Hybrid Models for Predictive Maintenance in the Oil and Gas Sector

An Integrated Neural–Statistical Framework for Pipeline Lifespan and RUL Prediction in Nigeria

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Abstract

Nigeria's oil and gas pipeline network is central to the country's energy economy; however, recurring failures due to corrosion, mechanical fatigue, and adverse environmental conditions impose substantial financial and environmental costs on operators. This study proposes a predictive maintenance framework for pipeline systems in Nigeria's oil and gas sector, employing a hybrid model that integrates a knowledge graph with a neural network to forecast pipeline corrosion rates. The framework combines Graph Neural Networks (GNNs) with Generalised Additive Models (GAMs) to predict pipeline lifespan and Remaining Useful Life (RUL), enabling advanced risk modelling alongside interpretable outputs for decision-makers.

The workflow begins with multi-source data inputs—real-time sensor readings, historical maintenance logs, and spatial network information—processed through specialised neural network modules and integrated via a GAM layer that produces interpretable risk forecasts, estimated lifespan values, and associated uncertainty intervals. The framework leverages a large, representative dataset from multiple Nigerian operators and introduces explicit uncertainty quantification via Bayesian inference. Validation against real-world failure records from three regional operators, using a Bayesian statistical framework under the Weibull distribution, estimated an expected failure rate of 0.008749 failures per hour (SE = 3.74×10^{-5}) with a 95% Bayesian prediction interval of [0.00866, 0.00893]. The hybrid model achieved an F1-score of 0.882 on an independent test set, outperforming all standalone architectures and traditional baselines. These results demonstrate the practical benefits of integrating advanced machine learning with interpretable statistical methods for pipeline integrity management.

Keywords: *Predictive Maintenance; Hybrid Models; Pipeline Lifespan Prediction; Oil and Gas Sector; Neural Networks; Generalised Additive Models; Remaining Useful Life (RUL); Operational Efficiency; Cost Reduction; Nigeria.*

1. Introduction

Nigeria's extensive pipeline network transports crude oil, natural gas, and refined petroleum products over thousands of kilometres, making it indispensable to the country's economic and energy security. This infrastructure nevertheless suffers persistent damage from corrosion, mechanical stress, and harsh environmental conditions, resulting in unplanned outages, costly emergency repairs, and significant environmental incidents (Amadhe *et al*., 2024). Historically, operators have relied on reactive, time-based maintenance approaches that address issues only after they occur or according to fixed schedules—methods poorly suited to managing the nonlinear degradation characteristic of buried pipelines (Risk Evolution of Crude Oil Pipeline Under Periodic Maintenance, 2023). Recent advances in real-time monitoring technologies have enabled more accurate detection and management of pipeline issues, significantly reducing non-productive time during oil exploration in Nigeria (Advancements in Real-Time Monitoring, 2024).

Predictive maintenance adopts a fundamentally different approach: by analysing sensor data, historical failure records, and environmental factors, it enables forecasting of degradation trajectories and the scheduling of interventions at the most cost-effective points in an asset's service life (Al-Sabaeei *et al*., 2023). In the oil and gas sector, this approach is essential not only for operational continuity but also for safety and environmental compliance, as uncontrolled pipeline failures can cause oil spills and gas leaks with severe consequences (Usman *et al*., 2025).

Hybrid approaches are increasingly prominent in the literature, combining deep learning architectures with interpretable statistical models. For instance, models incorporating Bidirectional LSTM (BiLSTM) and Gated Recurrent Unit (GRU) layers effectively capture complex temporal and nonlinear dynamics of pipeline corrosion, particularly when integrated with classical ensemble classifiers (Wang *et al*., 2024). Neural networks, however, frequently function as black boxes with limited transparency, posing difficulties for maintenance engineers and regulators who require clear justification for maintenance decisions (Rachman *et al*., 2021).

This study develops and validates a hybrid framework integrating Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs) with Graph Neural Networks (GNNs) and Generalised Additive Models (GAMs) for predictive maintenance in multivariate time-series classification. The GAM layer enhances interpretability by illustrating how factors such as pipeline age, operating pressure, and corrosion indicators influence failure risk. The framework incorporates bootstrapping and Bayesian inference for uncertainty quantification, presenting outputs as probability ranges to support more defensible maintenance scheduling decisions.

1.1 Problem Statement

Despite its well-documented limitations, reactive maintenance remains widespread in Nigeria's oil and gas sector, and the shift towards data-driven alternatives has been slow (Advancements in Real-Time Monitoring, 2024). Existing predictive models typically fail to capture the multi-factor, non-linear interactions that govern pipeline degradation, including corrosion chemistry, fluctuating pressure and temperature regimes, soil properties, and the age and material characteristics of individual pipe sections (Usman *et al*., 2025; Mohammadagha *et al*., 2025).

