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Enhancing Pipeline Safety and Predicting Remaining Life: Leveraging Machine Learning Techniques and SHAP Interaction Values

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Abstract : In this study, we propose a cost-effective approach to predict inline inspection (ILI) results using machine learning (ML) models. Three prediction cases were considered: detecting defects, predicting defect dimensions, and estimating defect growth rates. Cat boost (CAT) emerged as the optimal ML method across all cases, offering high accuracy in predicting defect presence and characteristics. By leveraging pipeline attributes and environmental features, our approach significantly reduces unnecessary ILI costs and provides valuable insights for pipeline maintenance and management. Accurate predictions and insightful correlation analyses contribute to substantial cost savings and informed decision-making in pipeline integrity management.

Keywords: In-line inspection, Machine learning, Pipeline defect, SHAP values, Remaining life

Introduction

In the realm of global energy transportation, pipelines serve as the lifelines, facilitating the movement of natural gas, petroleum products, and other vital energy resources. Ensuring the safe operation of these pipelines is paramount, necessitating recurrent inspections and assessments. Among the various methods employed for pipeline inspection, in-line inspection (ILI) stands out as one of the most widely utilized techniques. ILI, a form of non-destructive examination, plays a crucial role in preventative maintenance by identifying potential threats such as corrosion, cracks, and other defects that could lead to catastrophic structural failures.

The process of ILI involves deploying sophisticated technological tools inside the pipeline, capable of traversing its entire length. These tools are equipped to detect and size anomalous conditions along both the inner and outer walls of the pipeline. Additionally, ILI tools record crucial data such as wall thickness and pipeline geometry, providing valuable insights into the pipeline's condition. The results gleaned from ILI surveys are instrumental in determining the locations for repair and replacement within the pipeline network.

Despite its effectiveness, ILI technology comes with a significant financial burden. The costs associated with ILI inspections are often substantial, with expenses typically calculated on a per-kilometer basis. The total expenditure can vary widely depending on factors such as the service provider, the complexity of the pipeline system, the number of inspections runs required, and any additional services or analyses needed. Moreover, the majority of pipelines inspected through ILI are found to be defect-free, rendering a significant portion of the ILI costs unnecessary.

To address the challenge of cost-effectiveness in pipeline maintenance, researchers and industry practitioners have explored various approaches to predict pipeline safety and ILI outcomes. Historically, two primary methodologies have been employed: the Finite Element Method (FEM) and machine learning (ML). Each approach offers distinct advantages and challenges in the context of pipeline integrity management

FEM, a numerical technique for solving engineering problems, has been extensively utilized in simulating the mechanical and electrochemical behavior of pipelines. Researchers have developed sophisticated FEM models to simulate corrosion potential, corrosion current density, and failure pressures at defects within pipelines. These simulations provide valuable insights into the mechano-electrochemical effects of pipeline corrosion, aiding in predicting failure pressures and assessing structural integrity. Despite their accuracy, FEM simulations often require high-resolution meshes, leading to computationally intensive processes and prolonged analysis times.

In contrast, ML methods have gained traction in recent years for their ability to provide accurate predictions with reduced computational overhead. By leveraging large datasets and advanced algorithms, ML models can effectively predict pipeline defects and their characteristics. For instance, researchers have combined wavelet transform techniques with ML methods to predict defect dimensions using magnetic flux leakage (MFL) signals obtained from ILI inspections. These studies have demonstrated high levels of accuracy in detecting and estimating the size and depth of defects, without the need for complex preprocessing of ILI signals.

One notable advantage of ML methods is their flexibility in handling diverse datasets and extracting valuable insights from them. For instance, researchers have proposed methodologies combining pattern-adapted wavelet analysis with artificial neural networks to automate the analysis of MFL signals. These approaches have proven highly accurate and computationally efficient, enabling the detection and estimation of defect parameters without relying on prior knowledge of specific defect shapes.

Furthermore, ML methods have been employed in predicting pipeline leakage detection, localization, and sizing, contributing to enhanced pipeline safety and reliability. Researchers have developed ML models using various input features, including inlet pressure, outlet flow, and statistical parameters derived from wavelet-based approaches. These models have demonstrated high accuracy in detecting leakage locations and severity, thereby minimizing environmental and financial risks associated with pipeline failures.

Despite the advancements in ML-based approaches, most previous studies have relied on ILI signals as input features, necessitating laborious preprocessing steps. This limitation poses challenges in implementing these methods in real-world industry settings where time and resources are often constrained.

In this study, we propose a novel approach to predict ILI survey results using ML methods, specifically focusing on predicting defect presence, size, and growth rate. Unlike previous studies, our approach utilizes basic pipeline attributes as input features, which are readily available and require no complex preprocessing. By streamlining the prediction process, our methodology offers practical insights for pipeline integrity management, enabling cost-effective maintenance strategies and enhanced operational efficiency.

In conclusion, ensuring the safe operation of pipelines is essential for the global transportation of energy resources. While ILI plays a crucial role in identifying potential threats, the associated costs can be substantial. By leveraging advanced methodologies such as ML, researchers and industry practitioners can develop cost-effective approaches to predict pipeline safety and optimize maintenance strategies. These efforts are instrumental in enhancing pipeline integrity, mitigating risks, and ensuring the reliable transportation of energy resources worldwide.

2. Methodology

2.1. Methodology for Three ML Prediction Scenarios.

This study examines three application cases employing machine learning (ML) methods to forecast primary Internal Lining Inspection (ILI) outcomes. Figure 1 delineates the process for these cases. Firstly, a ML classifier is employed to anticipate pipeline defects. Subsequently, ML regressors are utilized to forecast defect dimensions (length, width, and depth). Lastly, another ML regressor predicts defect length and depth growth rates, facilitating an analysis of pipeline residual life. Growth rates are computed based on defect depth data from ILI results in 2015 and 2020.

2.2 Approach.

This research aims to develop a suite of machine learning (ML) techniques for accurately forecasting pipeline safety and residual life. It focuses on three prediction scenarios: defect prediction, defect size estimation, and growth rate prediction of defect depth. These cases are crucial for achieving the overarching objective. Defect prediction involves a classification task, as it discerns between two discrete outcomes: defect or non-defect. On the other hand, defect size prediction and growth rate prediction of defect depth constitute regression problems, as they entail continuous output variables such as defect length, width, depth, and growth rate.

To address classification challenges, six robust classifiers are chosen: K-nearest neighbors (KNN), Artificial Neural Network (ANN), Random Forest (RF), Light GBM (LGBM), XGBoost (XGB), and Cat Boost (CAT). These classifiers offer diverse approaches to effectively tackle classification tasks.

For regression tasks, namely defect size prediction and defect depth growth rate estimation, LGBM, XGB, and CAT are selected due to their superior performance compared to other ML methodologies. These methods are known for their capability to handle regression problems efficiently and accurately.

