotation must be expanded to provide training data for new development. Each of these will be discussed in detail.

Expansion of Machine Learning Sizing Models

MFL sizing models for corrosion are the most mature production algorithms within the ILI industry. Most are completely automated and constantly being refined. As more technologies are integrated, the MFL sizing methods will be extended to new technologies.

TDW recently updated the MFL sizing model to a more advanced machine learning algorithm and reduced the associated error specification by 1% for several feature geometries. This improvement may not initially seem substantial, but considering this is a 10% improvement for a technology that is approaching a physical lower limit, it is considerable. The algorithm architecture is based on XGB, a machine learning method based on tree methods [28].

Based on the success of the XGB based architecture, its use was expanded to include a new SMFL specific model and subsequently a hybrid MFL+SMFL model. Each new model showed significant sizing improvements. The hybrid model is the most accurate, due to integration of both datasets. However, when the MFL and SMFL signals differ significantly it is more accurate to prefer one dataset over the other. A corrective model, called the mixture model, was developed for this edge case. The mixture model combines signal data from MFL and SMFL datasets and the depth predictions from all three models, MFL, SMFL, and hybrid. Although the mixture and hybrid models work with similar information, the reduced set of features in the mixture model provides a more focused optimization, similar to an ensemble model. **Figure *9*** compares the MFL, hybrid and mixture models binned by SMFL/MFL signal amplitude differences. The tails of each distribution demonstrate that

https://doi.org/10.52202/078572-0038

the mixture model improves depth predictions by 4.5% to 6.5% when the MFL and SMFL signals differ by more 400 Gauss.

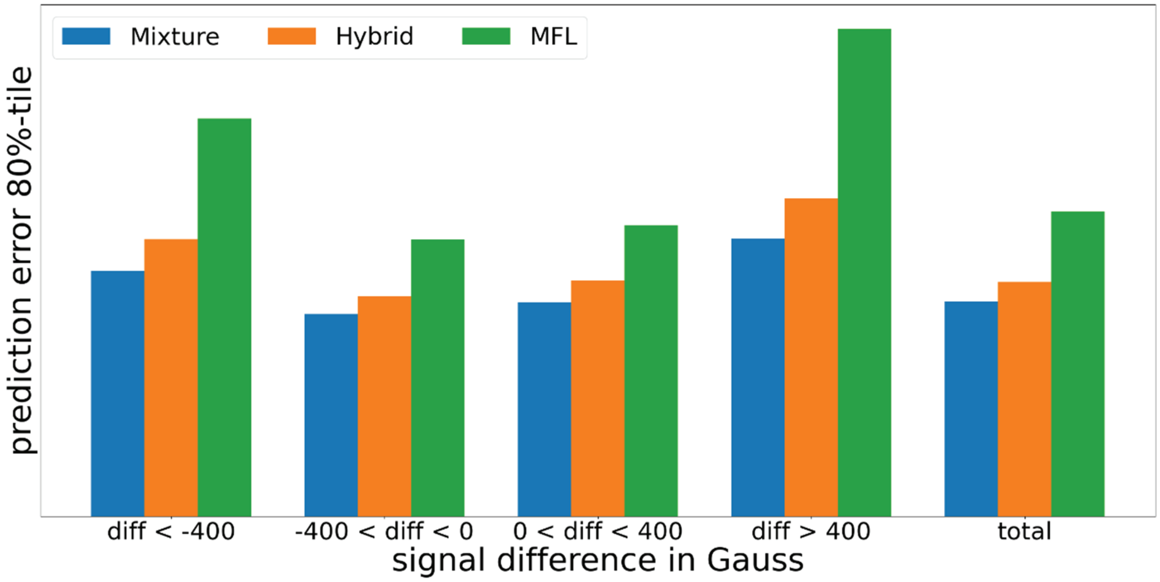

Figure 9: Depth sizing model improvements between MFL, hybrid and mixture models based on signal amplitude difference.

Extension of the XGB capabilities to other pipeline threats, such as SSWC, GvML, and girth weld anomalies will likely yield similar performance improvements as the architecture has shown to be extremely robust in solving classification and regression problems [29].

The SSWC threat is a good example of where the potential extension of newer models into historical problems could improve performance. Substantial work on SSWC detection, identification and sizing has been done [12] [20] and this has led to a published performance specification for classification [30]. **Figure *10*** shows two examples of where a classification model has been used to identify corrosion near the long seam that is general (left) and preferential (right).