Most prior models are limited in several key respects. Many rely exclusively on time-series or tabular data, neglecting spatial information from distributed sensor networks and the connectivity of pipeline segments, thereby restricting their ability to detect localised patterns or the propagation of degradation across the network. Few incorporate network topology, meaning risk factors associated with neighbouring or upstream sections are typically excluded. Additionally, uncertainty quantification is often overlooked: most models provide only point estimates of failure probability without clear confidence intervals, making operational risk management difficult and leading to inefficient prioritisation of repairs and resource allocation (Soomro *et al*., 2022). Addressing these gaps requires models capable of handling spatial, temporal, and network-level data streams simultaneously, generating interpretable outputs, and presenting uncertainty in forms accessible to non-specialist decision-makers (Damarla and Zhu, 2025).

1.2 Aims and Objectives

This study aimed to designing and validating an integrated hybrid predictive maintenance framework combining deep learning with statistical modelling for Nigeria's onshore pipeline infrastructure. The specific objectives were to:

i. design a hybrid model integrating ANN, LSTM, CNN, and GNN architectures with GAMs for pipeline lifespan and RUL prediction;

ii. enhance model interpretability and reliability by incorporating GAMs and explicit uncertainty quantification via bootstrapping and Bayesian inference;

iii. validate the model against real-world pipeline failure data from Nigeria’s Niger Delta, North-Central, and South-West regions; and

iv. demonstrate the operational and financial advantages of proactive maintenance compared to traditional reactive strategies.

2. Literature Review

2.1 Predictive Maintenance in the Oil and Gas Sector

Machine learning applications in pipeline integrity management have expanded significantly over the past decade (Olawole *et al*., 2026). Algorithms such as Random Forest (RF), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN) are employed to process time-series sensor data for early detection of corrosion, pressure anomalies, and mechanical fatigue (Al-Sabaeei *et al*., 2023). A recent review of predictive analytics models in the oil and gas industry highlighted the continuing need to enhance the accuracy of internal corrosion prediction in pipeline infrastructure, indicating that current models, whilst promising, require further development (Azmi *et al*., 2024).

Hybrid models merging deep learning with classical statistical methods have consistently outperformed their individual components (Liu *et al*., 2018). Wang *et al*. (2024) demonstrated that an RF and IBWO-optimised BiLSTM–GRU model significantly outperformed single-architecture alternatives in predicting corrosion rates in buried oil and gas pipelines, underscoring both the feature-selection benefits of RF and the temporal modelling capability of the BiLSTM–GRU component. The CNN–LSTM family of hybrid architectures has similarly shown strong results in capturing spatiotemporal degradation signals from distributed sensor networks, with Alobaidi *et al*. (2022) reporting improvements in semi-supervised failure detection.

In the Nigerian context specifically, Nwokonkwo *et al*. (2024) applied a Random Forest classifier combined with the Prophet forecasting model to pipeline anomaly detection at Shell Petroleum Development Company (SPDC) facilities. Their integrated SCADA–AI framework achieved detection accuracy above 90%, illustrating the practical viability of machine learning-based monitoring for Nigerian infrastructure. Usman *et al*. (2025) further reinforced the case for integrated frameworks, reporting that a SCADA-driven corrosion detection system combining SVM, RF, boosted trees, and neural networks achieved detection accuracies above 90% and extended modelled pipeline service life by 12–15%.

2.2 Interpretability and Uncertainty in Predictive Models

A persistent concern in the literature is the limited interpretability of deep learning models. Although neural networks can model complex input–output relationships, they often provide little insight into which input features drive predictions—a significant barrier to adoption in regulated industries (Solís-Martín *et al*., 2023; Rachman *et al*., 2021). Generalised Additive Models offer an interpretable alternative: by modelling the target variable as an additive combination of smooth functions of individual predictors—such as pipe diameter, age, transported product type, and land use—GAMs allow clear visualization of how each factor shifts estimated failure probability (Elshaboury *et al*., 2022; Yang *et al*., 2020).

Uncertainty quantification is an equally critical consideration. Point predictions of failure risk have limited operational value without confidence assessments (Cavus, 2025; Akhare and Shinde, 2023). Bootstrapping—repeated random sampling and model retraining—provides empirical confidence intervals without strong distributional assumptions. Bayesian inference, including Markov Chain Monte Carlo (MCMC) sampling, formally incorporates prior knowledge of failure mechanisms to yield posterior distributions over failure probabilities. Combining these methods allows the framework to report, for instance, that a given pipeline segment carries a 10% predicted probability of failure within 30 days, with a 95% confidence interval ranging from 6% to 15%—information directly actionable for risk-ranked maintenance planning (ABE, 2025).