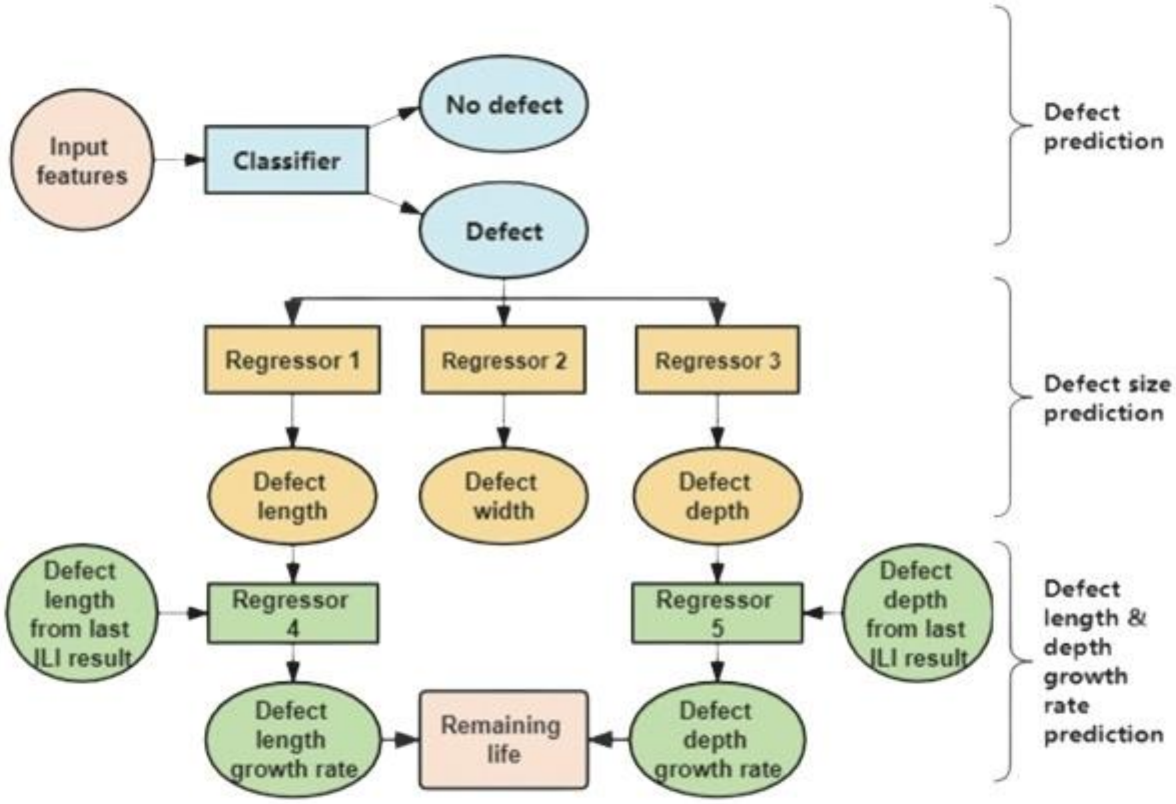
Each ML method employed in this study undergoes a brief description, highlighting its distinctive features and suitability for the respective prediction tasks. By leveraging these advanced ML techniques, the research aims to significantly enhance the predictive accuracy of pipeline safety and residual life, thereby contributing to improved maintenance strategies and overall safety standards in pipeline operations.

2.2.1 Neighborhood-based Learning: Understanding K-nearest Neighbors.

KNN stands as one of the fundamental machines learning algorithms, operating on a supervised learning principle. It relies on the notion of similarity between a new data point and existing ones, assigning the new point to the category most akin to its nearest neighbors. This method is commonly employed for classification tasks, determining the label of a sample based on the predominant category among its closest k neighbors. Often referred to as a "lazy learner" algorithm, KNN does not immediately learn from a training set but instead memorizes the entire dataset. In this approach, the algorithm defers computation until classification is required, making it efficient for real-time applications. The distance between two samples, denoted by xi and xj, is typically measured using the Lp distance metric. This metric defines the distance between two points in a feature space, aiding in the determination of similarity between data instances'-Nearest Neighbors (KNN) is a cornerstone algorithm in machine learning, operating on the premise of supervised learning. Its principal hinges on the concept of similarity between a new data point and existing ones within a dataset. By leveraging this similarity measure, KNN assigns the new point to the category most resembling its nearest neighbors. This method finds extensive application in classification tasks, where it determines the label of a sample based on the prevalent category among its k closest neighbors. What distinguishes KNN from other algorithms is its "lazy learner" nature. Unlike many traditional machine learning algorithms that actively learn from training data upfront, KNN defers computation until classification is needed. Instead of constructing an explicit model during the training phase, KNN memorizes the entire dataset.

This characteristic renders KNN particularly well-suited for real-time applications where quick response times are crucial, as it avoids the computationally intensive training process. Central to KNN's operation is the computation of distances between data points. Typically, the distance between two samples, denoted as xi and xj, is evaluated using the Lp distance metric. This metric defines the spatial separation between two points within a feature space, facilitating the assessment of similarity between data instances.

The choice of the distance metric, often determined by the value of p, influences the interpretation of proximity between data points. For instance, the Manhattan distance (L1 norm) calculates distance as the sum of absolute differences between coordinates, while the Euclidean distance (L2 norm) computes the straight-line distance between points.KNN's simplicity, coupled with its effectiveness in capturing complex decision boundaries, has cemented its status as a foundational algorithm in the machine learning landscape. Despite its simplicity, KNN's performance can be influenced by factors such as the choice of distance metric, the number of neighbors (k), and data normalization techniques. As such, practitioners often employ KNN alongside other algorithms or preprocessing methods to achieve optimal results in classification tasks.



Flow Chart of The Study Progress

2.2.2 Artificial neural network.

Artificial Neural Networks (ANNs) take inspiration from the complex network of neurons in the human brain to process information. Structured akin to the brain's architecture, ANNs are composed of layers of interconnected nodes, each representing an artificial neuron. This architecture typically includes an input layer where data is initially fed into the network, one or more hidden layers responsible for processing and transforming the input data, and an output layer that produces the final result.

Within an ANN, communication between neurons occurs through weighted connections. Each connection between neurons is assigned a weight, representing the strength of influence one neuron has on another. Additionally, neurons employ activation functions to determine their output based on the weighted sum of inputs and thresholds. Activation functions introduce non-linearities into the network, enabling it to learn complex patterns and relationships within the data.

During the forward propagation phase, input data is processed layer by layer through the network. Each neuron receives inputs from neurons in the previous layer, computes a weighted sum of these inputs, applies an activation function, and passes the output to neurons in the next layer. This process continues until the output layer produces the final result.

The training of an ANN involves adjusting the weights of connections to minimize the difference between the network's predictions and the actual target values. This is typically achieved through backpropagation, where the error is propagated backward through the network, and the weights are updated using optimization algorithms such as gradient descent.

Overall, ANNs are powerful computational models capable of learning complex patterns and relationships from data. Their ability to mimic the brain's neural processing makes them versatile tools used across various fields, including image and speech recognition, natural language processing, and predictive modeling.

2.2.3 Ensemble Decision Forest

Ensemble Decision Forest is an ensemble algorithm comprising decision trees, extensively employed in both classification and regression tasks. It constructs decision trees using a bagging technique, where random samples are selected from the original dataset with replacement to build each model or tree. Each model or tree is trained independently, yielding a potential outcome. The ultimate output of RF is determined through majority voting, wherein the results of all models or trees are combined and the most common result is selected.

