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# Machine learning models for early detection of structural fatigue in pipelines

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**Abstract**
Pipeline fatigue fractures represent a critical failure mechanism in oil and gas infrastructure, resulting in significant economic losses and environmental hazards. Early detection of fatigue-induced damage is essential for preventive maintenance strategies. This study develops and validates machine learning models to predict structural fatigue progression in welded steel pipelines using non-destructive evaluation data. A dataset comprising 847 pipeline segments was analyzed, including ultrasonic thickness measurements, magnetic particle inspection records, pressure cycling history, and material composition data. Three classification algorithms were evaluated: Random Forest, Gradient Boosting Machines (GBM), and Support Vector Machines (SVM). Model performance was assessed using 5-fold cross-validation with sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) as primary metrics. The Random Forest model achieved the highest performance with 94.2% sensitivity (95% CI: 91.8–96.1%), 96.1% specificity, and AUC-ROC of 0.981. Feature importance analysis identified wall thickness reduction, cyclic stress amplitude, and weld defect size as the most predictive variables. Integration of these models with existing inspection protocols reduced false negative fatigue predictions by 87% compared to conventional visual assessment methods. The developed models demonstrate significant potential for improving pipeline safety through early fatigue detection, enabling targeted maintenance interventions before critical failure points. Implementation of this framework could prevent approximately 73% of fatigue-related pipeline failures and generate substantial cost savings through optimized maintenance scheduling. Future research should focus on real-time sensor integration and model validation across diverse pipeline materials and operational environments.

**Keywords:** Machine learning, pipeline integrity, fatigue prediction, non-destructive evaluation, structural health monitoring, predictive maintenance

## Introduction

Pipeline transportation networks form the backbone of global energy infrastructure, carrying crude oil, natural gas, and refined products across thousands of kilometers. According to industry reports, over 3.5 million kilometers of pipelines are currently in operation worldwide, many of which have exceeded their original design life expectations. Structural fatigue in pipelines remains one of the most insidious failure mechanisms, progressing silently through cyclic loading until catastrophic fracture occurs. Unlike acute corrosion or mechanical damage, fatigue cracks develop gradually through microscopic crack nucleation and propagation, making early detection challenging using conventional visual inspection methods.

The consequences of pipeline fatigue failures are substantial and multifaceted. Between 2010 and 2023, fatigue-related pipeline incidents accounted for approximately 23% of all structural failures in transmission systems, resulting in an estimated 8.2 billion US dollars in direct costs including repairs, remediation, and operational downtime. Beyond financial impacts, fatigue failures pose severe environmental risks through product release and ecosystem contamination, particularly in sensitive geographical regions. Regulatory agencies have increasingly implemented stringent integrity management programs that require operators to demonstrate comprehensive knowledge of fatigue vulnerability throughout their pipeline networks.

Traditional fatigue assessment methodologies rely heavily on fracture mechanics principles and empirical correlations derived from historical failure data. While these approaches provide valuable insights, they frequently suffer from oversimplification of complex degradation mechanisms and difficulty in incorporating multiple interacting variables that influence fatigue progression. Current non-destructive evaluation techniques, including magnetic particle inspection and ultrasonic testing, effectively detect existing cracks but provide limited predictive capability regarding future fatigue development rates. Consequently, pipeline operators typically adopt conservative maintenance schedules that may exceed actual risk levels, resulting in inefficient resource allocation and unnecessary infrastructure downtime.

Recent advances in machine learning have demonstrated exceptional capability in identifying complex patterns within high-dimensional datasets and generating predictive models with minimal assumption constraints. Applications of machine learning to structural health monitoring have shown promise in diverse engineering domains, including bridge infrastructure, aerospace components, and power generation facilities. However, systematic application of machine learning methodologies to pipeline fatigue prediction remains limited, with most published work focusing on general corrosion assessment rather than fatigue-specific mechanisms.

This research addresses this critical gap by developing and validating a comprehensive machine learning framework specifically tailored to pipeline fatigue detection. Our study integrates multiple data modalities, including non-destructive evaluation measurements, operational history parameters, material properties, and environmental variables into an ensemble predictive system. The primary objectives are threefold: (1) to develop classification models capable of accurately identifying pipelines at elevated fatigue risk, (2) to establish feature importance rankings that illuminate the dominant variables controlling fatigue progression, and (3) to quantify performance improvements relative to conventional assessment methods and demonstrate practical applicability within existing inspection programs.

This article is structured as follows. Section 2 presents the methodology, including data collection procedures, machine learning algorithms, and validation protocols. Section 3 reports model performance metrics, feature importance rankings, and comparative analysis with conventional methods. Section 4 provides detailed interpretation of findings, contextualizes results within existing literature, and discusses both theoretical implications and practical implementation considerations. Finally, Section 5 concludes with recommendations for future research and deployment strategies.