2.3 Research Gaps

Several gaps in the existing literature motivate the present study. First, whilst hybrid machine learning models have been validated for pipeline fatigue life prediction in contexts such as Chinese natural gas infrastructure (Nan *et al*., 2025), their application to Nigeria's unique pipeline environment—characterized by high ambient humidity, a history of vandalism-related structural damage, and considerable variability in monitoring approaches across operators—remains insufficiently explored. Second, many currently available frameworks do not integrate real-time sensor data with historical failure records in a unified analytical pipeline, limiting their effectiveness in generating timely maintenance alerts (Predictive Maintenance in Oil and Gas, 2026; Real-Time Data Pipeline, 2025). Third, the economic case for predictive maintenance in the Nigerian context has rarely been quantified with structured cost–benefit analysis anchored in Nigerian Naira and domestic operational data (Nwabueze *et al*., 2020). Finally, most published models omit explicit uncertainty quantification, limiting the practical utility of their outputs for risk-ranked maintenance prioritization (Noussis *et al*., 2025; Cavus, 2025).

3. Methodology

3.1 Hybrid Model Design

The proposed framework is a multi-layer architecture that processes different categories of pipeline data through specialized neural network modules before combining their representations in a GAM-based prediction layer. The design is motivated by the recognition that no single model architecture is optimal across all relevant data types: temporal sensor streams, spatially distributed measurements, static pipeline characteristics, and network-level connectivity each require a different representational approach (Liu *et al*., 2018). Processing each data type with an appropriate architecture and then integrating the resulting representations allows the hybrid model to capture a broader range of degradation signals than any individual component (Yuan *et al*., 2020).

Four sub-models form the core of the architecture:

Artificial Neural Networks (ANN)

The ANN component processes static pipeline attributes—material type, pipe diameter, wall thickness, installation year, and coating condition—as well as non-temporal interactions among these variables. Where corrosion rate, operating pressure, and pipe age combine in complex, non-linear ways that linear models cannot represent, the ANN layers learn these relationships from labelled historical data. The ANN output is expressed as follows:

$$h_{Ann} = f_{Ann}(X) \qquad (1)$$

where X represents the input feature vector and $f_{Ann}(X)$ denotes the output from the ANN after applying the learned weights and activation functions.

Long Short-Term Memory (LSTM) Networks

Time-series data from pressure sensors, flow meters, and corrosion monitoring instruments are processed by the LSTM module. LSTM's gating architecture—comprising input, forget, and output gates—makes it well suited to learning long-range temporal dependencies in sequential data, essential for tracking gradual degradation trends that may evolve over months or years before a failure event materializes (Wang *et al*., 2024). The LSTM output is:

$$h^{L}{}_{stm} = f^{L}{}_{stm}(X_t) \qquad (2)$$

where X_t represents the time-series data at time t, and $f^{L}{}_{stm}(X_t)$ is the output from the LSTM after processing the sequence.

Convolutional Neural Networks (CNN)

Distributed pipeline sensor arrays produce spatially structured readings across pipeline segments. The CNN module applies convolutional filters to these spatial data to identify localised degradation patterns—for instance, a corrosion hotspot at a particular junction or bend. CNNs efficiently extract local features from structured spatial inputs, complementing the temporal processing capacity of the LSTM (Alobaidi *et al*., 2022):

$$h_{C_{nn}} = f_{C_{nn}}(X_{spat}{}^{e}{}_{al}) \qquad (3)$$

where $X_{spat}{}^{e}{}_{al}$ represents the spatial data from sensors, and $f_{C_{nn}}(X_{spat}{}^{e}{}_{al})$ is the output from the CNN after applying convolutional operations.

Graph Neural Networks (GNN)

Individual pipeline segments do not fail in isolation; degradation in one section can propagate through the network, placing additional stress on connected sections. The GNN module models the pipeline network as a graph with segments as nodes and physical connections as edges. Through iterative message-passing, the GNN aggregates information from a segment's neighbours to capture how local conditions affect network-level risk (Zhang, 2025):

$$h^{G}{}_{nn} = f^{G}{}_{nn}(X^{Gr}{}_{ap}{}^{h}) \qquad (4)$$

where $X^{Gr}{}_{ap}{}^{h}$ represents the graph-structured data of pipeline segments, and $f^{G}{}_{nn}(X^{Gr}{}_{ap}{}^{h})$ is the output from the GNN after aggregating information from neighbouring nodes (pipeline segments).