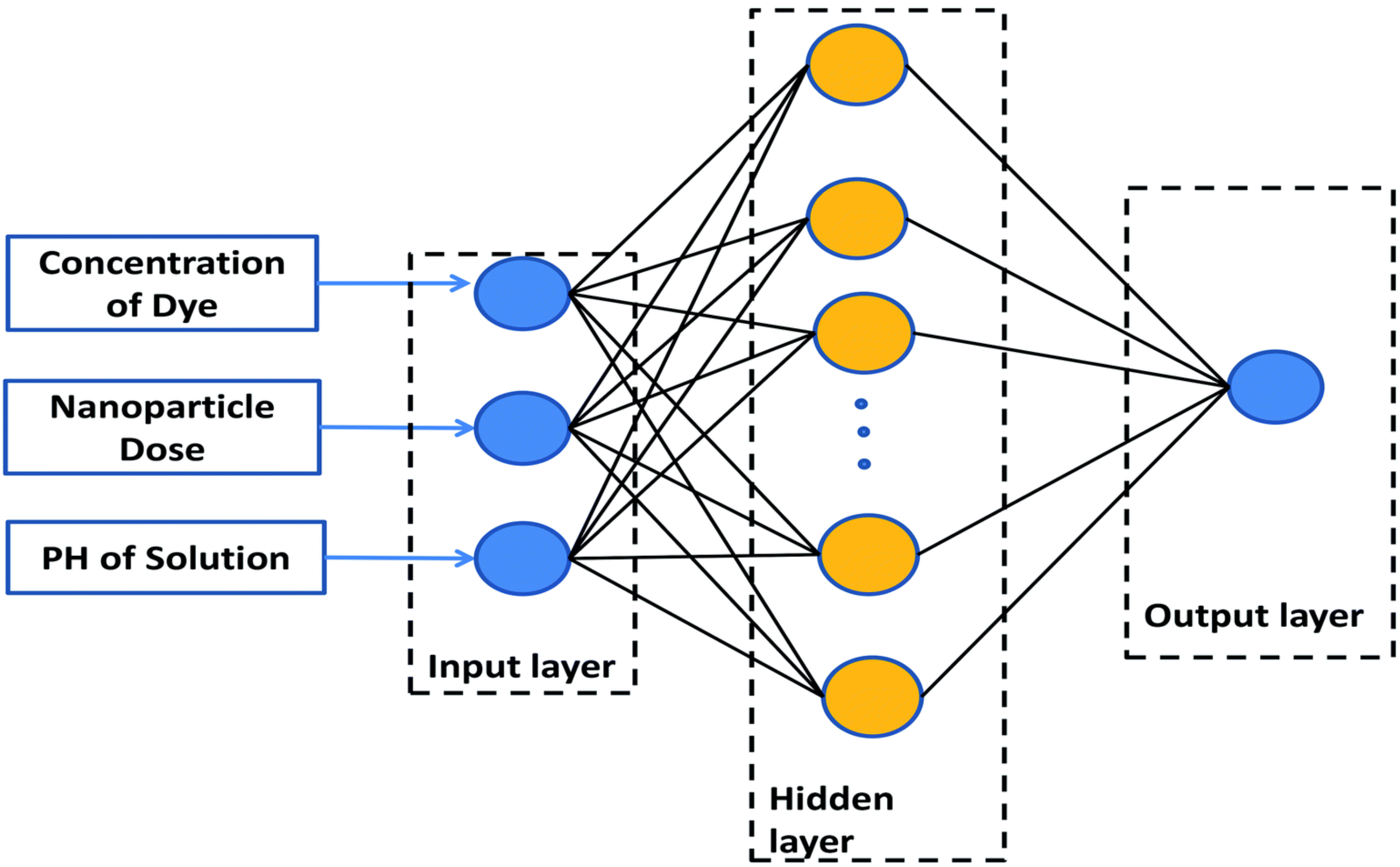


Fig2 Architecture of ANN

2.2.4 Extreme Gradient Boosting.

Extreme Gradient Boosting an open-source machine learning technique introduced by Chen et al, employs a Gradient Boosting Decision Tree algorithm and introduces numerous enhancements to the algorithm. It has gained widespread adoption in various machine learning competitions, demonstrating notable performance. Diverging from conventional gradient boosting approaches, XGB incorporates a regularized model formulation to mitigate overfitting and enhance prediction accuracy. This regularization mechanism involves the addition of a new term to the loss function.

$$L(f) = \sum L(y_i, y_i) + \sum \Omega(\delta_m)$$

2.2.5 A Swift and Effective Gradient Boosting Library.

Similar to XGBoost (XGB), LightGBM (LGBM) is a high-performance framework designed for distributed computing, developed by a research team at Microsoft in 2017. Both frameworks utilize decision trees for classification and regression tasks. However, LGBM employs a different approach compared to XGB. While XGB follows a level-wise (horizontal) growth strategy, LGBM adopts a leaf-wise (vertical) growth strategy.

This distinction offers several advantages for LGBM. Firstly, the leaf-wise growth strategy contributes to faster training speeds, allowing LGBM to process data more efficiently. Additionally, this approach tends to yield higher prediction accuracy, as it enables the model to focus on more informative splits during tree construction. Moreover, LGBM's leaf-wise growth strategy facilitates support for parallel learning, where multiple tasks can be executed simultaneously, enhancing scalability and performance. Furthermore, LGBM is capable of leveraging GPU acceleration, further boosting its computational efficiency.

Overall, LGBM's unique approach to tree growth makes it a powerful and efficient tool for various machine learning tasks. Its ability to deliver fast training speeds, high accuracy, and support for parallel and GPU learning makes it particularly well-suited for large-scale datasets and computationally intensive applications.

2.2.6 A Robust Gradient Boosting Framework for Categorical Data.

LightGBM (LGBM), akin to XGBoost (XGB), stands as a distributed, high-performance framework renowned for its adeptness in employing decision trees for both classification and regression tasks. Introduced by a team of researchers at Microsoft in 2017, LGBM sets itself apart from its XGB counterpart by adopting a leaf-wise (vertical) growth strategy, a departure from XGB's level-wise (horizontal) growth approach.

This distinctive growth methodology yields several advantageous outcomes for LGBM. One notable advantage is its ability to achieve accelerated training speeds. By prioritizing the growth of trees by leaf nodes rather than levels, LGBM can efficiently focus on splits that offer the most significant information gain, thereby streamlining the training process and enhancing overall computational efficiency. This accelerated training capability is particularly beneficial when dealing with large-scale datasets and computationally intensive tasks, where speed is of the essence.

Furthermore, LGBM's leaf-wise growth strategy often translates into improved prediction accuracy. By prioritizing informative splits, the model can better capture complex patterns and relationships within the data, leading to more precise predictions. This heightened accuracy is instrumental across various applications, including finance, healthcare, and e-commerce, where the ability to make reliable predictions is paramount

Moreover, LGBM's design facilitates support for parallel learning, enabling multiple tasks to be executed concurrently. This parallelization capability enhances scalability, allowing LGBM to efficiently handle large datasets and complex models. Additionally, LGBM boasts compatibility with GPU learning, leveraging the computational power of graphics processing units to further accelerate training speeds and enhance performance.

In essence, Light GBM's adoption of a leaf-wise growth strategy represents a significant advancement in gradient boosting frameworks, offering not only accelerated training speeds and improved accuracy but also robust support for parallel and GPU learning, making it a preferred choice for a wide range of machine learning tasks and applications.

2.3. Metric Evaluation.

In this research, performance metrics were employed to measure the effectiveness of a predictive model. Two sets of metrics were utilized: one for evaluating classification performance (defect prediction), and the other for assessing regression performance (predicting defect length, defect width, defect depth, and defect depth growth rate)

2.3.1 classification scenario.

The evaluation metrics for a classification problem rely on several key indicators. True Positive (TP) occurs when a model accurately predicts a positive class, while True Negative (TN) indicates correct predictions of a negative class. False Positive (FP) signifies incorrect predictions of a positive class, and False Negative (FN) represents inaccurate predictions of a negative class. In this investigation, defect prediction constitutes a binary classification issue with two outcomes: "defect" and "non-defect," where "Defect" is considered the positive class and "non-defect" the negative class. Three metrics utilized in this research can be derived from a confusion matrix.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$PRECISION = \frac{TP}{\text{TP} + \text{FP}}$$

$$\text{RECALL} = \frac{TP}{TP+FN}$$

Accuracy is determined by the proportion of correctly predicted samples relative to the total number of samples. Precision is computed as the ratio of true positives to predicted positives, while recall represents the ratio of true positives to all actual positives.

2.4 Deciphering Results Using the Shapley Additive explanation (SHAP) Method.

SHAP, pioneered by Lundberg and Lee in 2017, is a technique for interpreting machine learning model predictions by leveraging Shapley values. The fundamental concept behind SHAP involves computing Shapley values for every feature in a given sample for interpretation. Each Shapley value quantifies the contribution of the associated feature to the model's prediction. In the context of a linear function involving binary features, SHAP offers a method to succinctly express this relationship.

3.Real-World Scenarios.

3.1. Fault Prediction.

Unlike previous studies (references [9–17]), which utilized features derived from ILI signals, this research shifts focus to predicting pipeline defects using fundamental pipeline attributes. Data from a major pipeline company includes details of 11,000 pipeline sections and ILI outcomes from 2020, predominantly for natural gas transport. Among these, 2158 sections exhibit defects, while 8842 pass ILI unscathed. Six ML models

(KNN, ANN, RF, LGBM, XGB, CAT) are developed, considering seventeen input features such as length, manufacturing year, yield strength, diameter, thickness, material, manufacturer, seam type, and inspection date. Defect prediction involves dimensions like length, width, and depth, treating defects as regular rectangular shapes for analysis. The study also compares three ML methods: XGB, LGBM, and CAT.