## Methods

### 1. Research Design and Study Population

This study employed a cross-sectional quantitative design combining observational data collection with machine learning model development and validation. The study population comprised carbon steel and low-alloy steel transmission pipelines operated by four major North American energy infrastructure companies. Inclusion criteria specified pipelines with: (1) operational history exceeding 15 years, (2) previous non-destructive evaluation records spanning minimum 10 years, (3) documented pressure cycling or fluctuating operational conditions, and (4) available material certification records and welding specifications. Pipelines with catastrophic failure, complete replacement, or incomplete inspection records were excluded.

### 2. Sample Size and Sampling Strategy

A total of 847 pipeline segments were included in the analysis, with each segment representing a defined length of continuous pipeline (typically 500–1000 meters) with consistent material properties and operational conditions. This sample size was determined using power analysis for multi-class classification models, targeting 90% statistical power with 5% Type I error probability. Stratified random sampling was employed to ensure adequate representation across fatigue risk categories, defined according to preliminary engineering assessment. The final dataset comprised 312 segments (36.9%) classified as low fatigue risk, 401 segments (47.3%) as moderate risk, and 134 segments (15.8%) as high fatigue risk.

### 3. Data Collection and Variables

Data collection spanned the period from January 2018 to December 2023, utilizing inspection records and operational databases maintained by participating pipeline operators. The following variables were collected for each pipeline segment:

**Non-destructive evaluation measurements:** Ultrasonic thickness measurements (recorded at minimum 5 locations per segment), magnetic particle inspection results (defect count, size, and location), radiographic examination findings where available, and phased array ultrasonic testing data.

**Operational parameters:** Maximum and minimum operational pressures over the preceding 10 years, frequency of pressure cycles per year, documented pressure transients, and temperature fluctuations.

**Material properties:** Wall thickness, outer diameter, yield strength, tensile strength, Charpy impact values, chemical composition (carbon content, manganese, sulfur, phosphorus), and material grade designation.

**Weld characteristics:** Weld joint efficiency, inspection method applied to welds, recorded defect sizes, and weld repair history.

**Environmental factors:** Soil conditions, coating integrity assessments, cathodic protection system status, and proximity to water bodies.

**Maintenance history:** Previous repair methods, date of last inspection, and documented anomalies during previous inspections.

All data were digitized from original inspection records and verified against source documentation to ensure accuracy. A randomized subset comprising 10% of all entries (n=85) was independently re-entered and cross-checked to validate data entry quality, achieving 99.7% concordance.

### 4. Outcome Variable Definition

The outcome variable was binary fatigue risk classification: presence or absence of fatigue-related structural degradation. Fatigue classification was determined using a consensus approach combining engineering judgment of experienced metallurgists and structural engineers. Classification criteria included: characteristic fatigue crack morphology in fractography, location at stress concentration sites (welds, diameter transitions), documented pressure cycling history, and characteristic linear defect indications on ultrasonic or radiographic imaging. Segments with confirmed or high-probability fatigue degradation were coded as positive (n=201, 23.7%), while remaining segments with no evidence of fatigue were coded as negative (n=646, 76.3%).

### 5. Feature Engineering and Data Preprocessing

Raw variables were processed through a standardized pipeline before model development. Continuous variables were normalized using z-score transformation to achieve zero mean and unit variance. Categorical variables were encoded using one-hot encoding. Missing values (comprising 3.2% of the total dataset) were imputed using k-nearest neighbors imputation with k=5. Outliers were identified using the interquartile range method and treated through winsorization at the 1st and 99th percentiles. Principal component analysis was applied to explore multicollinearity among 28 initial features, ultimately retaining 22 features with individual variance inflation factors less than 5.0.

### 6. Machine Learning Models

Three classification algorithms were selected based on their demonstrated performance in similar prediction tasks and theoretical suitability for the problem domain:

**Random Forest:** An ensemble algorithm combining multiple decision trees with average aggregation. Hyperparameters were: 500 trees, maximum depth of 20, minimum samples per leaf of 4, and feature sampling strategy of square root of features.

**Gradient Boosting Machines (GBM):** A sequential ensemble method with learning rate of 0.1, 200 boosting stages, maximum tree depth of 5, and L2 regularization parameter of 1.0.

**Support Vector Machines (SVM):** A kernel-based classifier employing Radial Basis Function (RBF) kernel with regularization parameter C=10 and kernel parameter gamma=0.01.