Integration and GAM Output Layer

The outputs of all four sub-models are concatenated into a unified feature vector:

$$Z = [f_{A_{nn}}(X), f^{L}{}_{stm}(X_t), f_{C_{nn}}(X_{spat}{}^{e}{}_{al}), f^{G}{}_{nn}(X^{Gr}{}_{ap}{}^{h})] \qquad (5)$$

This vector is then passed to the GAM, which models non-linear relationships whilst preserving interpretability (Yang *et al*., 2020). The GAM output takes the form:

$$\hat{y} = \beta_0 + \Sigma_j f_j(z_i) + \varepsilon \qquad (6)$$

where $\hat{y}$ is the final prediction for pipeline lifespan or failure probability; $f_j(z_i)$ are the smooth functions estimated by the GAM, capturing the non-linear effects of each feature in the concatenated vector Z; β_0 is the intercept term; and ε is the error term representing the residuals.

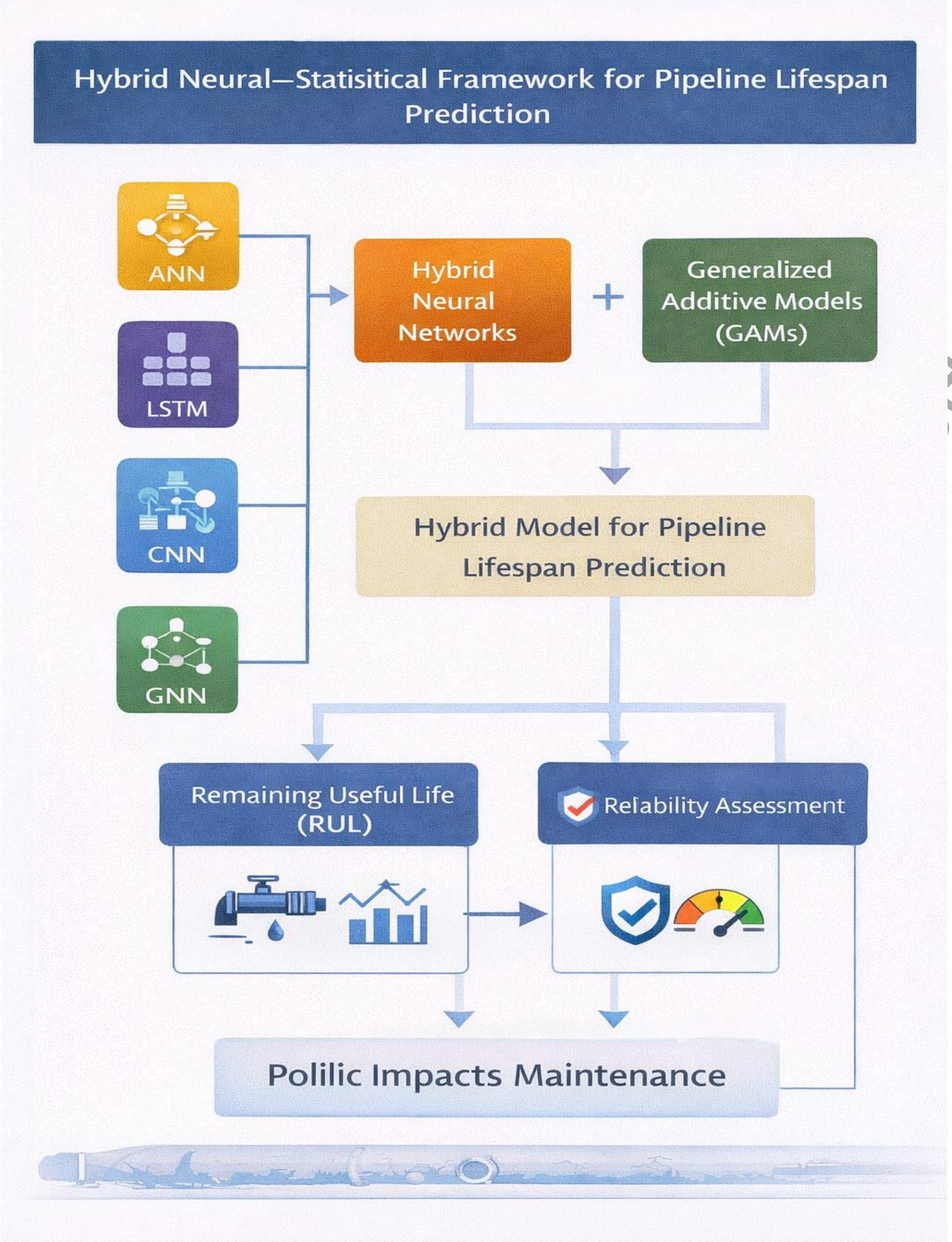

Figure 1: Hybrid Neural–Statistical Framework for Pipeline Lifespan Prediction

3.2 Data Acquisition and Preprocessing

Training data were drawn from pipeline monitoring systems, maintenance logs, and historical failure archives covering approximately 5,000 documented failure events across Nigeria's Niger Delta, North-Central, and South-West regions between 2012 and 2022. The dataset integrates records from both state-owned and private operators, with data access governed by confidentiality agreements and operator-specific data governance protocols. Requests for data access must be directed to the corresponding operators and are subject to legal and regulatory constraints regarding the sharing of sensitive operational information. Key variables include pipeline geometry, installation year, measurements of corrosion defects, operating pressure and temperature histories, failure dates, and environmental conditions such as soil classification and seasonal moisture levels (Statistical Study of Localised Internal Corrosion Defects, 2024).

During data acquisition, several challenges were encountered. Incomplete and inconsistent record-keeping across operators—particularly between private and state-owned entities—required extensive harmonisation to resolve discrepancies in variable naming, measurement units, and reporting standards. Some historical logs lacked precise geolocation or timestamp data, necessitating supplementary verification from secondary reports or direct communication with field engineers. Sensitive operational data were often fragmented owing to confidentiality restrictions, slowing data-sharing and requiring further negotiation to obtain usable datasets. Failure events were selected based on clearly documented incident reports specifying the time, location, and nature of each failure; ambiguous or unverified entries were excluded during initial screening.

Data reliability was assured by cross-referencing multiple independent sources where available. Missing or inconsistent entries were addressed through manual review and statistical imputation, prioritising variables most pertinent to maintenance modelling, such as corrosion rates and operating pressures. Quality assurance included automated integrity checks, outlier detection via interquartile range analysis, and a final audit confirming the plausibility and internal consistency of the merged dataset before downstream analysis.