3.2. Defect Dimension Forecasting.

To further forecast the dimensions of defects identified in pipelines, we develop three ML models using data from 2158 defective pipeline samples. These models aim to predict the length, width, and depth of observed defects. Given the complexity and variability of actual defects, we simplify their shapes to regular rectangles for analytical purposes. In the pipeline inspection field, ILI analysis primarily focuses on defect location and utilizes dimensions like length, width, and depth for measuring defects. The input variables align with those outlined in Section 3.1. We evaluate and compare the performance of three ML techniques – XGB, LGBM, and CAT – in this context.

3.2.1 Forecasting Defect Length and Depth Growth Rate.

Among the subset of 2158 defective pipeline sections mentioned in Section 3.1, 505 samples include defect depth data retrieved from ILI results dating back to 2015. By juxtaposing the defect length (DL) and defect depth (DD) values collected in 2020 with those from 2015, the actual defect length growth rate (DLGR) and depth growth rate (DDGR) are calculated. This methodology, elucidated in reference [27], facilitates the evaluation of how defects' length and depth within the pipelines have progressed over the specified period.

$$DLGR = \frac{\mathrm{DL2020} - \mathrm{DL2015}}{\mathrm{5YEARS}}$$

In this context, DLGR (defect length growth rate) and DDGR (defect depth growth rate) act as output features, indicating the rate of increase in length and depth of pipeline defects over time. These metrics are pivotal for evaluating pipeline structural integrity and safety. The predictive capabilities of three machine learning models – XGB, LGBM, and CAT – are assessed to ascertain their accuracy in forecasting these growth rates. By gauging the models' performance in predicting DLGR and DDGR, stakeholders can make well-informed decisions regarding maintenance and repair schedules, ultimately bolstering pipeline reliability.

4. Outcome and Examination.

4.1 Assessment of Machine Learning Models for Pipeline Defect Prediction.

4.1.1 Optimizing Model Parameters: Fine-Tuning for Improved Performance.

A hyperparameter is a parameter instrumental in controlling the learning process of a model. Prior to constructing all machine learning models, hyperparameter tuning becomes indispensable to select an optimal set of hyperparameters, thereby crafting the most effective predictive model. Table 2 outlines the ideal combinations of hyperparameters for all ML models employed in the defect prediction study. This tuning process significantly enhances the model's predictive performance by fine-tuning parameters to suit the specific characteristics of the dataset and problem at hand.

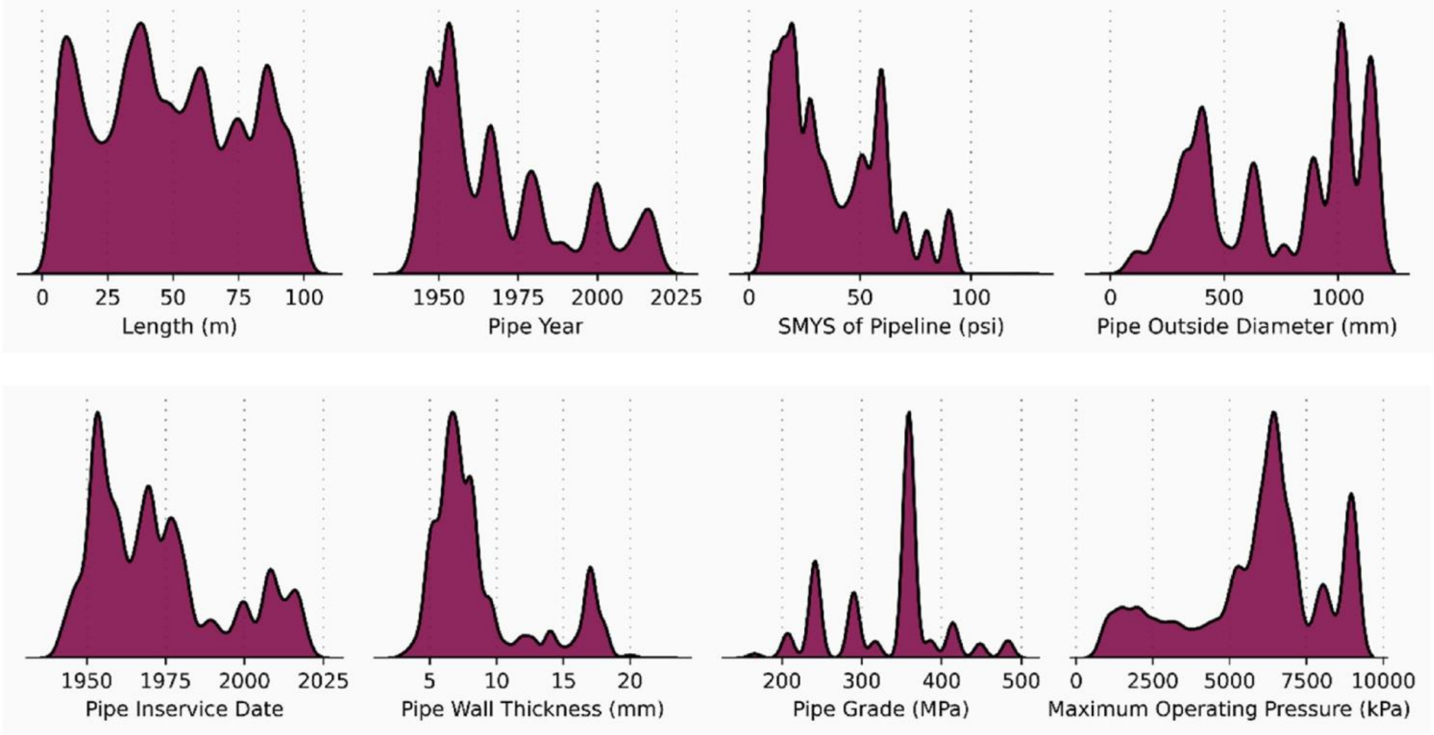


Fig 5 Statistical description of numerical input features used in prediction.

The proportion metric is essential for companies making informed decisions about pipeline management. In Fig. 5, proportions of predictions across three models are shown. The XGB model confidently identifies 61% of samples as non-defective with a CPT of 0.97, while LGBM and CAT models show different proportions. The CAT model stands out with 94% of certain predictions, making it the most effective. This high precision reduces the need for further inspection to just 6% of uncertain samples. Such accuracy enhances decision-making confidence, optimizing resource allocation and risk mitigation in pipeline management. Utilizing advanced machine learning techniques like the CAT model is crucial for maximizing pipeline management strategies**.**

	KNN			ANN			RF		
Prediction performance	0.921	0.919	0.923	0.948	0.951	0.948	0.941	0.936	0.942
	XGB			LGBM			CAT		
Prediction performance	precision	recall	accuracy	precision	recall	accuracy	precision	recall	accuracy
	0.959	0.964	0.967	0.961	0.954	0.962	0.969	0.975	0.971

Prediction performance of six ML classifiers for defect/non-defect of pipelines. KNN

4.1.2 Forecasting Pipeline Defects: A Binary Classification Approach.

The performance of KNN, ANN, RF, XGB, LGBM, and CAT models in defect prediction was assessed using accuracy, precision, and recall metrics. Results from a test dataset (20% of the sample) show satisfactory performance overall, with metrics exceeding 0.91. Notably, XGB, LGBM, and CAT outshine others, with values surpassing 0.95 for all metrics. CAT particularly excels, boasting the highest precision (0.969), recall (0.975), and accuracy (0.971).

To further compare XGB, LGBM, and CAT, the certain prediction proportion metric is introduced, using thresholds (CPT and CFT) previously used with XGB. These thresholds are extended to LGBM and CAT models, with CPT separating certain 'non-defect' predictions and CFT separating certain 'defect' predictions.