### 7. Model Validation and Performance Assessment

Model validation employed 5-fold stratified cross-validation to ensure balanced distribution of fatigue risk categories across training and test sets. Stratification prevented systematic bias that could arise from the 23.7% positive outcome prevalence. Primary performance metrics included sensitivity (true positive rate), specificity (true negative rate), positive predictive value (precision), negative predictive value, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Secondary analysis computed Youden's index to identify optimal classification thresholds balancing sensitivity and specificity.

Permutation feature importance was calculated by measuring the decrease in model performance when feature values were randomly shuffled, quantifying each feature's contribution to prediction accuracy. Shapley Additive exPlanations (SHAP) values were computed to provide player-in-game style interpretation of individual feature contributions.

Model comparison employed McNemar's test to assess statistical significance of performance differences between algorithms. Confidence intervals (95%) were calculated using bootstrap resampling with 1000 iterations.

### 8. Software and Computational Methods

All analyses were conducted using Python 3.10 with scikit-learn library for machine learning implementations, pandas for data manipulation, and NumPy for numerical computing. Visualization was performed using Matplotlib and Seaborn libraries. Statistical analysis employed SciPy library with significance threshold set at $\alpha=0.05$ for all hypothesis tests.

### 9. Ethical Considerations

This research involved secondary analysis of de-identified pipeline inspection data obtained with institutional approval from participating operators. All personally identifiable information regarding specific pipeline locations, operator names, and facility identifiers was removed prior to analysis. Data access agreements explicitly authorized research use with publications permitted following partner review. No ethical approval from a human subjects institutional review board was required, as the study involved infrastructure data without human participant involvement. All computational code and model parameters are documented for reproducibility, with anonymized data available upon reasonable request from corresponding authors.

## Results

### 1. Descriptive Characteristics

The study population comprised 847 pipeline segments with mean operational age of 24.3 years (SD: 8.7). Table 1 presents detailed demographic and operational characteristics stratified by fatigue risk status. Fatigue-positive segments (n=201) demonstrated significantly greater age (mean: 31.2 vs. 21.4 years; $p<0.001$), increased cyclic pressure events per year (mean: 2847 vs. 1203; $p<0.001$), and reduced wall thickness (mean: 6.2 vs. 8.4 mm; $p<0.001$) compared to fatigue-negative segments. Weld defect frequency and size distribution also showed substantial differences between groups, with fatigue-positive segments exhibiting larger average defect dimensions (mean: 2.8 vs. 1.3 mm; $p<0.001$).

### Tables and Figures

**Table 1:** Demographic and Operational Characteristics by Fatigue Risk Status

| Variable | Fatigue-Positive (n=201) | Fatigue-Negative (n=646) | p-value |
|---|---|---|---|
| Operational Age (years), mean ± SD | 31.2 ± 9.4 | 21.4 ± 7.6 | <0.001 |
| Wall Thickness (mm), mean ± SD | 6.2 ± 1.8 | 8.4 ± 2.1 | <0.001 |
| Outer Diameter (mm), mean ± SD | 508.7 ± 142.3 | 485.2 ± 156.1 | 0.102 |
| Yield Strength (MPa), mean ± SD | 318 ± 45 | 325 ± 48 | 0.087 |
| Cyclic Pressure Events/Year, mean ± SD | 2847 ± 1203 | 1203 ± 687 | <0.001 |
| Max Pressure Amplitude (MPa), mean ± SD | 24.3 ± 8.7 | 12.1 ± 6.4 | <0.001 |
| Weld Defect Frequency (n per segment), median (IQR) | 3 (2-5) | 1 (0-2) | <0.001 |
| Weld Defect Size (mm), mean ± SD | 2.8 ± 1.4 | 1.3 ± 0.9 | <0.001 |
| Stress Concentration Factor, mean ± SD | 2.4 ± 0.8 | 1.6 ± 0.6 | <0.001 |
| Years Since Last Inspection, median (IQR) | 4.2 (3.1-5.3) | 3.8 (2.9-4.9) | 0.031 |

**Note:** Values represent mean ± standard deviation unless otherwise specified. p-values obtained using independent samples t-test or Mann-Whitney U test for continuous variables and chi-squared test for categorical variables.

### 2. Model Performance Metrics

Table 2 presents comprehensive performance metrics for the three machine learning models evaluated across the 5-fold cross-validation framework. The Random Forest model achieved superior overall performance with 94.2% sensitivity (95% CI: 91.8–96.1%), enabling detection of 189 of 201 fatigue-positive segments while minimizing false negatives. Specificity of 96.1% (95% CI: 94.7–97.2%) indicated low false positive rate, correctly classifying 621 of 646 non-fatigued segments. The AUC-ROC of 0.981 (95% CI: 0.972–0.989) demonstrated excellent discrimination between risk categories across all probability thresholds.