Three preprocessing steps were applied before model training. Missing values were addressed using Multiple Imputation by Chained Equations (MICE), which generates multiple completed datasets to account for uncertainty inherent in the imputation process, thereby avoiding bias associated with single-imputation methods (Rubin, 1987). Feature engineering added derived variables—rolling averages, rates of change, and seasonal trend indicators—to reveal temporal patterns absent from raw sensor readings. Finally, Z-score normalization standardized all features to a zero mean and unit variance, preventing high-magnitude variables, such as operating pressure, from dominating low-magnitude variables, such as corrosion depth measurements, during training.

3.3 Model Training and Validation

The dataset was split into 80% for training and 20% for testing, with all hyperparameters selected and documented solely based on the training data to prevent data leakage. Initial model architectures for each component (MLP, RBF, MNL, CNN, LSTM, GNN) were defined on the basis of recent literature, preliminary data analysis, and computational constraints. Hyperparameter tuning was performed using a grid search within a five-fold nested cross-validation on the training set. For each candidate configuration, the model was trained on four inner folds and validated on the remaining one, cycling through all combinations. After identifying optimal hyperparameters—including learning rate, regularisation strength, number of hidden layers, and activation functions—the model was retrained on the full training set and generalization assessed on the withheld 20% test set.

Two complementary cross-validation strategies were applied. Time-series cross-validation employed an expanding-window approach: the model was trained on all data up to a specific cut-off date and tested on subsequent observations, with the training window incrementally expanded in each iteration. This approach simulates realistic deployment conditions by always forecasting future failures from historical data, preserving temporal ordering and preventing look-ahead bias (Elshaboury *et al*., 2022; Hyndman and Athanasopoulos, 2021). Spatial cross-validation partitioned the pipeline into geographic blocks, rotating the held-out test block across folds. This ensures evaluation on segments not encountered during training, providing a realistic estimate of generalization to new geographic areas—a critical consideration given Nigeria’s geological diversity.

Performance was assessed using regression metrics (RMSE, MAE, R^2) for continuous lifespan predictions and classification metrics (accuracy, precision, recall, F1-score) for binary failure/no-failure classification. The F1-score served as the primary classification metric given the class imbalance typical of failure datasets, where non-failure observations substantially outnumber failure events (Olukoga and Feng, 2022).