Figure 10: Examples of features investigated based on SSWC classification model results with general corrosion (left) and preferential (right).

Both the classification and sizing models used on this SSWC feature are effective, but relatively simple due the limited data sets with detailed NDE. These could be advanced using the experience

 https://doi.org/10.52202/078572-0038

and knowledge gained from the XGB metal loss sizing process. Extending models like this into multiple anomaly classes is an example of how new methods mature and expanded to solve multiple problems or even improve historical ones.

Automation of SMFL Scanning

MFL has been the primary dataset for automatically detecting metal loss features as this technology has been given the most time to mature and develop. Detection of axially oriented features using the SMFL dataset has historically been a manual process that would benefit greatly from automation. Two new automated processes have been developed to supplement the manual review process.

A direct SMFL scanner is now available for axially oriented signals. Some deep axial features (>40%) can have a shallow MFL response (<10%). Detection of these features starts by detecting raw signal peaks in the SMFL data and applies heuristic filtering methods for MFL to SMFL amplitude ratios and proximity to pipeline fixtures. The peaks are then clustered, as multiple peaks in a localized area can all related to the same feature. The process is designed to have high recall performance to catch features that may have been missed during the MFL scanning process. **Figure *11*** shows the recall of the scanner based on different detection thresholds and the associated SMFL signal amplitude. The left plot is detection for all metal loss features (pits) in the test set and the right displays the recall for all pipe joints containing at least one feature with the associated amplitude. As can be seen, a very high recall (detection) performance can be achieved for high amplitude features, which generally correlate to being the deepest.

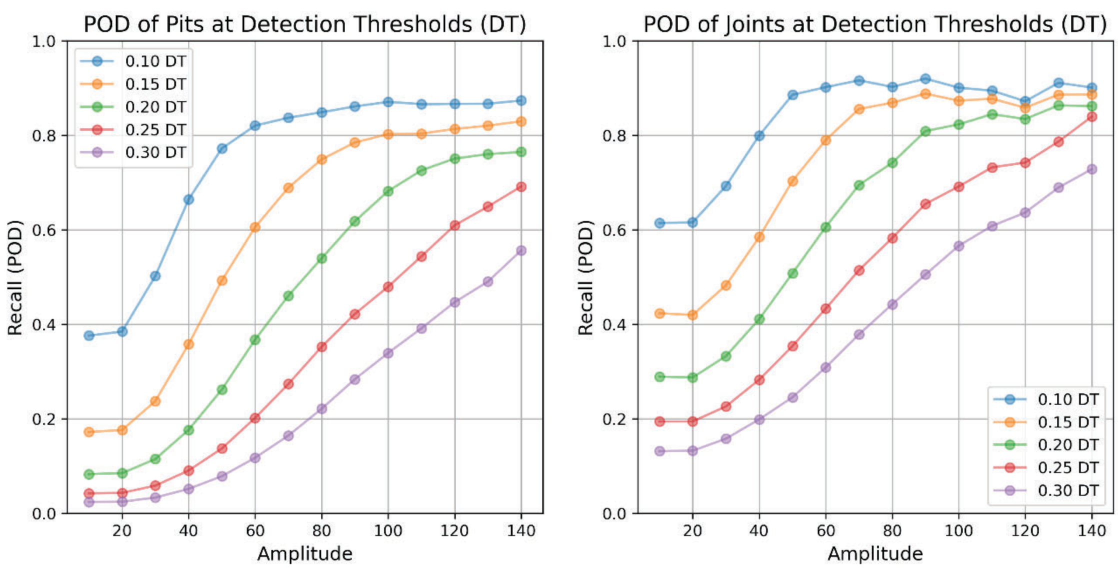

Figure 11: Recall (detection) curves at different thresholds for all metal loss features (left) and joint with at least one feature of a given amplitude (right).

Since SMFL scanning follows MFL scanning, SMFL features are paired with MFL features that are in close proximity, avoiding duplicating an already detected feature. Conversely, a new automated

https://doi.org/10.52202/078572-0038

process is in development to find the SMFL component for each scanned MFL feature. This automation leverages recent improvement in location alignment between the SMFL and MFL bodies. Automated hybrid sizing utilizes the mixture model defined above for actual sizing. The SMFL scanner used in conjunction with automated identification of SMFL components for MFL features gives 100% automated coverage for the SMFL dataset.

