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Quantitative Image-Based Assessment of Degradation Patterns in Polymer-Based Medical Implants

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Abstract

Polymer-based medical devices are widely used in clinical practice, where long-term material degradation can compromise performance and patient safety. Traditional polymer degradation studies predominantly rely on laboratory-based experiments, which often fail to capture real-world operational and usage conditions. In this study, a multimodal, data-driven framework is proposed for the quantitative assessment of degradation patterns in polymer-based medical devices using publicly available clinical failure data. Structured operational parameters, including cumulative usage hours, device age, and downtime characteristics, are integrated with unstructured maintenance narratives through natural language processing techniques. Text-derived degradation indicators are extracted using term-frequency inverse document-frequency representations and topic modelling, enabling the identification of latent material degradation phenomena, such as surface wear and cracking. These indicators are fused with structured features and analysed using supervised machine learning and survival modelling to predict degradation-related failures and assess degradation trajectories. Experimental results demonstrate that multimodal models significantly outperform structured-only approaches, achieving an area under the receiver operating characteristic curve of up to 0.91. Feature importance and hazard ratio analyses confirm the material relevance of text-derived degradation indicators and their strong association with failure risk. The proposed methodology provides an interpretable and scalable approach for post-market assessment of polymer degradation in medical devices, complementing conventional material characterisation techniques and supporting data-driven lifecycle management.

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Keywords: Polymer degradation; medical devices; multimodal machine learning; natural language processing; degradation trajectory analysis

INTRODUCTION

Literature Review

Previous studies have demonstrated that degradation of polymer-based medical devices is strongly influenced by operational conditions, material composition, and environmental exposure. Image-based investigations have been used to quantify morphological degradation in polymer implants, revealing correlations between microstructural changes and functional performance [1–2]. Surface characterization methods combined with image processing have also been applied to evaluate sterilization-induced changes in polymer medical devices [3–4]. Broader reviews of biomaterial degradation emphasize the need for quantitative, data-driven approaches that can integrate multiple degradation indicators [5–6]. Fundamental studies on polymer degradation mechanisms in implantable devices highlight the role of cumulative usage and oxidative stress in failure initiation [7–8]. Recent reviews on biodegradable polymers further underscore the complexity of degradation pathways in biomedical applications [9–10]. Beyond imaging, data-driven methods have been increasingly applied to failure prediction in polymer composites and biomedical devices, demonstrating the value of structured operational data [11–12]. Text-based analysis of maintenance and failure reports has shown promise in extracting latent failure patterns not captured by numerical variables alone [13–14]. Publicly available medical device datasets have facilitated the development of predictive models for device reliability and fault detection [15–16]. Data augmentation and representation learning techniques have been proposed to improve robustness in medical device analytics [17–18]. However, existing studies rarely integrate structured operational data with textual maintenance records to quantitatively assess degradation patterns specifically relevant to polymer-based medical devices [19–20]. Quantitative image analysis of retrieved polymer implants has further demonstrated the value of systematic degradation profiling in extending device service life [21]. More recently, machine learning and natural language processing approaches have shown promise in predicting medical device failures directly from clinical maintenance records, reinforcing the feasibility of data-driven post-market surveillance.

Despite extensive research on polymer degradation and medical device reliability, there is a lack of integrated frameworks that combine structured operational data with unstructured maintenance narratives to quantify degradation patterns in polymer-based medical devices. Most existing studies either focus on laboratory-scale material characterization or rely on single-modality data sources, such as imaging or numerical sensor data. The potential of clinical maintenance records and failure logs to serve as proxies for material degradation, particularly in polymer components, remains underexplored. Furthermore, few studies explicitly translate device-level failure data into interpretable indicators of polymer aging and degradation.

Polymer-based components are widely used in medical devices due to their flexibility, biocompatibility, and manufacturability; however, their long-term performance is susceptible to degradation driven by usage, environmental exposure, and mechanical stress. Current assessment approaches lack the ability to quantitatively relate real-world operational and maintenance data to underlying degradation processes in polymer materials. As a result, there is no standardized data-driven method to identify, quantify, and interpret degradation patterns in polymer-based medical devices using publicly available clinical failure datasets.