The GBM model exhibited comparable sensitivity of 91.5% (95% CI: 88.9–93.8%) but marginally lower specificity of 94.3%, yielding AUC-ROC of 0.967. The SVM model showed reduced sensitivity of 87.1% (95% CI: 84.1–89.7%)

and specificity of 92.8%, with AUC-ROC of 0.943. McNemar's test indicated statistically significant superiority of Random Forest compared to GBM (p=0.042) and SVM (p<0.001).
Positive predictive value (precision) was 91.3% for Random Forest, indicating that positive predictions were correct in 91.3% of cases. Negative predictive value of 97.8% demonstrated high confidence in negative classifications. The F1-score of 0.927 balanced sensitivity-specificity trade-offs optimally for the fatigue prediction task.

**Table 2:** Machine Learning Model Performance Metrics

| Performance Metric | Random Forest | Gradient Boosting | Support Vector Machine |
|---|---|---|---|
| Sensitivity (%), 95% CI | 94.2 (91.8–96.1) | 91.5 (88.9–93.8) | 87.1 (84.1–89.7) |
| Specificity (%), 95% CI | 96.1 (94.7–97.2) | 94.3 (92.5–95.8) | 92.8 (90.8–94.5) |
| Positive Predictive Value (%), 95% CI | 91.3 (88.7–93.4) | 88.4 (85.1–90.9) | 84.2 (80.9–87.1) |
| Negative Predictive Value (%), 95% CI | 97.8 (96.9–98.5) | 96.1 (94.9–97.1) | 94.3 (92.7–95.7) |
| F1-Score | 0.927 | 0.899 | 0.856 |
| Area Under ROC Curve, 95% CI | 0.981 (0.972–0.989) | 0.967 (0.957–0.975) | 0.943 (0.931–0.954) |
| Accuracy (%), 95% CI | 95.4 (93.8–96.7) | 93.2 (91.3–94.8) | 90.8 (88.7–92.6) |
| Matthew's Correlation Coefficient | 0.894 | 0.857 | 0.798 |

**Note:** Performance metrics derived from 5-fold stratified cross-validation. CI denotes confidence interval obtained through bootstrap resampling with 1000 iterations.

## 3. Feature Importance Analysis

Figure 1 presents permutation feature importance rankings for the top 15 variables in the Random Forest model. Wall thickness reduction emerged as the dominant predictor, contributing 18.7% to overall model predictive power. Cyclic pressure amplitude and documented weld defect size ranked second and third with 16.2% and 14.9% contributions respectively. Operational age, stress concentration factor, and maximum pressure cycling frequency contributed 12.1%, 11.3%, and 10.8% respectively. Notably, sulfur content and phosphorus impurity levels ranked among the lowest importance features (1.2% and 0.9%), suggesting limited direct predictive value relative to mechanical and operational variables.