Automation of Pipeline Fixture Detection

Detection and identification problems are not isolated anomalies within a pipeline system. Fixtures, while not often seen as an ILI identifiable threat, are important in the analysis process. MFL signals at the edges of tees, valves, or forged bends often produce signal that resemble metal loss, leading to false anomaly calls and extra manual intervention around these locations. Fixtures must be boxed accurately so the buffer regions around them can be excluded from subsequent scans. Additionally, pipe tally information that includes pipeline fixtures is beneficial for record keeping and updating, operating logistics, and feature locating during field investigations.

Improved fixture detection and identification can be done using semantic segmentation, an advanced deep learning computer vision technique designed specifically for object identification [18]. This method can be applied to pipeline fixtures to reduce labor for analysis detection, identification, and annotation processes. **Figure *12*** shows the results from a deep learning semantic segmentation model trained specifically for pipeline fixtures in MFL ILI data. The input image is on the left, the labeled classification targets are in the center, and the model predications are on the right.

Figure 12: Results of a deep learning semantic segmentation model for pipeline fixtures with model inputs (left), targets (center), and predictions (right) shown.

This model shows promising results in detecting and identifying features and the architecture allows for immense scalability. Additional datasets, such as other ILI technologies, previous inspection pipe

 https://doi.org/10.52202/078572-0038

tallies or as built information, can be supplemented to further improve performance. Deep learning models like this one require lots of training data, orders of magnitude more than the previously mentioned random forest or XGB methods and pixel-level annotations. This is relatively easy to accumulate for pipeline fixtures as field investigation are nearly never needed to have a high confidence in the target classification. Conversely, all the other features discussed in this paper require field investigations to have a high confidence in their target classification or depth. Accumulating good training data is the crux of any machine learning application [17].

Generation of Training Data

Machine learning techniques all require annotated training data for model development. TDW uses a curated data set of real-world field measurements that have had the matching NDE provided, correcting misalignments and evaluating the quality of provided "truth" data. Increasingly, high-resolution scan data derived from NDE technologies like automated ultrasonic testing (AUT) or external laser profilometry are being provided. Scan data gives a complete picture of the pipe, including both shallow and deep pits and a fine view of the connected nature of clusters. This dataset can be large, full circumferential scans of entire pipe joints or more, and consuming, correlating and utilizing as much data as possible is extremely important. Using these methods a single field investigation site can produce hundreds of real-world examples for training prediction models or assessing system performance. In efficiently utilizing this data, specific applications need to be developed to help ingest a large and complex dataset, allow for correlation of ILI feature and signal data, and cache the results in an easy to retrieve form. **Figure *13*** shows an application designed to do all of this by taking annotated markings from the ILI data (bottom) and superimposes them on top of the scan data (top). This allows rapid correlation of both the ILI and field results.