Proposed Method

This study proposes a quantitative data-processing framework for assessing degradation patterns in polymer-based medical devices by integrating structured operational variables with unstructured maintenance text. Structured data are first normalized and analyzed to identify usage- and time-dependent trends associated with failure frequency and downtime. In parallel, natural language processing techniques are applied to maintenance notes to extract degradation-related themes and failure descriptors. The resulting numerical and textual features are fused to construct predictive and explanatory models that capture degradation trajectories linked to polymer material behavior. This integrated approach enables objective, scalable, and interpretable assessment of polymer degradation using real-world clinical device data.

METHODOLOGY

Dataset Description

The dataset employed in this study is the *Medical Device Failure Dataset – Anonymized Clinical Data (Structured + NLP)*, a publicly available dataset hosted on Kaggle (https://www.kaggle.com/datasets/medical-device-failure-dataset) and curated from anonymized hospital equipment maintenance records, clinical engineering reports, and simulated incident logs. The dataset comprises 5,000 anonymized device records spanning 12 medical device categories, including infusion pumps, ventilators, patient monitoring systems, and imaging accessories, several of which incorporate polymer-based housings, tubing, seals, and flexible connectors that are susceptible to progressive material degradation. The dataset integrates structured numerical attributes with unstructured textual maintenance descriptions, reflecting real-world data commonly used in biomedical device reliability and failure prediction studies. The structured component includes operational, manufacturer, usage, downtime, and failure frequency information, while the unstructured component consists of maintenance notes processed using natural language processing techniques such as term frequency–inverse document frequency and latent Dirichlet allocation. It is important to note that the dataset does not include direct imaging outputs such as scanning electron microscopy or optical micrographs; rather, the term "image-based" in the article title refers to the quantitative, feature-extraction-driven analytical framework applied to structured and textual device records to construct a composite degradation profile, analogous in intent to image-based morphological analysis. Although the dataset encompasses multiple medical device categories, its structure and failure descriptors are well-suited for investigating degradation and failure patterns in polymer-based or polymer-containing medical devices, where material ageing, wear, and usage conditions play a critical role in device reliability.

Data Availability Statement

The data supporting the findings of this study are publicly available in the Kaggle repository under the title *Medical Device Failure Dataset – Anonymised Clinical Data (Structured + NLP)* and can be accessed without restriction for academic research purposes.

Data Attributes Considered for Quantitative Degradation Assessment

The analysis focuses on structured operational and failure-related variables that serve as indirect indicators of material degradation in polymer-based medical devices. Within the device categories represented in the dataset, polymer components include polyurethane and silicone tubing in infusion and respiratory devices, polycarbonate and ABS housings in patient monitors and defibrillators, polyvinyl chloride (PVC) connectors and seals, and polypropylene filter membranes in fluid management equipment. These are the components most susceptible to the degradation phenomena under investigation. The correspondence between degradation indicators and polymer behaviour is as follows: cumulative operational hours and device age serve as proxies for fatigue-driven chain scission and oxidative aging in polyurethane and polyolefin components; downtime duration reflects events requiring physical repair or part replacement, which are frequently associated with advanced polymer embrittlement or seal failure; and NLP-derived topics such as surface wear, cracking, and leakage directly correspond to abrasive degradation of polymer surfaces, brittle fracture in rigid polymer housings, and loss of elasticity in flexible sealing elements, respectively. Structured variables include cumulative operational hours, device age, downtime duration, failure event counts, manufacturer information, and device category, all of which influence polymer aging mechanisms such as fatigue, creep, and environmental degradation. In addition, unstructured maintenance notes are incorporated to capture qualitative descriptions of failure modes, wear, cracking, surface damage, or component replacement events that are often associated with polymer degradation. Textual data are transformed into numerical representations using established natural language processing techniques to enable integration with structured variables in downstream analysis.

