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Research Article

Predictive Maintenance of Oil and Gas Infrastructure Using AI Models: Enhancing Operational Efficiency and Economic Output

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Nigeria's oil and gas sector, the bedrock of the national economy accounting for over 87% of foreign exchange earnings, suffers chronic infrastructure deterioration resulting in annual production losses estimated at \$3–5 billion. Conventional preventive and reactive maintenance paradigms have proven inadequate for the scale and operational hazards of Nigerian petroleum infrastructure. This study develops, validates, and compares five AI-based predictive maintenance (PdM) models – Long Short-Term Memory (LSTM) networks, Random Forest, Support Vector Machine (SVM), XGBoost, and Temporal Fusion Transformer (TFT) – for fault detection and Remaining Useful Life (RUL) prediction, using a dataset of 52,840 multi-sensor time-series observations collected from operational Nigerian oil and gas installations over 2019–2024. The stacked ensemble model achieved the highest classification accuracy of 98.1% (F1-Score: 0.977; AUC-ROC: 0.994), outperforming the TFT (97.3%), LSTM (96.7%), and XGBoost (95.1%) individually, and substantially exceeding the conventional preventive maintenance baseline (71.4%). Economic impact analysis reveals that AI PdM deployment reduced annual unplanned downtime by 68.2% (from 4,218 to 1,342 hours), decreased maintenance expenditure by 47.3% (from \$521.4M to \$274.8M), and recovered an estimated \$5.64 billion in previously lost production revenue annually. Macroeconomic modelling projects a 1.5 percentage point uplift in the oil sector's contribution to Nigeria's GDP. These findings establish a compelling evidence base for the systematic adoption of AI predictive maintenance across Nigeria's petroleum infrastructure and provide actionable policy recommendations for NUPRC, NNPC Limited, and international oil company (IOC) operators.

Keywords: *Predictive Maintenance, Artificial Intelligence, LSTM; XGBoost, Transformer, Oil and Gas Infrastructure, Nigeria, Operational Efficiency, Economic Output, Industry 4.0*

Introduction

The Nigerian oil and gas sector operates one of Africa's most extensive petroleum infrastructure networks, encompassing over 5,000 kilometres of pipelines, 275 flow stations, numerous offshore platforms, and onshore processing facilities (NNPC, 2023; NUPRC, 2023). Despite constituting the engine of the national economy, this infrastructure is afflicted by alarming levels of deterioration: between 2018 and 2023, Nigeria recorded more than 1,800 pipeline incidents attributable to equipment failures, resulting in cumulative production losses estimated at \$9.4 billion and precipitating severe environmental damage in the Niger Delta (Amnesty International, 2022; World Bank, 2022).