https://doi.org/10.52202/078572-0038

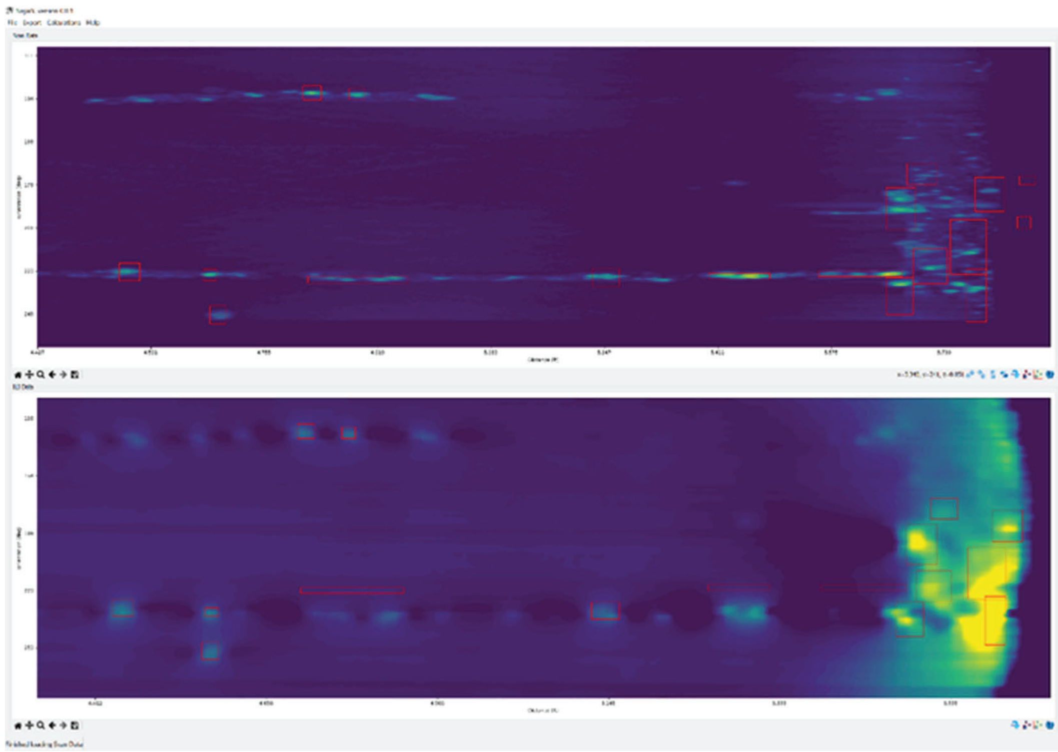

Figure 13: Application designed to quickly correlate NDE scan data (top) to ILI data and the associated feature annotations (bottom).

This application improves the ability to consume scan data, which in turn can produce more training data to feed larger and more complex models, and potentially even support generative AI in the future.

Key Insights and Emerging Directions

ILI systems have evolved significantly over the last half a century and the future trajectory shows this trend is likely to continue. Not only will the number of technologies and resolution on a single platform grow, but datasets from external sources will provide additional insight. As shown here, machine learning models can assist in solving complex problems and are instrumental in ensuring the safe operation of our energy infrastructure. The future growth of data will continue to require machine learning, AI and advanced computing to be an integral part of the process. Their ability to consume vast and complex datasets to provide actionable data will be indispensable.

Acknowledgments

The authors would like to acknowledge the following individuals for their contributions to the writing of this paper or to the vision and advancement of MDS Pro: James Simek, Jed Ludlow, Philip Morrison, Chuck Harris, Matthew Romney, Rob Coleman, Davin Saderholm, Chis Goller, Paul Dalfonso.

https://doi.org/10.52202/078572-0038

References

[1] S. Timashev and A. Bushinskaya, "Basics of ILI of Pipelines," in *Diagnostics and Reliability of Pipeline Systems*, New York, Springer, 2016, pp. 45-71.

[2] K. Grimes, "The Changing Role of Inspection," in *Proceedings of the 1998 2nd International Pipeline Conference*, Calgary, Alberta, CA, 1998.

[3] H. M. Crump and S. Papenfuss, "Utilization of Magnetic Flux Leakage Inspection Pigs for Hard Spot Detection and Repair," in *Corrosion91*, Cincinnati, Ohio, 1991.

[4] "Pipeline Rupture and Susequent Fire in Bellingham, Washington," National Transportation Safey Board, Washington, DC, June 10, 1999.

[5] A. E. Crouch and R. C. Beavers, "Pipeline Inspection Apparatus for Detection of Longitudinal Defects". New York, New York, USA Patent 3483466, 9 December 1969.

[6] J. B. Nestleroth, "Evaluation of Circumferential Magnetic Flux for In-Line Detection of Stress Corrosion Cracks and Selective Seam Weld Corrosion," Pipeline Research Council International, Houston, TX, 1999.

[7] T. W. Krause, R. W. Little, R. Barnes, R. M. Donaldson, B. Ma and D. L. Atherton, "Effect of Stress Concentration on Magnetic Flux Leakage Signals from Blind-Hole Defects in Stressed Pipeline Steel," *Research in Nondestructive Evaluation,* vol. 8, no. 2, pp. 83-100, 1996.

[8] R. Davis, T. Bubenik and A. Crouch, "Final Report on the Feasibility of MFL ILI as a Method to Detect and Characterize Mechanical Damage," in *Review of Progress in Quantitative Nondestructive Evaluation, Vol 16*, Boston, MA, Springer, 1997, pp. 1291-1298.

[9] C. Goller, J. Simek and J. Ludlow, "Multiple Data Set ILI for Mechanical Damage Assessment," in *Proceedings of the 2012 9th International Pipeline Conference*, Calgary, Alberta, CA, 2012.

[10] J. Simek, J. Ludlow and P. Tisovec, "Oblique Field Magnetic Flux Leakage Inline Survey Tool: Implementation and Results," in *Proceedings of the 8th International Pipeline Conference*, Calgary, Alberta, CA, 2010.