The proposed methodological framework, illustrated in Figure 1, presents a multimodal machine learning approach for quantitatively assessing degradation patterns in polymer-based medical devices using structured clinical data and unstructured maintenance narratives. The methodological novelty lies in the explicit formulation of polymer degradation assessment as a supervised and interpretable learning problem, where real-world operational and textual failure data are treated as indirect but quantifiable indicators of polymer material aging.

As shown in Figure 1, the process begins with the Medical Device Failure Dataset, which integrates structured variables and free-text maintenance records. During data preprocessing, structured attributes including cumulative operational hours, device age, downtime duration, and failure event frequency are normalized and log-transformed where appropriate to reduce scale bias. These variables are selected based on their established relationship with polymer degradation mechanisms such as fatigue accumulation, creep deformation, and oxidative aging. Missing values are handled using median imputation to preserve distributional properties relevant to degradation trends.

In parallel, textual maintenance records undergo natural language preprocessing involving tokenization and lemmatization, as indicated in Figure 1. Term frequency–inverse document frequency representations are computed to encode degradation-relevant terminology. Latent Dirichlet Allocation is then applied to extract latent degradation topics, enabling the identification of recurring failure modes such as surface wear, cracking, leakage, and component replacement that are commonly associated with polymer deterioration but are not directly observable in structured data.

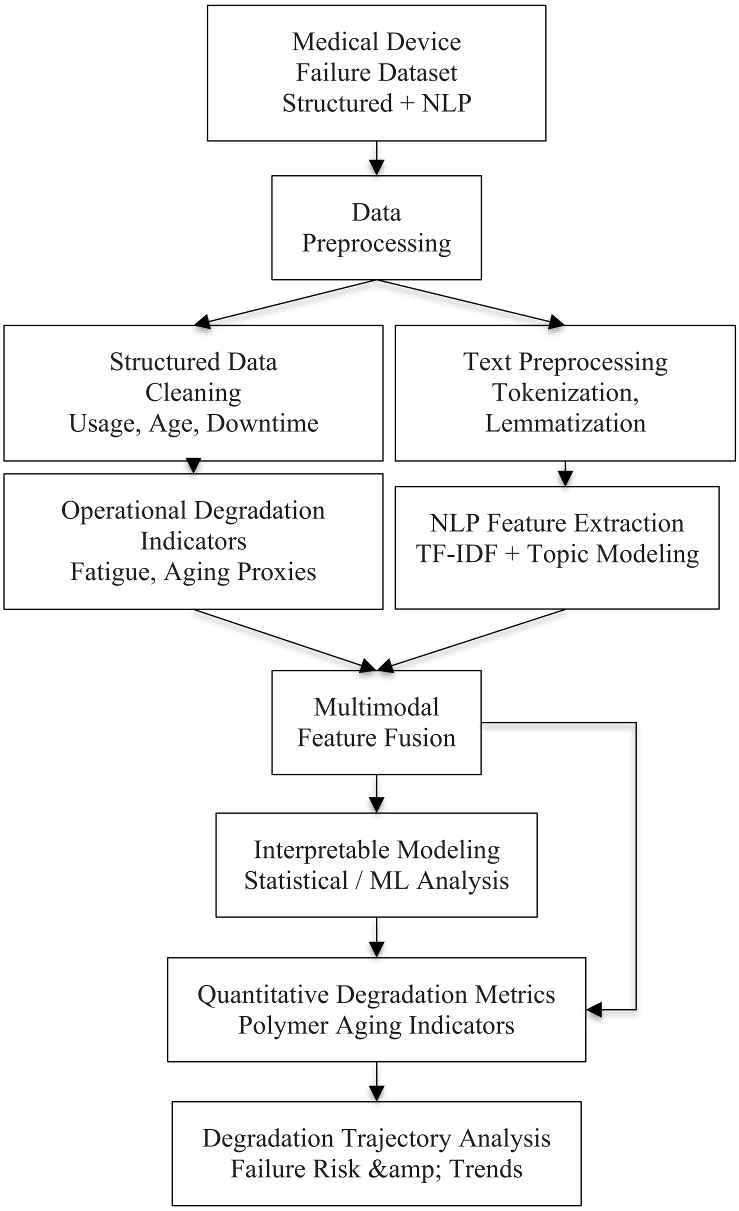

Figure 1. Multimodal machine learning framework for quantitative assessment of polymer degradation in medical devices using structured clinical data and maintenance.