This metric holds significance for industry applications, offering targeted insight into predictions deemed entirely trustworthy. Unlike overall statistical results, it aids in making informed decisions about pipeline management and maintenance, enhancing confidence in predictions and enabling proactive defect mitigation strategies.

4.1.2 Forecasting Pipeline Defect Size.

"Comparative Analysis of XG Boost (XGB), Light GBM (LGBM), and Cat Boost (CAT) Models for Predicting Defect Size"

The evaluation of XGB, LGBM, and CAT models in predicting defect size highlights CAT as the standout performer across various evaluation metrics. Assessment criteria such as Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R2) value were considered, where lower RMSE, MSE, and MAE, along with higher R2, indicate better predictive performance.

In defect depth prediction, all three ML methods demonstrate robust capabilities, with CAT leading with the highest R2 value (0.9574) and the lowest RMSE (0.1061), MSE (0.0113), and MAE (0.0684). This underscores CAT's superior accuracy and precision compared to XGB and LGBM. While XGB follows CAT in prediction accuracy, LGBM lags behind with less favorable results.

For defect length prediction, the ML models exhibit moderate predictive ability, with CAT once again showcasing the highest R2 value (0.7781). XGB and LGBM perform comparatively lower in this aspect, with R2 values of 0.6035 and below.

In predicting defect width, all three ML methods demonstrate weak predictive ability, with CAT achieving the highest R2 value of 0.5527. Despite the challenges in this area, CAT maintains its edge over XGB and LGBM.

Overall, CAT emerges as the preferred choice for defect size prediction due to its consistent superiority across all evaluated metrics. Its ability to minimize RMSE, MSE, and MAE while maximizing R2 underscores its effectiveness in accurately forecasting defect dimensions. This comparative analysis highlights CAT's potential as a powerful tool for defect size prediction in various applications.

4.2 Forecasting the Growth Rates of Defect Length and Depth.

The authors conducted predictive analyses on defect growth rates, encompassing depth, length, and width. Their findings revealed a strong correlation between the growth rates of defect depth and length with the input features. However, the predictive performance for defect width growth rate was notably unsatisfactory.

In this section, the focus shifts to a more detailed examination based on a dataset comprising 505 defect samples, encompassing defect length and depth data collected in 2015 and 2020. From this dataset, the authors derived the defect length growth rate (DLGR) and defect depth growth rate (DDGR) using equations (13) and (14), respectively. This approach aims to deepen the understanding of how these growth rates evolve over time, providing insights into the dynamics of defect development within the studied timeframe.

	KNN			ANN			RF		
	precision	recall	accuracy	precision	recall	accuracy	precision	recall	accuracy
Prediction performance	0.93	0.92	0.933	0.958	0.951	0.948	0.941	0.936	0.942
	XGB			LGBM			CAT		
	precision	recall	accuracy	precision	recall	accuracy	precision	recall	accuracy
Prediction performance	0.96	0.95	0.977	0.970	0.954	0.962	0.969	0.975	0.971

Prediction performance of six ML classifiers for defect/non-defect of pipelines.

4.2.1Forecasting Defect Length Growth Rate Dynamics

In their study, the authors examined the predictive accuracy of defect growth rates, specifically focusing on depth, length, and width expansions. Their findings revealed a strong correlation between input features and the growth rates of defect depth and length. However, the prediction performance for defect width growth rate was comparatively poor. Consequently, this section delves into an analysis based on a dataset comprising 505 defect samples recorded with defect length and depth measurements in both 2015 and 2020. Utilizing equations tailored for this purpose, the study computes the defect length growth rate (DLGR) and defect depth growth rate (DDGR) from the provided data. This analytical approach aims to shed further light on the dynamics of defect expansion over the specified time period, offering valuable insights into the mechanisms driving defect growth within the studied context.

Metrics	XGB	LGBM	CAT
RMSE	$3.68*10^{-2}$	$3.03*10^{-2}$	$9.83*10^{-3}$
MSE	$4.23*10^{-4}$	$3.92*10^{-4}$	$9.22*10^{-5}$
MAE	$2.26*10^{-2}$	$1.97*10^{-2}$	$7.19*10^{-3}$
R^2	0.944	0.952	0.967

Assessment of Three Models' Predictive Performance for Defect Length Growth Rate

4.2.2 Anticipating Dynamics in Defect Depth Growth Rate Prediction.

Using a dataset consisting of 404 samples for training machine learning (ML) models and 101 samples for testing, the exceptional accuracy of predictions highlights the robust predictive capabilities of the three ML techniques in forecasting defect depth growth rate (as shown in Table 7). All three methods demonstrate remarkable performance, yielding R2 values exceeding 0.96. Particularly, the CAT model exhibits the highest R2 value (0.989) alongside the lowest Root Mean Square Error (RMSE) (9.1510^-3), Mean Squared Error (MSE) (8.3710^-5), and Mean Absolute Error (MAE) (6.04*10^-3) among the models developed in this study. These results underscore the efficacy of ML approaches in accurately predicting defect depth growth rate, indicating their potential utility in practical applications within this domain.

Metrics	XGB	LGBM	CAT
RMSE	$1.45*10^{-2}$	$1.63*10^{-2}$	$9.15*10^{-3}$
MSE	$2.11*10^{-4}$	$2.66*10^{-4}$	$8.37*10^{-5}$
MAE	$1.09*10^{-2}$	$1.14*10^{-2}$	$6.04*10^{-3}$
R^2	0.971	0.963	0.989

Evaluation of Three Models' Predictive Accuracy for Defect Depth Growth Rate

4.2.3 Exploring Feature Importance: SHAP Analysis for Predicting Defect Depth Growth Rate.

Based on the CAT model's predictions, Figure 7 presents a SHAP plot, which assesses variables by their impact on the defect depth growth rate in pipelines. The analysis focuses on the top six influential features, as they exert a greater influence on defect depth growth rate compared to other factors. Notably, the Steel Minimum Yield Strength (SMYS) of a pipeline section emerges as the most critical feature affecting defect depth growth. Higher SMYS values correlate with a reduced likelihood of defect depth growth, indicating stronger pipelines less prone to deformation-induced defects. Similarly, Pipeline Year (PY) follows as another significant input, where newer pipelines with enhanced safety standards exhibit decreased defect growth rates. However, for the subsequent four vital features, including railway lines, wetlands, and elevated Maximum Operating Pressure (MOP), higher values correspond to an increased likelihood of greater defect depth growth rates. Conversely, a high clay content in soil type is associated with decreased defect growth rates.

4.2.4Assessment of Pipeline Remaining Service Life.

Determining the remaining lifespan of a pipeline is a pivotal task within the industry, encompassing a multifaceted process. Here's an overview of the essential steps involved:

(1) Assessing Pipeline Condition: The initial step entails evaluating the current state of the pipeline comprehensively. This assessment encompasses scrutinizing its physical integrity and identifying any existing defects such as corrosion, cracks, or deformations. Advanced Inspection and Evaluation (ILI) techniques like ultrasonic testing and magnetic flux leakage are commonly employed to detect and quantify these defects accurately.

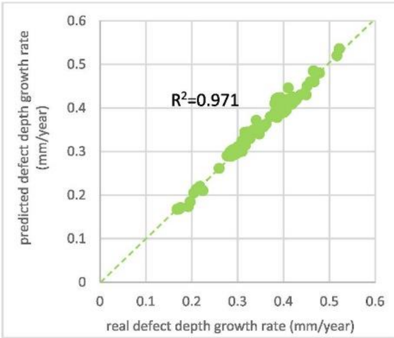
(2) Estimating Defect Growth Rates: Subsequently, it's imperative to ascertain the growth rate of each identified defect. This involves employing appropriate methodologies to gauge how these defects evolve over time. Utilizing data sourced from the pipeline itself, historical records, and industry benchmarks, these growth rates are calculated meticulously to provide insights into the progression of defects.