[11] A. Belanger and T. Barker, "Multiple Data Inspection of Hard Spots and Cracking," in *Proceedings of the 2014 10th International Pipeline Conference*, Calgary, Alberta, CA, 2014.

[12] B. Nestleroth, J. Simek and J. Ludlow, "New Classification Approach for Dents with Metal Loss and Corrosion along the Seam Weld," in *Proceedings of the 2016 11th International Pipeline Conference*, Calgary, Alberta, CA, 2016.

[13] D. Burden, N. Roniger and M. Romney, "Puddling Puddle Welds," in *Proceedings of the 2020 13th International Pipeline Conference*, Calgary, Alberta, CA, 2020.

[14] M. Romney and D. Burden, "Detection of Non-Axial Stress Corrosion Cracking (SCC) using MFL Technology," in *Pipeline Pigging and Integrity Management Conference*, Houston, 2020.

[15] P. Ramuhali, L. Udpa and S. Upda, "Neural network-based inversion algorithms in magnetic flux leakage nondestructive evaluation," *Journal of Applied Physics,* vol. 93, no. 10, pp. 8274-8276, 2002.

[16] D. Burden, P. Dalfonso and A. Belanger, "The Current Progeny of In-Line Inspection Machine Learning," in *PPIM 2020 - 32nd Pipeline Pigging and Integrity Management, Conference Proceedings* , Houston, TX, 2020.

[17] A. Belanger, D. Burden and P. Dalfonso, "Not All Data is Good Data: The Chalenges of Using Machine Learning," in *Proceedings of the 2022 14th International Pipeline Conference*, Calgary, Alberta, CA, 2022.

https://doi.org/10.52202/078572-0038

[18] A. Behbahanian, R. Lundstrom, A. Belanger, P. Dalfonso and R. Coleman, "PIPENet: A Semantic Segmentation Approach to Pipeline Component Detection from Magnetic Flux Leakage Readings," in *International Conference on Machine Learning and Applications (ICMLA)*, Jacksonville, Florida, 2023.

[19] M. Romney, J. Hardy, D. Burden and M. Dr. Kirkwood, "Highlighting the Threat of Circumferential Stress Corrosion Cracking (CSCC) with Advanced In-line Inspection Tools," in *The 37th International Pipeline Pigging & Integrity Management Conference* , Houston, Texas, USA, 2025.

[20] B. Nestleroth and J. Simek, "Improve and Develop ILI Tools to Locate, Size, and Quantify Complex/Interacting Metal Loss Features and Dents," Kiefner and Associates, Inc., Columbus, 2016.

[21] L. Breiman, "Random Forests," *Machine Learning,* vol. 45, pp. 5-32, 2001.

[22] D. Burden and M. Romney, "A Case Stufdy Applying Gouge Classification to Mechanical Damage Defects," in *International Pipeline Conference*, Calgary, 2022.

[23] A. P. Institude, "API RP 1183: Assessment and Management of Pipeline Dents," American Petroleum Institude, 2020.

[24] E. B. Clark, B. N. Leis and R. J. Eiber, "Integrity Characteristics of Vintage Pipelines," Interstate Natural Gas Association of America, Columbus, OH, 2004.

[25] M. J. Rosenfeld, S. Slater, B. Nestleroth and G. Wilkowski, "Pipe Body Hard Spot Susceptibility - White Paper," Pipeline Research Council International, 2024.

[26] "Pipeline Incidents By Cause," US DOT Pipeline and Hazardous Materials Safety, 4 12 2024. [Online]. Available: https://portal.phmsa.dot.gov/analytics. [Accessed 4 12 2024].

[27] W. contributors, "Flood fill," Wikipedia, The Free Encyclopedia., 14 11 2024. [Online]. Available: https://en.wikipedia.org/wiki/Flood_fill. [Accessed 3 12 2024].

[28] W. contributors, "XGBoost," Wikipedia, The Free Encyclopedia, 05 11 2024. [Online]. Available: https://en.wikipedia.org/w/index.php?title=XGBoost&oldid=1255538163. [Accessed 5 12 2024].

[29] N. Didrik, "Tree Boosting With XGBoost - Why Does XGBoost Win "Every" Machine Learning Competition?," Norwegian University of Science and Technology, Trondheim, 2016.

[30] M. Romney, D. Burden and R. Lundstrom, "Validating Selective Seam Weld Corrosion Classification Using ILI Technology," in *Pipeline Pigging and Integrity Managmeent*, Houston, TX, 2023.

 https://doi.org/10.52202/078572-0038