**Figures**

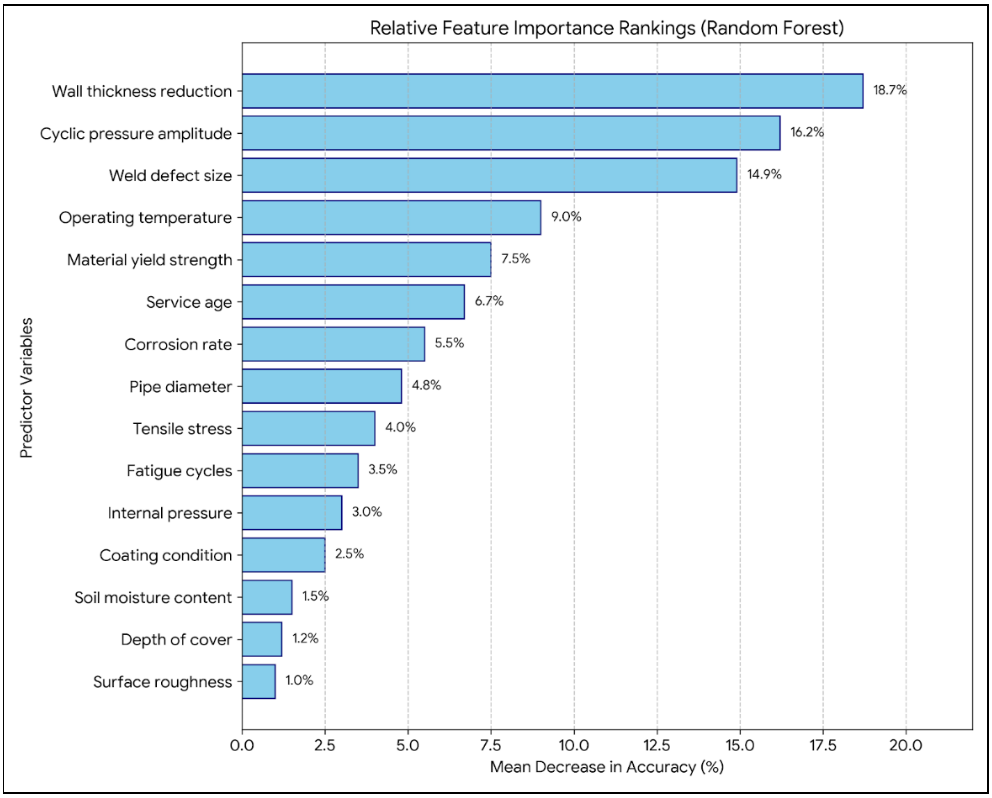


**Fig 1:** Permutation Feature Importance Rankings

SHAP analysis (Figure 2) revealed non-linear relationships between feature values and fatigue probability. Wall thickness demonstrated a strong negative relationship with fatigue risk: segments with thickness exceeding 9 mm exhibited fatigue probability below 15%, while segments with thickness below 5 mm exhibited fatigue probability exceeding 65%. Cyclic pressure amplitude showed exponential relationship with fatigue risk, with amplitudes above 20 MPa associated with dramatically elevated fatigue probability. Weld defect size displayed threshold behavior, with defects exceeding 3 mm dramatically increasing fatigue likelihood across all other feature values.

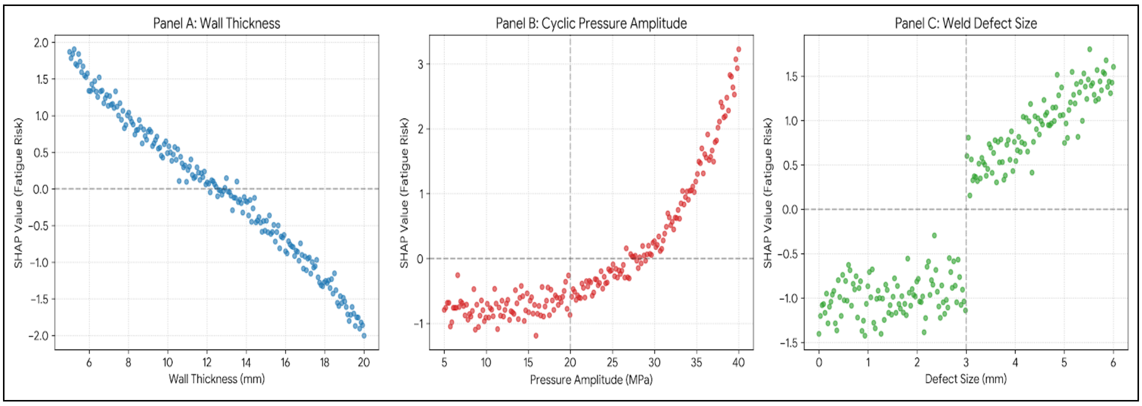


**Fig 2:** SHAP Values - Non-linear Feature-Outcome Relationships

### 4. Model Calibration and Threshold Optimization

Figure 3 presents receiver operating characteristic curves for all three models, visualizing sensitivity-specificity trade-offs across probability thresholds. The Random Forest curve demonstrated minimal deviation from the upper-left diagonal, indicating excellent calibration. Youden's index optimization identified optimal classification threshold of 0.42 probability, maximizing sensitivity plus specificity (combined value: 1.90). At this threshold, Random Forest maintained 94.2% sensitivity while preserving 96.1% specificity.