Unplanned equipment downtime alone costs the sector an estimated \$3–5 billion annually, driven by the failure of ageing assets whose average age exceeds 40 years (PwC Nigeria, 2023; Adeleke & Ogunleye, 2023). The global petroleum industry has increasingly turned to Predictive Maintenance (PdM) – enabled by Artificial Intelligence (AI), Industrial Internet of Things (IIoT), and real-time sensor analytics – as a transformative response to the inadequacies of reactive and preventive maintenance regimes (Carvalho et al., 2023; Zhang et al., 2023). AI-based PdM leverages machine learning algorithms and deep learning architectures to identify early signatures of impending equipment failure in multi-dimensional sensor data streams, enabling targeted maintenance interventions that minimise downtime, extend asset lifespan, and substantially reduce maintenance expenditure (Hasan et al., 2024; Li et al., 2024). The global predictive maintenance market, valued at \$6.9 billion in 2023, is projected to reach \$23.5 billion by 2029 at a compound annual growth rate (CAGR) of 22.8% (MarketsandMarkets, 2024). Despite this global momentum, the systematic application of AI PdM to Nigeria's oil and gas infrastructure remains nascent. A comprehensive audit of 14 NNPC installations by Adeleke & Ogunleye (2023) found that over 78% relied exclusively on time-based preventive maintenance, with fewer than 12% operating any form of condition monitoring. Alabi et al. (2023) presented a proof-of-concept AI fault detection model for a Nigerian gas compression station, but the study was limited to a single facility and did not assess economic impact or conduct multi-model comparisons. To the authors' best knowledge, no published peer-reviewed study has: (i) developed and validated a multi-architecture AI PdM framework using large-scale, empirical multi-sensor data from Nigerian oil and gas installations; (ii) quantified the macroeconomic implications of AI PdM adoption for Nigeria; or (iii) derived evidence-based policy recommendations for Nigerian petroleum regulators and operators. This paper addresses these gaps through a comprehensive AI PdM study encompassing five model architectures, 52,840 sensor observations from operational Nigerian installations, rigorous comparative benchmarking, and a structured economic impact assessment. The remainder of the paper is organised as follows: Section 2 reviews the relevant literature; Section 3 describes the methodology; Section 4 presents and discusses results; Section 5 outlines policy implications; and Section 6 concludes. The literature on AI-based PdM has expanded rapidly since 2019, driven by advances in deep learning and IIoT sensor proliferation. Zhang et al. (2023) demonstrated that LSTM networks outperformed traditional ARIMA-based approaches in predicting bearing failures in rotating machinery, achieving a root mean square error (RMSE) of 0.032 across a 30-day forecast window. Hasan et al. (2024) applied Temporal Fusion Transformer (TFT) architectures to multi-sensor data from subsea pipelines, reporting fault classification accuracy of 97.3% with a false positive rate below 2%. Carvalho et al. (2023), in a systematic review of 148 PdM studies, concluded that ensemble methods consistently outperform single-model approaches in industrial fault prognosis tasks. In the oil and gas sector, Li et al. (2024) deployed hybrid CNN-LSTM models on real-time offshore platform data in the South China Sea, reducing unplanned shutdowns by 42% over a two-year period. Al-Dahidi et al. (2022) demonstrated that Bayesian deep learning approaches provide calibrated uncertainty quantification in RUL prediction – a critical capability in high-consequence petroleum environments. Atamuradov et al. (2023) reviewed Prognostics and Health Management (PHM) frameworks for the petroleum sector, identifying sensor data quality, model interpretability, and domain expert integration as critical success factors. Jardine et al. (2021) provided a foundational review of condition-based maintenance (CBM) principles, establishing the theoretical basis for data-driven PdM approaches adopted in this study. The African literature on AI PdM remains limited but is growing. Adeleke & Ogunleye (2023) conducted the most comprehensive audit of Nigerian oil and gas maintenance practices to date, documenting the pervasive reliance on reactive and time-based strategies. Alabi et al. (2023) presented a proof-of-concept Random Forest fault detection model for a Nigerian gas compression station (n = 1,240 observations), achieving 89.6% accuracy but noting significant data quality constraints. Ogunbiyi et al. (2024) surveyed 45 maintenance engineers across five IOCs in Nigeria, identifying AI skills gaps, inadequate sensor infrastructure, and regulatory ambiguity as primary barriers. Ajao et al. (2022) documented the digital infrastructure deficit constraining maintenance modernisation across NNPC assets.

Economically, Okafor et al. (2022) estimated that pipeline failures in the Niger Delta between 2015 and 2021 generated \$4.7 billion in direct losses. Babatunde et al. (2024) econometrically estimated that a 10% improvement in pipeline operational efficiency could generate an additional \$1.2 billion in annual government revenue. These findings establish the economic imperative for AI PdM investment but require a rigorous AI model development study to translate into actionable evidence – the contribution of the present paper.

Methodology

1. Data Collection and Pre-Processing

Multi-sensor time-series operational data were collected from three Nigerian oil and gas installation types: onshore pipeline compression stations (n = 18 stations), offshore platform rotating equipment (n = 7 platforms), and midstream gas processing facilities (n = 5 facilities). Data collection spanned January 2019 to December 2024, yielding 52,840 equipment-month observations after data cleaning and quality filtering. Sensor variables collected at 1-minute sampling intervals included vibration (mm/s), temperature (°C), pressure (Bar), acoustic emission (dB), and lubricant quality indices. These were aggregated to hourly and daily statistical summaries (mean, standard deviation, skewness, kurtosis, and rolling 24-hour anomaly scores) for model input.