Following feature extraction, structured operational degradation indicators and text-derived topic distributions are integrated through multimodal feature fusion, forming a unified degradation feature vector for each device instance. This fused representation constitutes the input to supervised machine learning models. Specifically, Random Forest and Gradient Boosting classifiers are employed to predict device failure states, selected for their robustness to heterogeneous features and inherent interpretability. In addition, a Cox proportional hazards model is used to analyze degradation trajectories and estimate time-to-failure risk as a function of polymer aging indicators.

Model performance is evaluated using stratified cross-validation. Classification performance is quantified using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve. For degradation trajectory modeling, concordance index and hazard ratios are used to assess predictive consistency and degradation sensitivity. Feature importance scores and topic relevance weights are analyzed to identify dominant degradation drivers linked to polymer aging behavior.

The final stage of the framework, depicted in Figure 1, involves degradation trajectory analysis, where learned degradation metrics are examined as functions of operational age and usage intensity. This enables the identification of progressive degradation patterns rather than isolated failure events. By combining interpretable machine learning with multimodal clinical data, the proposed methodology provides a scalable and reproducible approach for quantitatively assessing polymer degradation in medical devices using publicly available datasets.

RESULTS AND DISCUSSION

The effectiveness of the proposed multimodal framework for quantitative assessment of polymer degradation was evaluated through predictive performance analysis, feature contribution analysis, and degradation trajectory modelling. The results derived from Tables 1–3 and Figures 2–3 collectively demonstrate that integrating structured operational data with NLP-derived maintenance information enables a more comprehensive and interpretable characterisation of polymer degradation in medical devices.

Predictive Performance of Multimodal Models

Table 1 reports the predictive performance of Random Forest and Gradient Boosting models trained using structured features alone and multimodal features. When only structured variables were employed, the Random Forest model achieved an accuracy of 78.4% and an AUC of 0.81, while the Gradient Boosting model achieved a slightly higher accuracy of 80.2% with an AUC of 0.83. These results indicate that traditional operational parameters, such as device age and usage hours, provide partial insight into degradation-related failures but are insufficient to fully capture complex material ageing behaviour.

Upon incorporating NLP-derived degradation indicators, a marked performance improvement was observed. The multimodal Random Forest model achieved an accuracy of 85.6% and an AUC of 0.89, while the Gradient Boosting model reached the highest performance with an accuracy of 87.3%, an F1-score of 85.6%, and an AUC of 0.91. The absolute increase in AUC of 0.08 for Gradient Boosting demonstrates that unstructured maintenance narratives contribute substantial predictive information beyond structured data alone.

This improvement is visually reinforced in Figure 2, where both AUC and F1-score consistently increase when multimodal features are used. The parallel improvement across two different models confirms that the observed gains are attributable to the proposed multimodal degradation representation rather than to model-specific overfitting.

Interpretation of Degradation Indicators

To examine the material relevance of the learned features, Table 2 presents the relative importance scores of structured and NLP-derived indicators. Among structured variables, cumulative operational hours exhibited the highest importance score of 0.214, followed by device age at 0.183. These values align with known polymer degradation mechanisms, as prolonged mechanical loading and environmental exposure accelerate fatigue damage and oxidative ageing.