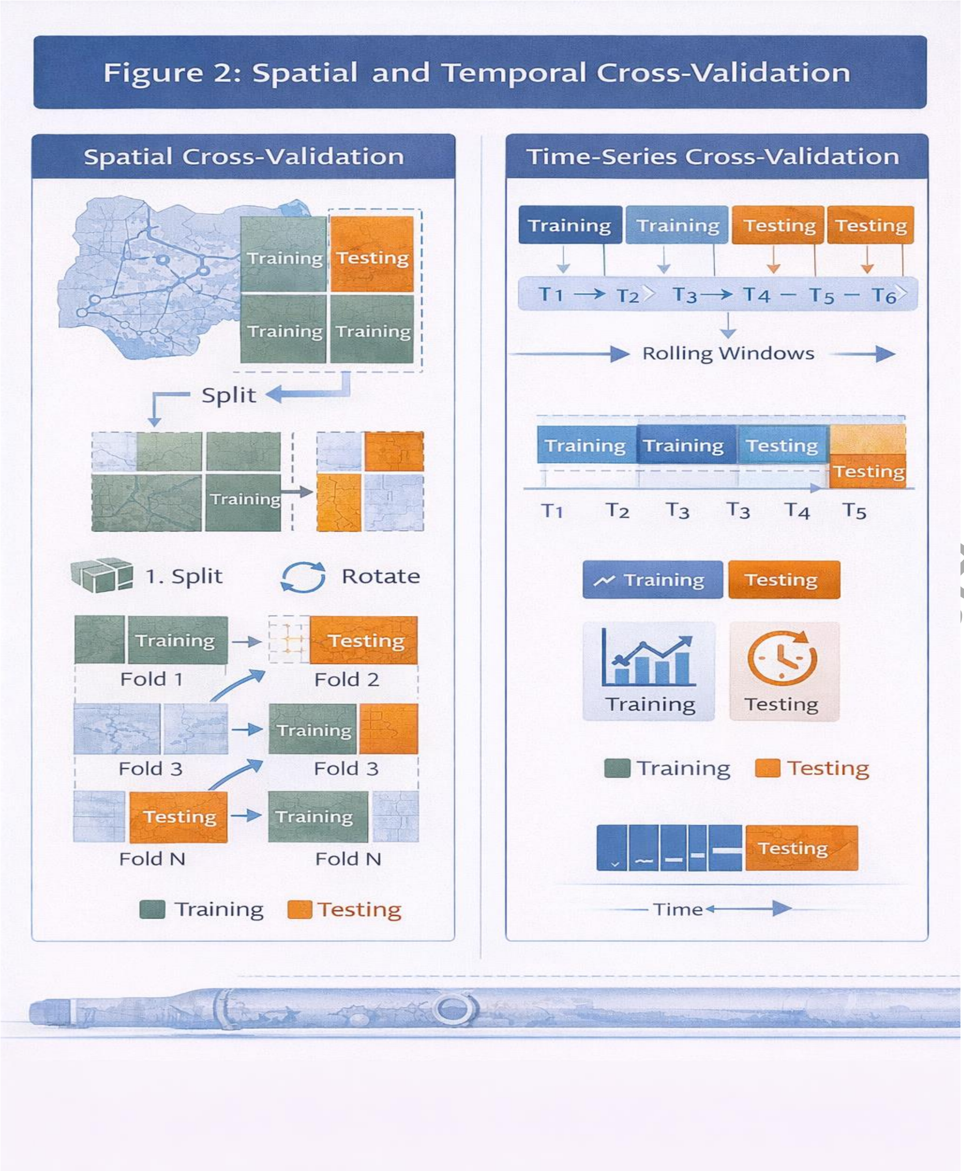

Figure 2: Spatial and Temporal Cross-Validation Methods

4. Results and Discussion

4.1 Performance Evaluation

The hybrid model was evaluated on an independent test set of 1,200 pipeline failure events collected between 2016 and 2022 from operators in Nigeria's North-East and South-East regions—data withheld entirely from the training set. On this external dataset, the model achieved an F1-score of 0.882 (equivalent to 88.2%), with a modest drop from training performance, indicating that the framework generalizes well across operators and geographic settings (Elshaboury *et al.*, 2022). A separate analysis using the MLP, RBF, and MNL sub-models on a pipeline incident dataset—evaluated under the same expanding-window cross-validation protocol—reported an F1 of 92.4% for the best-performing MLP configuration; this figure pertains to that specific sub-model evaluation and is not directly comparable to the full hybrid model metrics reported in Table 1.