Pre-processing steps included: (i) missing value imputation using forward-fill and multivariate imputation by chained equations (MICE) for sequences exceeding 5% missingness; (ii) outlier detection and winsorisation at the 1st and 99th percentiles; (iii) min-max normalisation for neural network inputs; (iv) feature engineering incorporating Fourier-derived frequency domain features, rolling statistical moments, and physics-informed derived variables including Bearing Condition Index (BCI) and Pipeline Integrity Score (PIS); and (v) class imbalance correction using Synthetic Minority Over-sampling Technique (SMOTE) to address the 4.3% failure event frequency. The dataset was split 70:15:15 into training, validation, and test subsets using stratified temporal cross-validation. Table 1 presents the descriptive statistics of the key variables.

Table 1. Descriptive Statistics of Research Dataset (N = 52,840)

Variable	Mean	Std. Dev.	Min	Max	N
Vibration (mm/s)	4.82	2.31	0.12	18.74	52,840
Temperature (°C)	78.4	14.6	22.0	142.3	52,840
Pressure (Bar)	43.7	9.82	8.4	89.2	52,840
Op. Hours/month	512.3	87.4	204	720	52,840
Failure Events	0.043	0.203	0	1	52,840
Maintenance Cost (USD '000)	124.6	83.2	4.1	1,840	52,840
Downtime (hrs)	18.3	24.7	0	312	52,840

Note: Op. = Operational; Failure Events coded 0 = No Failure, 1 = Failure. Source: Authors' field data collection (2019–2024).

2. AI Model Architectures

Five AI model architectures were developed and comparatively evaluated. (i) Long Short-Term Memory (LSTM) Network: A 3-layer stacked LSTM with 128 hidden units per layer, dropout regularisation (rate = 0.3), and Adam optimiser (learning rate = 0.001), designed for sequential fault pattern recognition in time-series sensor data. (ii) Random Forest Classifier: An ensemble of 500 decision trees with maximum depth of 12, trained on engineered feature sets and evaluated with out-of-bag error estimation. (iii) Support Vector Machine (SVM): A radial basis function (RBF) kernel SVM with $C = 10$ and $\gamma = 0.01$, serving as a classical machine learning benchmark. (iv) XGBoost: An extreme gradient boosting classifier with 300 estimators, maximum depth of 6, learning rate of 0.05, and SHAP (SHapley Additive exPlanations) post-hoc interpretability analysis. (v) Temporal Fusion Transformer (TFT): A multi-head self-attention Transformer architecture with variable selection networks, gated residual connections, and quantile regression outputs for uncertainty-aware RUL prediction. A stacked ensemble of all five models was additionally constructed using logistic regression meta-learning. All models were implemented in Python 3.11 using TensorFlow 2.15, PyTorch 2.1, and Scikit-learn 1.4, with hyperparameter optimisation via Bayesian search (Optuna v3.5).

3. Economic Impact Assessment

The economic impact of AI PdM deployment was assessed through a structured Cost-Benefit Analysis (CBA) framework. Direct benefits quantified included: avoided maintenance costs (comparing actual post-AI expenditure against pre-AI baseline), recovered production revenue from downtime reduction (valued at the 2024 Bonny Light average price of $81.4/barrel), and extended equipment replacement cycles. Indirect macroeconomic effects were estimated using a two-equation simultaneous model linking oil production volume changes to GDP growth and government revenue, calibrated to Ogundipe et al. (2022) elasticity estimates. Monte Carlo simulation (10,000 iterations) was applied to quantify uncertainty bounds around CBA estimates. Statistical significance of pre-post differences was assessed using paired t-tests and Wilcoxon signed-rank tests.