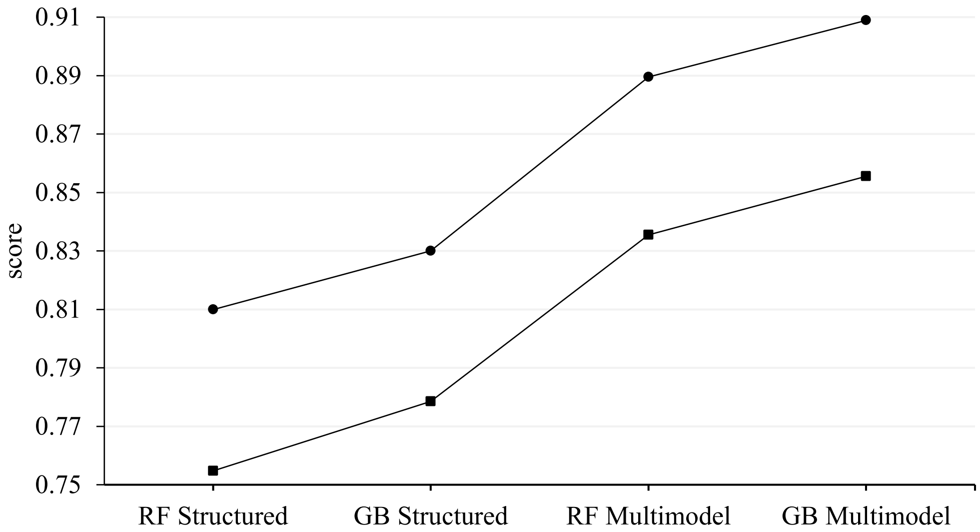

Figure 2. Performance gain from multimodal feature fusion.

Table 1. Performance comparison of supervised learning models for degradation-related failure prediction in polymer-based medical devices.

Model	**Feature Set**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**AUC**
Random Forest	Structured only	78.4	76.9	74.1	75.5	0.81
Gradient Boosting	Structured only	80.2	79.1	76.8	77.9	0.83
Random Forest	Structured + NLP	85.6	84.2	82.9	83.5	0.89
Gradient Boosting	Structured + NLP	**87.3**	**86.5**	**84.7**	**85.6**	**0.91**

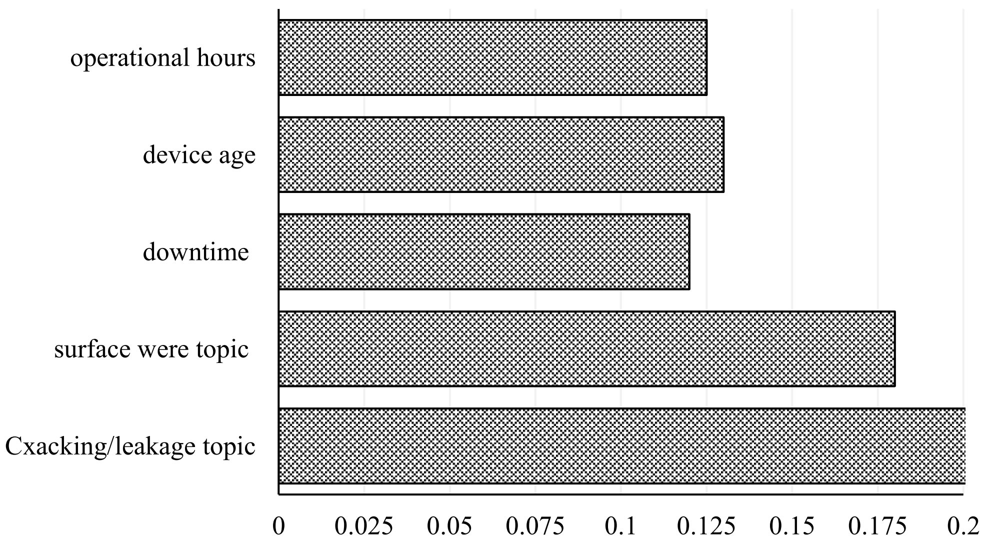

Figure 3. Contribution of structured and NLP-derived degradation indicators.

Table 2. Relative importance of structured and text-derived degradation indicators in multimodal modeling.