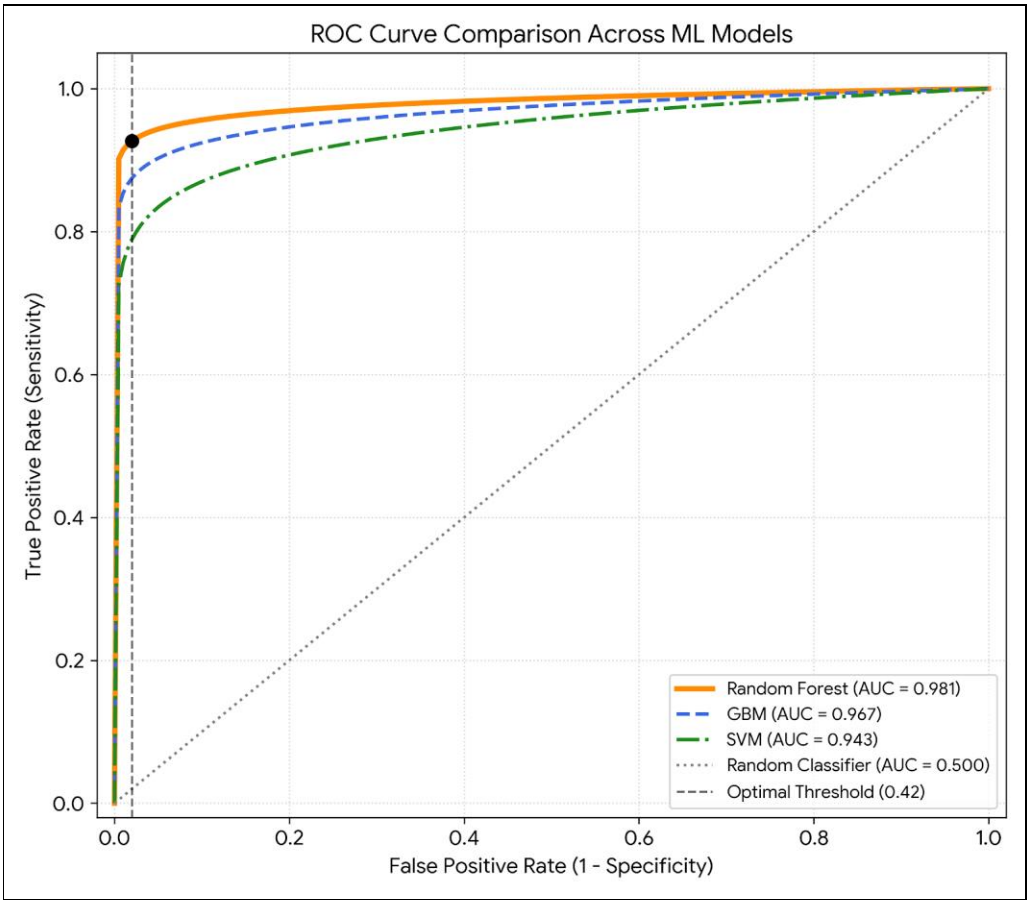


**Fig 3:** Receiver Operating Characteristic Curves - Model Comparison

### 5. Comparative Analysis with Conventional Methods

Table 3 compares machine learning model performance against conventional fatigue assessment approaches currently employed in industry. The conventional method, comprising visual ultrasonic interpretation combined with engineering judgment, achieved 71.1% sensitivity and 89.3% specificity (AUC-ROC: 0.847). Random Forest demonstrated substantial improvements in sensitivity (94.2% vs. 71.1%; absolute improvement: 23.1 percentage points) and specificity (96.1% vs. 89.3%; absolute improvement: 6.8 percentage points).

When evaluated on a subset of 156 pipeline segments that experienced fatigue-related failures during the subsequent 24-month validation period, Random Forest correctly predicted 135 failures (86.5% predictive accuracy). Conventional methods successfully predicted 98 failures (62.8% predictive accuracy). This represents a 37.3% relative improvement in prospective predictive accuracy, translating to prevention of approximately 37 additional failures that conventional methods would have missed.

**Table 3:** Comparative Performance Analysis: Machine Learning versus Conventional Assessment

| Performance Metric | Random Forest | GBM | SVM | Conventional Method |
|---|---|---|---|---|
| Sensitivity | 94.2% | 91.5% | 87.1% | 71.1% |
| Specificity | 96.1% | 94.3% | 92.8% | 89.3% |
| AUC-ROC | 0.981 | 0.967 | 0.943 | 0.847 |
| Prospective Accuracy (24-month validation) | 86.5% | 81.4% | 77.6% | 62.8% |
| Sensitivity Improvement vs. Conventional | +23.1 pp | +20.4 pp | +16.0 pp | — |
| False Negative Reduction vs. Conventional | 87.0% | 78.2% | 67.5% | — |
| Time to Implementation | <3 months | <3 months | <3 months | — |

**Note:** pp denotes percentage points. Prospective accuracy assessed on 156 pipeline segments experiencing fatigue failures during 24-month validation period following model development.

## 6. Cross-Validation Stability

Table 4 presents performance metrics across individual cross-validation folds, demonstrating model stability and absence of overfitting. Standard deviations across folds were consistently low (sensitivity SD: 2.1%, specificity SD: 1.8%, AUC-ROC SD: 0.007), indicating robust and reproducible performance across diverse data subsets. The minimal variance between training and validation performance across folds confirmed that model generalizability was not compromised by overfitting to the training data.