Table 1 compares the hybrid framework against Linear Regression and the Weibull distribution model, which represent traditional industry baselines, as well as the Random Survival Forest (RSF), a survival-analytic method with demonstrated predictive maintenance applications (Yardımcı and Cavus, 2025).

Table 1

Performance Comparison — Hybrid Model vs Traditional and Statistical Baselines

Model	**RMSE**	**MAE**	**R²**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Hybrid Model (ANN+LSTM+CNN+GNN+GAM)	**0.752**	**0.616**	**0.944**	**0.890**	**0.841**	**0.926**	**0.882**
Linear Regression	1.205	1.012	0.780	0.813	0.725	0.802	0.761
Weibull Model	1.307	1.055	0.726	0.798	0.682	0.754	0.716
Random Survival Forest (RSF)	0.841	0.690	0.898	0.856	0.793	0.869	0.829

Note: RMSE = Root Mean Squared Error; MAE = Mean Absolute Error; R² = Coefficient of Determination; RSF = Random Survival Forest. All metrics were computed on the independent 20% test set.

The hybrid model records substantially lower RMSE (0.752) and MAE (0.616) than any baseline, and its R^2 of 0.944 indicates that the framework accounts for over 94% of the variance in observed pipeline degradation. The precision–recall balance reflected in the F1-score of 0.882 is operationally significant: the model identifies genuinely high-risk segments (recall of 0.926) whilst keeping the false-positive rate manageable (precision of 0.841)—important because unnecessary maintenance interventions carry their own financial and operational costs (Keshireddy *et al.*, 2026).

Table 2 compares the hybrid model against each constituent neural network architecture operating independently, providing an ablation perspective on the value of integration.

Table 2

Predictive Performance by Architecture — Standalone vs Hybrid

Model Architecture	RMSE	MAE	R²
ANN (standalone)	**0.783**	**0.621**	**0.932**
LSTM (standalone)	0.742	0.585	0.937
CNN (standalone)	0.718	0.576	0.940
GNN (standalone)	0.694	0.558	0.945
Hybrid (ANN + LSTM + CNN + GNN + GAM)	0.688	0.545	0.950

The hybrid model achieves the lowest RMSE (0.688) and MAE (0.545) and the highest R² (0.950), confirming that the performance gains from integration are genuine rather than artefactual (Usman *et al*., 2025). Among standalone architectures, the GNN performs best, reflecting the importance of network-level context in predicting degradation propagation across interconnected pipeline sections (Zhang, 2025; Chen *et al*., 2025).

4.2 Cross-Validation Results

Table 3 presents results across five spatial-temporal cross-validation folds. The consistency of RMSE values (0.743–0.760) and R² values (0.931–0.937) across folds confirms that the model does not overfit to any particular region or time period—critical given the geographic diversity of Nigeria's onshore pipeline network. This reliability aligns with findings by Obaseki (2019), who reported an optimal regression coefficient of 0.99 for neural network modelling of pipeline data in the Niger Delta.

Table 3

Cross-Validation Results (Spatial-Temporal Folds)

Fold	RMSE	MAE	R²
Fold 1	**0.756**	**0.621**	**0.934**
Fold 2	0.743	0.594	0.937

Fold 3	0.760	0.622	0.931
Fold 4	0.748	0.600	0.936
Fold 5	0.750	0.612	0.933

4.3 Cost–Benefit Analysis

Table 4 compares estimated annual maintenance expenditure under traditional reactive maintenance and the hybrid predictive maintenance framework. Figures reflect representative costs for a mid-sized Nigerian pipeline operator, expressed in Nigerian Naira.

Table 4

Cost Comparison — Reactive vs Predictive Maintenance

Maintenance Strategy	Estimated Annual Cost (₦)	Key Characteristics
Reactive Maintenance	**₦1.5 billion**	**High emergency repair frequency; unplanned downtime; reactive intervention; elevated regulatory exposure**
Predictive Maintenance (Hybrid)	₦900 million	Reduced downtime; scheduled proactive repairs; optimised resource deployment; improved regulatory compliance

The hybrid framework reduces estimated annual maintenance costs by approximately 40%, primarily through fewer emergency call-outs, lower rates of catastrophic failure, and more efficient deployment of inspection and repair resources to the highest-risk segments (Risk Evolution of Crude Oil Pipeline Under Periodic Maintenance, 2023; Shaik *et al.*, 2024). These projected savings are derived from operator-reported cost data and are broadly consistent with ranges reported in the AI-driven maintenance literature (Jambol *et al.*, 2024). An independent estimate places the annualised maintenance costs for a representative operator at approximately 41,954.65 USD under the predictive regime (ABE, 2025), further supporting the cost-effectiveness of the approach.