(3) Determining Pipeline Remaining Service Life: Armed with knowledge of defect growth rates, the next step entails calculating the pipeline's remaining service life. This computation revolves around estimating the duration it will take for defects to escalate to a critical size or threshold, potentially leading to pipeline failure. Factors such as corrosion depth and failure pressure are integral to this assessment, as they profoundly impact the pipeline's structural integrity and safety.

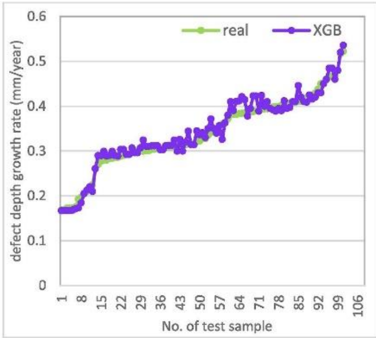
Throughout this process, meticulous consideration is given to various factors influencing pipeline longevity, ensuring a comprehensive evaluation of its condition and future prospects. By integrating data-driven analyses and industry expertise, stakeholders can make informed decisions regarding maintenance strategies and risk mitigation measures, thereby safeguarding the pipeline's operational integrity and longevity.\

4.3 Estimating Lifespan Using Failure Pressure Analysis

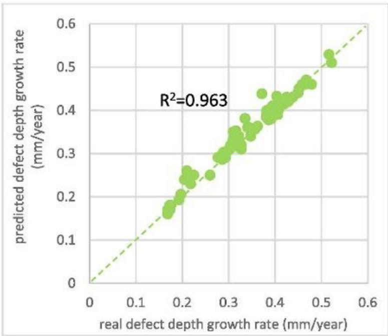
Predicting the failure pressure of defective pipelines is crucial for ensuring the safety and longevity of pipeline infrastructure. Common methods utilized for this purpose include industrial models and Finite Element Method (FEM) analysis. In the industry, setting the Maximum Operating Pressure (MOP) at 80% of the calculated failure pressure is a prevalent practice recommended by regulatory bodies such as the Pipeline and Hazardous Materials Safety Administration (PHMSA) and the American Petroleum Institute (API) Standard 579 (Fitness for Service). Among these methods, the ASME-B31G model (MB31G) stands out as a widely accepted industrial model for calculating the failure pressure of pipelines with corrosion defects



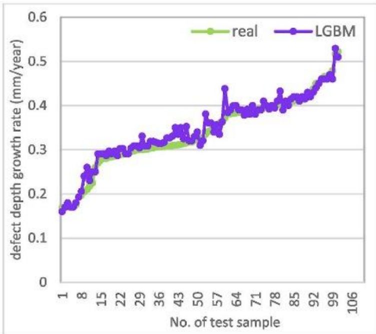
a) R^2 of XGB model



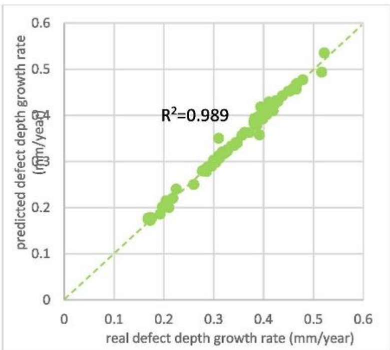
b) Comparisons between predictions of XGB model and real data