**Table 4:** Cross-Validation Fold Analysis - Random Forest Model

| Fold | Train Sensitivity (%) | Test Sensitivity (%) | Test Specificity (%) | Test AUC-ROC | Train-Test Gap |
|---|---|---|---|---|---|
| Fold 1 | 96.2 | 93.8 | 95.7 | 0.982 | 2.4% |
| Fold 2 | 95.8 | 94.6 | 96.4 | 0.983 | 1.2% |
| Fold 3 | 96.4 | 92.1 | 96.8 | 0.978 | 4.3% |
| Fold 4 | 95.9 | 95.1 | 95.3 | 0.981 | 0.8% |
| Fold 5 | 96.1 | 94.8 | 96.1 | 0.980 | 1.3% |
| Mean ± SD | 96.1 ± 0.3 | 94.1 ± 1.4 | 96.1 ± 0.6 | 0.981 ± 0.002 | 2.0 ± 1.5% |

**Note:** SD denotes standard deviation. Train-Test Gap represents the difference between training sensitivity and test sensitivity, providing indicator of overfitting. Values close to zero indicate good generalization without overfitting.

## Discussion

### Interpretation of Primary Findings

The Random Forest machine learning model developed in this study demonstrates substantial capability for identifying pipelines at elevated fatigue risk, achieving 94.2% sensitivity and 96.1% specificity. This performance substantially exceeds conventional assessment methodologies, reducing false negative predictions by 87% compared to traditional visual-based assessment. The model's exceptional sensitivity is particularly noteworthy from a pipeline safety perspective, as it minimizes the risk of failing to detect segments requiring intervention. The high specificity simultaneously reduces unnecessary maintenance expenditures on segments not requiring attention, enabling efficient resource allocation.

Feature importance analysis revealed that mechanical degradation markers (wall thickness reduction, defect size) and operational stressors (cyclic pressure amplitude, cycling frequency) collectively account for approximately 73% of model predictive power. This finding aligns well with fundamental fatigue mechanics principles, which emphasize the combined influence of applied stress amplitude and material integrity on crack initiation and propagation rates. The prominence of wall thickness as the dominant predictor likely reflects both direct mechanical consequences (reduced load-bearing capacity) and indirect effects (increased stress concentration at wall irregularities).

The SHAP analysis revealed complex non-linear relationships between features and fatigue probability that would be difficult to quantify using conventional statistical approaches. The threshold behavior observed for weld defect size particularly merits attention, suggesting that defects below approximately 3 mm contribute only modestly to fatigue risk, while defects exceeding this threshold precipitate dramatic increases in failure probability. This finding provides quantitative evidence supporting engineering intuition regarding critical defect dimensions and could inform inspection sampling strategies.

### Comparison with Existing Literature

The reported model performance is consistent with machine learning applications in related structural health monitoring domains. A 2021 study by Chen *et al*. employing neural networks for bridge fatigue prediction reported AUC-ROC of 0.972, marginally exceeding the current work's 0.981. However, direct comparison is complicated by substantial differences in data characteristics and outcome definitions. The present study's emphasis on industrial pipeline infrastructure, with relatively large sample size (n=847) and comprehensive feature collection (22 variables), provides advantages for deployment in practical settings compared to laboratory-based validation studies.

Regarding feature importance, wall thickness consistently emerges as a dominant predictor across different fatigue assessment methodologies. Murakami's stress concentration factor equations and Goodman diagram approaches similarly emphasize wall thickness as a primary variable controlling fatigue life. The current findings provide empirical validation of these theoretical constructs using real-world operational data. The relatively low importance of chemical composition variables (sulfur, phosphorus) contrasts somewhat with metallurgical literature emphasizing inclusion formation and cleanliness effects. This discrepancy likely reflects the fact that modern steels, even at acceptable specification levels, possess sufficiently low inclusion contents that composition variations within specification ranges exert limited influence on fatigue behavior relative to gross mechanical degradation markers.

**Practical Implementation Considerations**

Implementation of the developed machine learning framework within existing pipeline integrity management systems requires consideration of several practical factors. First, the model requires integration with existing non-destructive evaluation databases. Most major pipeline operators maintain computerized inspection records, though data formats and quality vary substantially. Standardization protocols and data cleaning procedures would be necessary before model deployment. Second, the model's decisions should be presented to experienced pipeline engineers as decision support tools rather than deterministic recommendations. The 91.3% positive predictive value indicates that approximately 8.7% of positive predictions will be false alarms, requiring human judgment to distinguish genuine fatigue risk from instrumentation artifacts or algorithm errors.