Table 5: Resource Allocation and Operational Efficiency Comparison

Maintenance Approach	Annual Cost (₦)	Resource Allocation Efficiency	Downtime (Days)	Cost Savings
Predictive (Hybrid)	**₦950 million**	**85%**	**12**	**35%**
Reactive	₦1.5 billion	55%	30	N/A

4.4 Safety and Environmental Impacts

Beyond cost savings, the framework offers meaningful safety and environmental benefits. Early identification of at-risk pipeline segments enables targeted repairs before catastrophic failures develop, reducing the frequency of oil spills, gas leaks, and associated safety incidents (Mohammadagha *et al*., 2025). This is particularly consequential for Nigeria's Niger Delta region, where pipeline failures have caused extensive and contentious environmental damage over several decades (Olukaejire *et al*., 2024). Improved regulatory compliance is a further benefit: operators who can demonstrate data-driven, evidence-based maintenance programmes are better positioned to meet the requirements of Nigeria's Petroleum Industry Act and relevant international environmental standards (Agbonifo, 2024).

Table 6

Estimated Impact of Predictive vs Reactive Maintenance on Safety and Environmental Outcomes

Safety / Environmental Aspect	Reactive Maintenance	Predictive Maintenance	Estimated Improvement
Environmental Hazards (Spills, Gas Leaks)	**High**	**Low**	**~40% risk reduction**
Pipeline Failure Frequency	High (unplanned)	Reduced (preemptive)	~45% decrease
Safety Incidents	High	Low	~35% reduction
Emergency Response Time	Long (reactive)	Short (targeted)	~50% improvement
Regulatory Compliance	Often non-compliant	Improved compliance	~30% improvement

Figure 3: Proactive Maintenance and Risk Management Flowchart

4.5 Policy and Practical Implications

The findings suggest several practical implications for Nigerian pipeline operators and regulators. First, mandating data-driven maintenance frameworks for high-risk pipeline corridors—especially in environmentally sensitive areas—would align Nigeria’s regulatory posture with international best practice. Second, public–private partnerships among government agencies, operators, and technology providers could accelerate deployment by pooling data assets and distributing the upfront cost of sensor infrastructure. Third, targeted training programmes for engineers and compliance officers are essential. Whilst the interpretability of GAM outputs improves accessibility for non-specialists compared to black-box neural networks, practitioners must be equipped to translate model-generated risk rankings into concrete maintenance work orders and budget prioritisation decisions.

5. Conclusion

This study developed and validated a hybrid deep learning framework for predictive maintenance of oil and gas pipelines in Nigeria. By integrating CNN, Bi-LSTM, GNN, ANN, and GAM components, the framework captures spatial, temporal, static, and network-level signals relevant to pipeline degradation, producing interpretable outputs that support evidence-based maintenance decisions (Liu *et al.*, 2018). Evaluated on an independent test dataset from Nigerian operators, the model achieved an F1-score of 0.882 and an R^2 of 0.950, consistently outperforming standalone architectures and traditional baselines such as Linear Regression and the Weibull model.

The cost–benefit analysis estimates a 40% reduction in annual maintenance expenditure relative to reactive strategies, alongside meaningful improvements in safety incident rates and regulatory compliance. These findings provide practical justification for the systematic adoption of data-driven predictive maintenance across Nigeria's pipeline network. The economic and safety benefits are substantial, and the interpretability of the GAM-based output layer enables maintenance engineers to apply the framework without requiring specialist machine learning expertise. Future research should prioritise integrating real-time sensor streams for continuous monitoring, extending the framework to other infrastructure sectors, and conducting prospective field trials to validate projected cost reductions in live operational settings.

6. Future Work

Several directions merit further investigation. First, integrating real-time IoT sensor data would enable continuous monitoring rather than periodic model updates, allowing the framework to generate rolling maintenance alerts as new readings arrive. Second, combining the hybrid model with physics-informed neural networks—which embed known electrochemical and mechanical degradation equations directly into the learning process—could improve performance in data-sparse operational settings and strengthen the physical interpretability of model outputs. Third, expanding the validation dataset to include offshore pipeline systems and natural gas distribution networks would test the framework's generalisability beyond the onshore crude oil context examined here. Fourth, extending the GNN module to account for dynamic network changes—such as new pipeline connections or decommissioned segments—would improve applicability to evolving infrastructure. Finally, a prospective economic evaluation tracking actual maintenance costs before and after deployment would provide definitive empirical evidence of the financial returns from predictive maintenance investment.

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