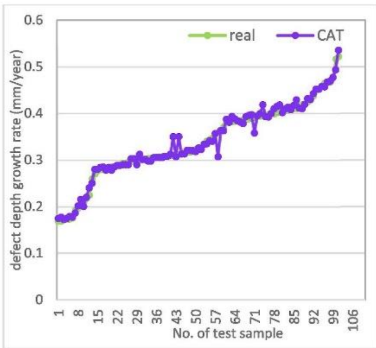
c) R^2 of LGBM model



d) Comparisons between predictions of LGBM model and real data

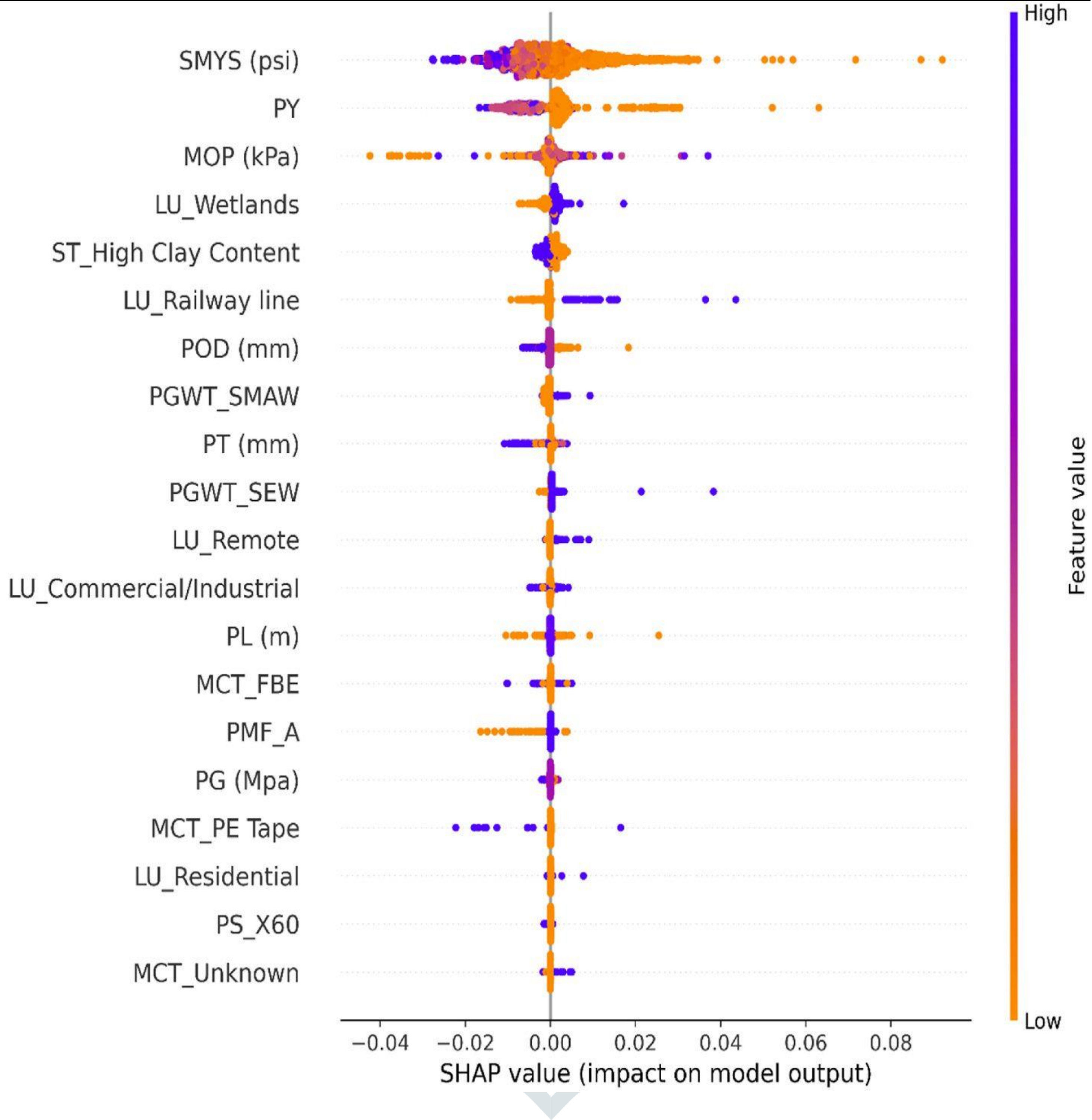


e) R^2 of CAT model

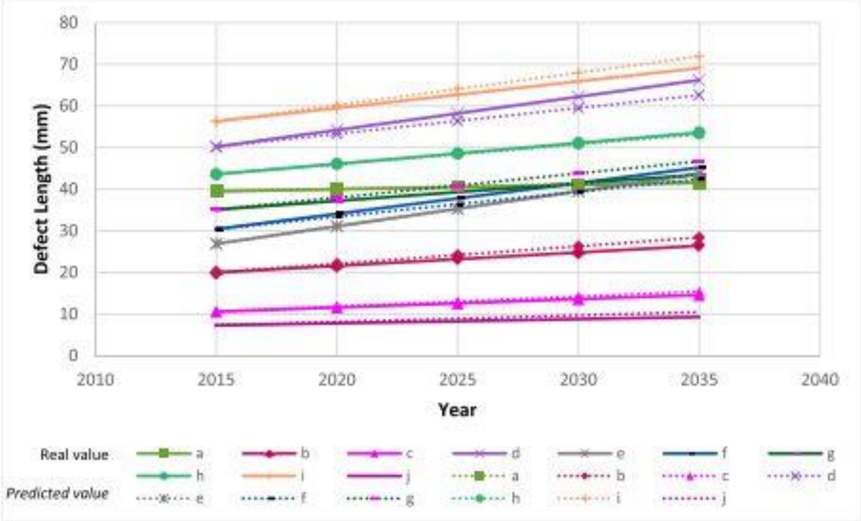


f) Comparisons between predictions of CAT model and real data

R2 Value Plots and Comparative Analysis of Three Models' Predictions for Defect Depth Growth Rate



SHAP Value Plot Analysis: CAT Model's Predictions for Defect Depth Growth Rate"



Contrasting Defect Length Changes: Predicted DLGR vs. Actual DLGR.

Pipeline Failure Pressure Prediction Methods.

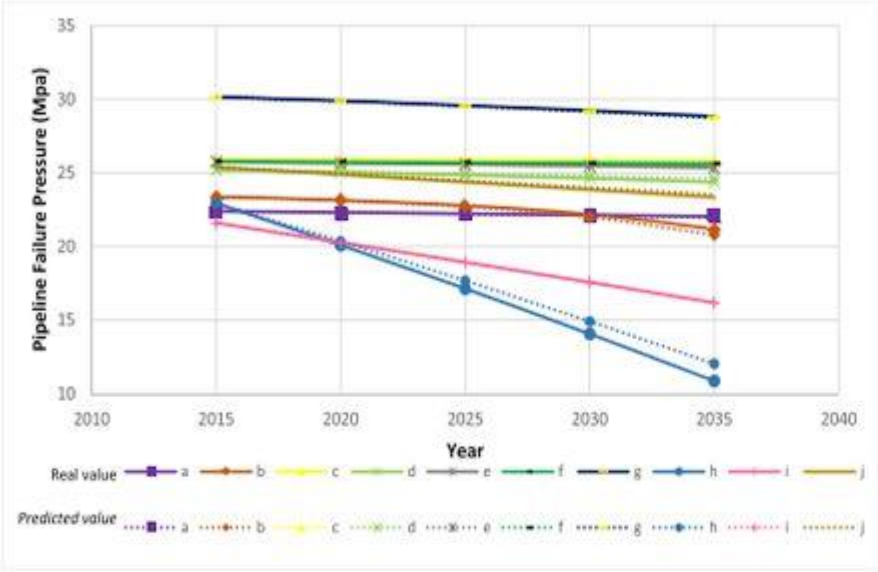
Industrial models and FEM analysis are the primary approaches employed to predict the failure pressure of pipelines with defects. Industrial models, such as the ASME-B31G model, utilize simplified equations and empirical data to estimate failure pressure. These models consider factors such as defect size, shape, and orientation, as well as material properties and operating conditions. On the other hand, FEM analysis provides a more detailed understanding by simulating the behavior of the pipeline under various loading conditions. While FEM analysis offers higher accuracy, it requires significant computational resources and expertise, making it less accessible for routine assessments.

Guidelines for Setting Maximum Operating Pressure:

The practice of setting the MOP at 80% of the calculated failure pressure is based on safety considerations to provide a margin of safety against unexpected failures. This approach ensures that the pipeline operates within a safe operating range while allowing for variations in operating conditions and uncertainties in the prediction models. Regulatory bodies such as PHMSA and API Standard 579 endorse this practice to promote the integrity and reliability of pipeline systems.

Role of ASME-B31G Model in Failure Pressure Prediction:

The ASME-B31G model, commonly referred to as MB31G, is widely recognized and utilized in the industry for predicting the failure pressure of pipelines with corrosion defects. This model incorporates factors such as defect dimensions, depth, and location to estimate the remaining strength of the pipeline. By considering the interaction between defects and material properties, MB31G provides engineers with a practical tool for assessing the structural integrity of pipelines and making informed decisions regarding maintenance and operational strategies.



Comparing Pipeline Failure Pressure: Predicted DDGR-DLGR vs. Actual DDGR/DLGR

4.3.1Assessing Pipeline Remaining Life Through Defect Depth Analysis.

The management of pipeline corrosion is crucial for ensuring the safety and longevity of Canada's pipeline infrastructure. Regulations and standards set by the Canadian Energy Regulator (CER) mandate regular inspections and maintenance activities to uphold pipeline integrity. The allowable corrosion depth varies depending on factors such as pipeline type, material, and location. This article explores the regulatory framework governing pipeline corrosion in Canada and presents a methodology for calculating the remaining life of pipelines based on defect depth.

Regulatory Framework for Pipeline Corrosion:

The CER establishes guidelines for managing pipeline corrosion in Canada, aiming to prevent accidents and environmental harm. These regulations require pipeline operators to conduct inspections and maintenance to detect and address corrosion issues promptly. Specific standards dictate the maximum allowable corrosion depth based on factors like pipeline material and diameter. For instance, pipelines made of carbon steel typically have a maximum allowable corrosion depth of 50% of the pipe wall thickness, while those made of API 5L Grade X60 steel may permit up to 80% of the nominal wall thickness.

Application and Analysis:

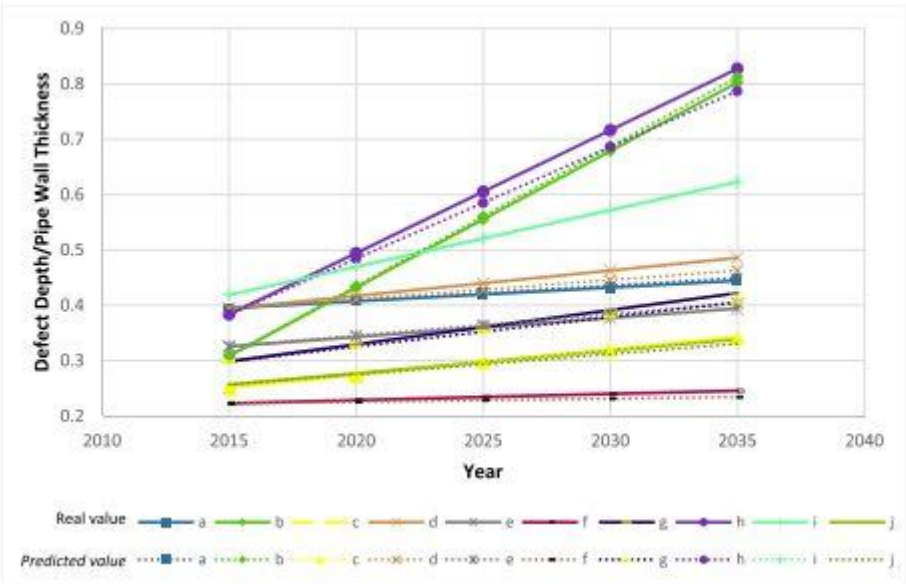
Figures 8 and 9 illustrate the growth of defect depth values over time and the corresponding changes in defect depth to pipe wall thickness ratio (D/T) for ten defects. These figures demonstrate how predicted defect depth growth closely aligns with actual values, facilitating accurate estimation of remaining life. Notably, while some defects exhibit significant depth, their relatively low growth rates result in longer remaining life spans compared to defects with higher growth rates. For instance, defect "d" has the highest depth but a small growth rate, allowing the associated pipeline to remain in service until 2035 within a 50% allowable D/T limit. Conversely, defects "b" and "h" exhibit shorter remaining lives due to their high growth rates, necessitating inspection and repair by 2022–2023.The assessment of pipeline integrity based on corrosion depth is essential for ensuring the safe and reliable operation of Canada's pipeline network. By adhering to CER regulations and employing methodologies for calculating remaining life, pipeline operators can effectively manage corrosion-related risks and prioritize maintenance activities. Continuous monitoring and proactive maintenance strategies are paramount to extending the lifespan of pipelines and minimizing the likelihood of failures, thereby safeguarding public safety and environmental integrity.

n the realm of pipeline management and maintenance, accurately predicting failure points is paramount to ensure safety, efficiency, and cost-effectiveness. Various methods, such as Finite Element Method (FEM) and MB31G model, are employed to estimate failure pressures and defect growth rates. This study delves into the comparative analysis of these methods, shedding light on their accuracy, computational efficiency, and practical applicability.