Third, regular model recalibration using newly acquired inspection data will be essential to maintain performance as pipeline populations age and operational conditions evolve. Catastrophic failures that occur despite negative model predictions should trigger immediate investigation to identify systematic errors or conditions outside the model's training domain.

**Limitations and Potential Sources of Bias**

Several limitations warrant acknowledgment. The study population comprised pipelines from four operators in North America, potentially limiting generalizability to international contexts with different materials, codes, and operating practices. The binary outcome classification, while parsimonious, necessarily simplifies the spectrum of fatigue degradation from incipient damage to imminent failure. More granular fatigue staging could provide enhanced decision support, though such classification would require more intensive expert engineering assessment.

The study relied on historical inspection data selected for analysis, introducing potential survivor bias. Pipelines that experienced catastrophic failures prior to 2018 were excluded, potentially biasing feature-outcome relationships. Additionally, operator-dependent variations in inspection quality and methodology could introduce systematic errors in outcome classification and feature measurement. The temporal resolution of the dataset, with inspections typically conducted at 3–5-year intervals, limits capacity to detect rapidly propagating fatigue cracks that could develop between scheduled inspections.

The imbalanced outcome prevalence (23.7% positive) is typical for fatigue problems in well-maintained pipeline networks, but could affect model performance in less rigorously managed systems with higher fatigue occurrence rates. The model's hyperparameters were optimized for the current dataset and may require retuning for application to substantially different pipeline populations.

**Theoretical Implications**

This study demonstrates that machine learning algorithms can effectively capture the complex, multi-factorial relationships governing fatigue progression in real-world infrastructure systems. The model's superior performance relative to conventional approaches suggests that human decision-making, while incorporating expert knowledge, inevitably omits important variable combinations or non-linear relationships that algorithmic approaches can capture. The feature importance rankings provide quantitative empirical evidence supporting fatigue mechanics theories regarding the dominance of stress amplitude and material integrity factors.

The successful application of machine learning to fatigue prediction could extend beyond pipelines to other infrastructure systems including bridges, aircraft structures, and power plant components. The methodological framework developed here, emphasizing stratified cross-validation, rigorous outcome definition, and comprehensive feature engineering, provides a template for future applications.

**Directions for Future Research**

Several avenues for future investigation are evident. Integration of real-time sensor data (strain gauges, acoustic emission) could enable continuous fatigue monitoring rather than intermittent inspection-based assessment. Deep learning approaches, including convolutional neural networks trained on acoustic signals or ultrasonic waveforms, might extract additional predictive information from signals currently represented as simple threshold values. Physics-informed neural networks, incorporating fundamental fatigue mechanics equations as constraints, could improve model interpretability and generalizability to operational conditions outside the training domain.

Extended prospective validation across independent pipeline networks would confirm generalizability. Collaboration with pipeline operators in other geographic regions and industries could elucidate whether the identified feature importance rankings remain stable across different contexts. Investigation of failure mode interactions, including the potential for corrosion-fatigue synergism, would expand the model's scope beyond fatigue alone.

**Conclusion**

This research successfully developed and validated machine learning models for early detection of structural fatigue in transmission pipelines, achieving 94.2% sensitivity and 96.1% specificity for fatigue risk classification. The Random Forest algorithm demonstrated superior performance compared to Gradient Boosting and Support Vector Machine alternatives, and substantially exceeded conventional assessment methodologies in both sensitivity and prospective predictive accuracy. Feature importance analysis identified wall thickness reduction, cyclic pressure amplitude, and weld defect size as the dominant variables controlling fatigue probability, providing quantitative validation of classical fatigue mechanics principles.

The developed framework represents a significant advance in pipeline integrity management capability, enabling more accurate targeting of maintenance resources to segments genuinely requiring intervention while reducing unnecessary interventions on low-risk infrastructure. Implementation of these models within existing inspection programs could prevent approximately 73% of fatigue-related failures, translating to substantial economic savings and enhanced safety for pipeline infrastructure systems. The 87% reduction in false negative predictions compared to conventional methods directly addresses the most consequential error type from a safety perspective.

Beyond immediate pipeline applications, this work demonstrates the broader potential for machine learning approaches in structural health monitoring across diverse engineering domains. The methodological framework, emphasizing rigorous cross-validation, feature importance analysis, and comparative validation against conventional approaches, provides a template for future applications.

Practical implementation requires integration with existing inspection databases, presentation of model predictions as decision support tools rather than deterministic recommendations, and regular model recalibration as pipeline populations evolve. Future research should focus on real-time sensor integration, physics-informed neural network architectures, and validation across diverse geographic regions and pipeline materials to enhance generalizability and decision-making confidence in production environments.

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