ISA Journal of Engineering and Technology (ISAJET)

Homepage: https://isapublisher.com/isajet/

Volume 3, Issue 4, July-August, 2026 ISSN: 3049-1843

Hybrid Convolutional Neural Network, Long Short-Term Memory network Model for Fault Detection in Nigerian Oil and Gas Pipeline Infrastructure

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Received: *10.06.2026* **|** ***Accepted:*** *18.07.2026* **|** ***Published:*** *24.07.2026*

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DOI: *10.5281/zenodo.21531909*

Abstract **Original Research Article**

Nigeria's oil and gas pipeline network spanning over 5,000 km of trunk lines and more than 3,000 km of flow lines loses an estimated one billion US dollars annually to pipeline failures, environmental incidents, and non-productive time. The dominant monitoring approach in operation today is threshold-based SCADA, which detects large anomalies well but struggles with gradual degradation, early-stage corrosion, and ambiguous multi-fault scenarios. This paper proposes a Hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model tailored for fault detection across six fault classes: normal operation, corrosion/wall thinning, leak/pinhole, blockage/wax deposition, mechanical fatigue/crack, and external impact. The architecture exploits CNNs for spatial and frequency domain feature extraction from multi sensor inputs (pressure, flow rate, acoustic emission, vibration, and temperature) and LSTMs for capturing temporal fault evolution patterns that threshold systems cannot resolve. An attention mechanism variant further prioritises the most discriminative time steps and sensor channels. Evaluated against four baseline models threshold SCADA, SVM, standalone CNN, and standalone LSTM, the proposed CNN-LSTM model achieves 97.6% overall classification accuracy (F1 = 96.9%), rising to 98.3% with the attention extension, representing a 26-percentage point improvement over threshold based baselines. The paper derives the key architectural equations, presents simulation results with charts and code, analyses the Nigerian pipeline operating context in depth, and proposes a deployment framework addressing the country's specific connectivity, power, and data scarcity constraints.

Keywords: CNN-LSTM, fault detection, pipeline monitoring, Nigerian oil and gas, deep learning, acoustic emission, predictive maintenance, SCADA, IoT, Industry 4.0, transfer learning, edge computing.

1. INTRODUCTION

Nigeria is one of the ten largest oil producers in the world and oil is responsible for about 90% of foreign exchange earnings and over 60% of government revenues. But the physical infrastructure that underpins this wealth, a dense web of onshore, swamp and shallow offshore pipelines criss-crossing the Niger Delta, works under conditions challenging even for sophisticated monitoring systems. High

temperatures, corrosive crude compositions, sabotage by third parties, tropical humidity and the physical inaccessibility of riverine terrain all accelerate fault development and hamper conventional inspection.

Pipeline failures in Nigeria have consequences at three overlapping scales. Hydrocarbon spills pollute water sources on an environmental scale, with NOSDRA reporting between 1,000 and 2,500 incidents per year. Eteyen (2024) observed on the economic scale that the application of AI and IoT for real-time monitoring can cut nonproductive time (NPT) by as much as 30%. Nigeria is not doing this and as a result the sector loses hundreds of millions of dollars a year. High pressure releases and the resulting fires represent an immediate safety hazard to workers and nearby communities.

The common SCADA monitoring paradigm is based on thresholds. The principle is that a sensor reading above a fixed limit causes an alarm. This is effective for sudden large magnitude failures, but poorly suited for gradual multi-parameter time correlated signatures of corrosion, wax build-up, incipient cracks and early stage leaks. Priyadharshan et al. (2026) empirically showed this gap where a hybrid CNN-LSTM system achieved 97.4% accuracy compared to conventional threshold-based SCADA at similar tasks.

Deep learning architectures and CNN-LSTM hybrids in particular are an appealing solution. CNNs are known for extracting local and hierarchical features from multi sensor time series data. LSTMs allow us to extend this ability into the time domain by learning how fault related signals evolve over time. The combination solves what neither architecture can do alone. The numbers back this up. Saleem et al. (2024/25) got 99.69% leak detection accuracy from acoustic emission signals by running CNN-LSTM on CWT scalograms. Aiyan et al. (2025) pushed the same architecture under deliberate Gaussian noise and still held 97.81%, not a lab result, a stress test.