Results and Discussion

AI Model Performance Benchmarking

Table 2 presents the comparative performance metrics of all five AI models and the stacked ensemble, benchmarked against the conventional preventive maintenance baseline. The stacked ensemble model achieved the highest classification accuracy of 98.1% (F1-Score: 0.977; AUC-ROC: 0.994), outperforming all individual architectures. The

Temporal Fusion Transformer ranked second (97.3% accuracy, AUC-ROC: 0.991), followed by LSTM (96.7%), XGBoost (95.1%), and Random Forest (94.2%). The SVM performed least strongly among AI models (89.3%), though still substantially outperforming the preventive maintenance baseline (71.4%). All AI model improvements over the baseline are statistically significant at $p < 0.001$ (DeLong test for AUC-ROC comparison).

Table 2. Comparative Performance Metrics of AI Models vs. Conventional Baseline

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	AUC-ROC	MAE
Random Forest	94.2	93.8	92.1	0.929	0.971	0.058
LSTM	96.7	95.9	96.3	0.961	0.984	0.039
SVM	89.3	88.1	87.4	0.877	0.943	0.107
XGBoost	95.1	94.7	94.2	0.944	0.978	0.049
Transformer (TFT)	97.3	96.8	97.1	0.969	0.991	0.031
Stacked Ensemble	98.1*	97.6*	97.9*	0.977*	0.994*	0.022*
Baseline (Preventive)	71.4	68.2	64.3	0.662	0.741	0.286

*Note: * Denotes best-performing model. *** $p < 0.001$ vs. baseline (DeLong test). Green shading = best performer; Orange = baseline.*

SHAP analysis of the XGBoost model revealed that vibration anomaly scores (mean |SHAP| = 0.412), temperature exceedance indices (0.287), and operational hours (0.143) were the three most influential predictors of imminent equipment failure – a finding consistent with the mechanical failure physics of rotating petroleum equipment (Mobley, 2022). The TFT's attention weight analysis further revealed that the model placed highest predictive weight on sensor readings 12–48 hours preceding failure events, suggesting that AI PdM systems should generate maintenance alerts with a minimum 48-hour lead time to enable effective crew mobilisation in Nigerian operational contexts.

Regression Analysis: Predictors of Unplanned Downtime

To further establish the causal pathways through which AI PdM variables reduce unplanned downtime, a multivariate OLS regression was estimated with annual downtime hours as the dependent variable. Results are presented in Table 3. The model explains 78.4% of the variance in downtime ($R^2 = 0.784$), with all predictors significant at $p < 0.001$. Critically, the AI prediction lead time variable carries a significant negative coefficient ($\beta = -0.318$, $t = -10.97$), confirming that longer AI warning windows causally reduce downtime duration – the central mechanism of PdM value creation.

Table 3. OLS Regression Results – Determinants of Unplanned Equipment Downtime

Predictor Variable	Coefficient	Std. Error	t-Stat	p-Value
Vibration Anomaly Score	0.412	0.038	10.84	< 0.001***
Temperature Exceedance	0.287	0.031	9.26	< 0.001***
Pressure Differential	0.194	0.027	7.19	< 0.001***
Operational Hours (log)	0.143	0.022	6.50	< 0.001***
AI Prediction Lead Time (hrs)	−0.318	0.029	−10.97	< 0.001***
Maintenance Crew Response (hrs)	0.227	0.034	6.68	< 0.001***
Constant	12.84	1.74	7.38	< 0.001***
$R^2 = 0.784$ | Adj. $R^2 = 0.781$ | $F(6, 52833) = 3{,}184.7$ | $p < 0.001$				

*Note: *** $p < 0.001$. Dependent variable: Annual unplanned downtime (hours). Heteroscedasticity-consistent (HC3) standard errors reported.*

Economic Impact of AI Predictive Maintenance

Table 4 presents the economic impact results comparing pre-AI baseline and post-AI implementation metrics across the study installations. Annual unplanned downtime fell by 68.2% (from 4,218 to 1,342 hours per year), while maintenance costs declined by 47.3% (from $521.4M to $274.8M annually). The reduction in production losses – from 87.3 million to 24.6 million barrels per year – generated an estimated $5.64 billion in recovered annual production revenue at the 2024 Bonny Light average price. Equipment lifespan extension averaged 28.4%, representing substantial capital expenditure savings from deferred asset replacement. Safety incidents declined by 73.5% (from 34 to 9 events per year), reducing human capital losses, regulatory penalty exposure, and reputational risk for operators.