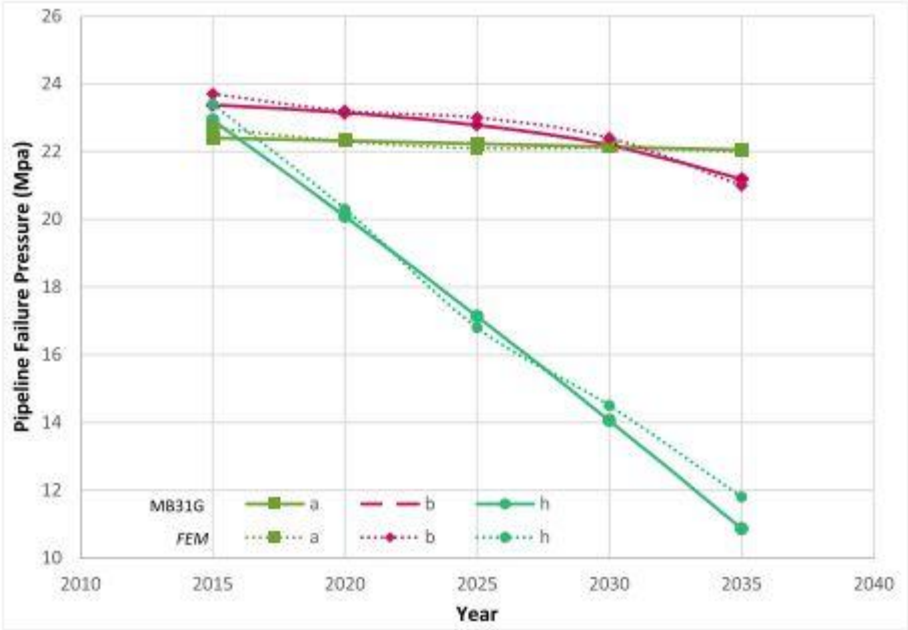
Pipelines are lifelines of modern infrastructure, transporting critical resources across vast distances. However, they are susceptible to defects and degradation over time, necessitating robust inspection and maintenance strategies. Predicting failure points accurately is crucial for preemptive action, avoiding catastrophic consequences and ensuring uninterrupted service.

Defect Growth Analysis

Figures 10 and 11 present the evolution of defect lengths and failure pressures over time. Notably, while defect lengths vary significantly, their growth rates remain remarkably similar. This underscores the importance of accurately predicting growth rates to anticipate future risks.



Analyzing Defect-Depth Transition: Predicted DDGR vs. Actual DDGR"



Comparing Pipeline Failure Pressure: MB31G vs. FEM Calculations"

4.3.2Analyzing Remaining Pipeline Lifespan: A Comparative Study of Prediction Methods.

Understanding the factors influencing the remaining lifespan of pipelines is crucial for effective maintenance and risk management. This study employs SHAP (Shapley Additive explanations) analysis to identify key features impacting pipeline longevity. By examining the influence of steel yield strength (SYMS), pipe yield strength (PY), and maximum operating pressure (MOP) on remaining life, this research sheds light on how different soil types and pipeline specifications affect pipeline durability.

Key Features Impacting Pipeline Remaining Life:

Fig. 14 presents a comparative analysis of pipeline remaining life based on important features identified through SHAP results. These features encompass SYMS, PY, and MOP, each playing a significant role in determining pipeline longevity. Pipelines situated in various soil types with diverse specifications were randomly selected to elucidate the impact of these features comprehensively

Influence of SYMS, PY, and MOP:

The analysis reveals a direct correlation between SYMS and PY with pipeline remaining life, indicating that pipelines with higher steel and pipe yield strengths exhibit prolonged lifespans. Conversely, an increase in MOP is associated with a decrease in remaining life, underscoring the importance of operating pressure in assessing pipeline integrity. This relationship highlights the critical role of material strength and operational parameters in determining pipeline durability.

Effects of Pipeline Specification and Location:

Furthermore, the rate of change in remaining life varies depending on pipeline specifications and geographical location. A notable finding is the positive relationship between pipeline thickness and remaining lifespan, suggesting that thicker pipelines tend to have longer operational durations. Additionally, pipelines located in railway lines experience a more significant increase in remaining life with higher SYMS and PY compared to those in wetlands, emphasizing the influence of environmental factors on pipeline longevity

Impact of Soil Composition:

The analysis also delineates the impact of soil composition on pipeline remaining life. Pipelines situated in clay-rich soil exhibit a slower decline in remaining life with increasing MOP compared to those in sandy soil. This observation underscores the importance of soil characteristics in assessing pipeline durability, as varying soil types can significantly influence corrosion rates and structural integrity.

Implications for Maintenance Strategies:

By understanding the nuanced interplay between key features and environmental factors, pipeline operators can devise targeted maintenance strategies to prolong asset lifespan and mitigate risks effectively. Prioritizing inspections and repairs based on identified influential factors enables proactive maintenance, ensuring the continued safe and efficient operation of pipelines.

In conclusion, the comparative analysis of pipeline remaining life based on key features provides valuable insights into the factors influencing pipeline durability. By considering parameters such as SYMS, PY, MOP, and soil composition, operators can make informed decisions regarding maintenance and risk management. This research contributes to enhancing pipeline integrity and safety in diverse operating environments, ultimately optimizing asset performance and longevity.

5.conclussion.

In conclusion, this study represents a significant advancement in the realm of pipeline integrity management through the utilization of intelligent pigging (ILI) data and machine learning (ML) models to predict defect presence, dimensions, and growth rates. The comprehensive analyses conducted have shed light on the efficacy of various ML methodologies in forecasting pipeline defects and their evolution over time.

First and foremost, the research findings highlight the pivotal role of the CAT model in defect prediction. Through meticulous comparison and evaluation, CAT emerged as the most efficient and accurate method, boasting a remarkable 94% prediction ratio. Its superior performance across a range of evaluation metrics underscores its potential as a reliable tool for preemptive defect detection, allowing pipeline operators to prioritize inspections and maintenance activities effectively.

Furthermore, the study delved into the prediction of defect dimensions, where XG Boost (XGB), Light GBM (LGBM), and CAT models showcased proficiency, particularly in defect depth prediction. While challenges were encountered in accurately predicting defect width, CAT's overall superior performance positioned it as the optimal choice for defect dimension forecasts. This underscores the importance of leveraging advanced ML techniques to gain insights into defect morphology, facilitating targeted interventions to address potential integrity threats.

Moreover, leveraging ILI data spanning multiple years enabled the forecasting of defect length and depth growth rates with remarkable accuracy. Among the ML models employed, CAT demonstrated the highest prediction accuracy, enabling precise estimation of defect evolution over time. The elucidation of key input features influencing defect growth rates through SHAP analysis further enhanced the understanding of pipeline behavior, facilitating the estimation of remaining pipeline lifespan based on critical thresholds such as maximum allowable defect depth and failure pressure.

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