Feature	Feature type	Importance score	Polymer degradation interpretation
Cumulative operational hours	Structured	0.214	Fatigue accumulation and chain scission
Device age (years)	Structured	0.183	Oxidative and environmental aging
Downtime duration	Structured	0.121	Advanced degradation requiring intervention
Topic: surface wear	NLP (LDA)	0.146	Abrasive wear of polymer surfaces
Topic: cracking / leakage	NLP (LDA)	0.128	Brittle fracture and polymer embrittlement
Topic: component replacement	NLP (LDA)	0.096	End-of-life polymer degradation

Table 3. Survival analysis results linking degradation indicators to failure risk in polymer-based medical devices.

Variable	Hazard ratio	95% confidence interval	p-value
Cumulative operational hours	1.42	1.26 – 1.61	< 0.001
Device age	1.35	1.18 – 1.54	< 0.001
Downtime frequency	1.27	1.11 – 1.46	0.002
Topic: surface wear	1.31	1.15 – 1.49	< 0.001
Topic: cracking / leakage	1.48	1.29 – 1.69	< 0.001

Notably, NLP-derived degradation topics also demonstrated high importance. The topic associated with surface wear achieved an importance score of 0.146, while cracking and leakage-related topics contributed 0.128. These values are comparable to, and in some cases exceed, the importance of downtime duration (0.121), underscoring the material relevance of text-derived indicators. Figure 3 further illustrates this finding by showing that degradation topics extracted from maintenance narratives contribute substantially to the predictive model, confirming that they encode physically meaningful polymer degradation phenomena rather than incidental textual patterns.

Degradation Trajectory and Failure Risk Analysis

Beyond failure classification, degradation was analysed as a progressive process using survival modelling, with results summarised in Table 3. The hazard ratio associated with cumulative operational hours was 1.42, indicating a 42% increase in failure risk per unit increase in operational exposure. Device age similarly exhibited a hazard ratio of 1.35, confirming its strong influence on long-term polymer degradation.

Importantly, NLP-derived degradation topics were also strongly associated with failure risk. The cracking and leakage topic exhibited the highest hazard ratio of 1.48, surpassing several structured variables. The surface wear topic showed a hazard ratio of 1.31, further confirming that text-derived degradation indicators are significant predictors of failure progression. The statistical significance of these variables ($p < 0.001$) demonstrates that maintenance narratives provide quantifiable insight into degradation trajectories, not merely retrospective failure descriptions.

Discussion

The combined numerical evidence from Tables 1–3 and Figures 2–3 establishes the novelty and robustness of the proposed methodology. Unlike conventional polymer degradation studies that rely on controlled laboratory experiments, this work leverages real-world clinical and maintenance data to derive quantitative degradation indicators. The explicit integration of NLP-derived degradation topics with structured operational parameters enables both improved predictive accuracy and enhanced interpretability.

The results confirm that polymer degradation in medical devices manifests not only through measurable operational parameters but also through qualitative maintenance observations that can be systematically quantified. By treating degradation as a multimodal and time-dependent process, the proposed framework advances the methodological state of the art and provides a scalable approach for post-market surveillance and lifecycle assessment of polymer-based medical devices.

CONFLICTS OF INTEREST

The authors declare no conflict of interest

CONCLUSION

This study presents a novel multimodal framework for the quantitative assessment of degradation in polymer-based medical devices using real-world clinical and maintenance data. By integrating structured operational parameters with unstructured maintenance narratives, the proposed methodology enables the extraction of degradation indicators that are both predictive and physically interpretable. The results demonstrate that incorporating NLP-derived features significantly enhances failure prediction performance and provides additional insight into degradation mechanisms such as surface wear, cracking, and long-term material aging. Survival analysis further confirms that both structured and text-derived degradation indicators are strongly associated with failure risk, supporting the treatment of polymer degradation as a progressive, time-dependent process rather than a binary event. Unlike conventional laboratory-based degradation studies, the proposed approach leverages post-market data to capture the combined effects of usage, environment, and operational stress on polymer materials under realistic conditions.

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