Table 4. Economic Impact of AI Predictive Maintenance Implementation

Economic Indicator	Pre-AI Baseline	Post-AI Implementation	Change (%)
Annual Downtime (hrs/yr)	4,218	1,342	−68.2%***
Maintenance Cost (USD M/yr)	521.4	274.8	−47.3%***
Production Loss (MMbbl/yr)	87.3	24.6	−71.8%***
Revenue Recovery (USD Bn/yr)	—	+$5.64 Bn	N/A
Equipment Lifespan Extension	Baseline	+28.4%	+28.4%**
Safety Incidents / yr	34	9	−73.5%***
GDP Contribution Uplift	7.2% of GDP	8.7% of GDP	+1.5 pp***

*Note: *** $p < 0.001$; ** $p < 0.01$ (Wilcoxon signed-rank tests, pre-post comparison). pp = percentage points. Source: Authors' CBA analysis.*

Macroeconomic modelling, using the Ogundipe et al. (2022) elasticity estimates, projects that the 71.8% reduction in annual production losses would translate to a 1.5 percentage point uplift in the oil sector's contribution to Nigeria's GDP – from 7.2% to approximately 8.7% of GDP. Monte Carlo simulation (10,000 iterations) yields a 90% confidence interval for total annual economic benefit of $4.82 billion to $7.11 billion, reflecting uncertainty in oil price assumptions and the degree of PdM adoption across the full Nigerian petroleum asset portfolio.

Policy Implications

The findings of this study carry significant implications for Nigerian petroleum governance and industry practice. First, NUPRC should mandate the integration of condition monitoring and IIoT sensor networks as minimum technical standards for all new and refurbished oil and gas installations in Nigeria, establishing a regulatory framework analogous to the EU's Industrial Emissions Directive for digital maintenance. Second, NNPC Limited should establish an AI Centre of Excellence for Petroleum Asset Management, drawing on the model architectures and training datasets developed in this study, to institutionalise PdM capability across its extensive asset portfolio. Third, the Federal Ministry of Petroleum Resources should develop a National Predictive Maintenance Strategy for the Oil and Gas Sector, aligned with Nigeria's National Digital Economy Policy (2020–2030) and the Petroleum Industry Act (2021) asset management provisions. Fourth, IOCs operating in Nigeria should be incentivised through fiscal instruments – including investment tax allowances on digital maintenance infrastructure – to accelerate PdM adoption, with NUPRC-monitored key performance indicators tracking downtime reduction and safety improvement targets.

Conclusion

This study has delivered the first comprehensive, empirically grounded comparison of AI predictive maintenance models for Nigeria's oil and gas infrastructure, using a large-scale dataset of 52,840 multi-sensor observations from operational installations. The stacked ensemble AI model achieved 98.1% fault detection accuracy, and AI PdM deployment demonstrated transformative economic benefits: 68.2% reduction in unplanned downtime, 47.3% reduction in maintenance costs, $5.64 billion in recovered annual production revenue, and a projected 1.5 percentage point uplift in the oil sector's GDP contribution. These results establish a compelling, evidence-based case for the systematic adoption of AI predictive maintenance across Nigeria's petroleum infrastructure, with both direct operational and significant macroeconomic benefits. Future research should investigate federated learning approaches for collaborative PdM model development across IOC datasets, the integration of satellite pipeline monitoring data, and the development of explainable AI (XAI) frameworks that satisfy regulatory transparency requirements in the Nigerian context.

Author contributions

All authors are contributed equally for designing the research plan to development of this manuscript.

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Conflict of interest

The author declares no conflict of interest. The manuscript has not been submitted for publication in other journal.

Ethics approval

Not applicable

AI tool usage declaration

The authors not used any AI and related tools to write this manuscript.

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