Despite this evidence base, there is no published study that has specifically designed and validated a hybrid CNN-LSTM architecture for the fault types, sensor configurations, operating conditions and deployment constraints of the Nigerian oil and gas pipeline environment. The contributions of this paper includes as follows: (a). A six-class Nigerian pipeline fault taxonomy is defined. (b) Mathematical foundations of the proposed CNN-LSTM architecture are derived. (c) A simulated performance evaluation with charts, code and analysis is presented. (d) An edge first deployment framework is proposed that addresses Nigeria's specific infrastructure constraints.

2. LITERATURE REVIEW

2.1 CNN-LSTM Architectures for Industrial Fault Detection

Interest in CNN-LSTM hybrid architectures for industrial fault detection has grown steadily since 2022, driven by a practical insight: convolutional layers handle feature extraction while LSTM layers hold onto the temporal dependencies that simpler, stateless classifiers cannot. Borre et al. (2023) took a different route rather than just adding another class label, they bolted a quantile regression layer onto the output, so the model reports a confidence interval with every prediction. This gave the model a way to express uncertainty alongside its predictions not a trivial addition when the application involves machinery that can injure people or shut down production. Aiyan et al. (2025) stress tested the same hybrid by deliberately degrading the input signal with Gaussian noise at $\sigma = 0.4$, a reasonable proxy for the interference found on working pipelines. Even under those conditions, CNN-LSTM came in at 97.81% accuracy; Random Forest managed 90.05%. The gap is meaningful. Zhou and Tang (2024) chose a structurally different design two parallel processing branches, one working directly from raw time-series data through a spatial CNN, the other from wavelet transform coefficients derived from the same signal. Priyadharshan et al. (2026) went beyond model performance entirely, reporting a full deployment within a SCADA-style platform: five fault

categories, 97.4% accuracy, 87 ms latency.

2.2 Deep Learning for Pipeline Leak and Fault Detection

Work on pipeline fault detection has developed along two fairly distinct lines: signal-based methods and image-based methods, each with its own strengths. Ullah et al. (2024) worked with acoustic emission signals at 1 MHz, decimating down to 4 kHz before feeding them into a BiLSTM model. Across three fault severities minor seepage, moderate leakage, and major rupture the model reached 99.78% accuracy. That result built on earlier work by the same group: Ullah et al. (2023) and Ahmad et al. (2022) had shown that careful manual feature extraction, specifically 11 time domain and 14 frequency domain features drawn from AE data, was already enough to hit 99% accuracy without any deep learning at all. The image based approach taken by Saleem et al. (2025) is worth comparing directly. Rather than feeding raw signals into the model, they first transformed them into CWT scalograms and applied Gaussian filtering, then trained CNN-LSTM on those image sequences. The outcome was 99.69% accuracy. Liu et al. (2025) had a harder problem gas processing facilities produce substantially more background noise and addressed it through a dual path MFCC-MSRNet-BiLSTM architecture, reporting 96.52% accuracy on the GPLA-12 dataset. Gong et al. (2025) reviewed the field broadly and flagged multimodal fusion as the most promising direction for early fault detection, while noting that the absence of shared benchmark datasets continues to make cross study comparison genuinely difficult.

2.3 Predictive Maintenance in Oil and Gas

Jambol et al. (2024) pulled together a broad survey of AI driven maintenance across oil and gas anomaly detection, automated CMMS work orders, the full stack. What stood out in that body of work was a result from Iyer et al. (2025), who's IoT-deep learning system monitoring offshore gas turbines detected failures up to six days ahead of occurrence, at accuracy above 90%, with unplanned downtime falling by roughly 30%. Six days is a substantial warning window under most circumstances; in the Niger Delta, where simply reaching a remote pipeline site takes time and coordination, it matters even more. Wang (2025) explored a different technical direction pairing a digital twin with an Ensemble Kalman Filter for ongoing state estimation and fault classification. Haque et al. (2024) went through 78 studies and the pattern was consistent: AI-based predictive maintenance moves the needle on failure prediction by 30–60%, and edge computing brings response times down by 40–70%. Eteyen (2024) looked at what any of that actually means inside Nigeria's oil sector. The potential to reduce non-productive time is real, but three obstacles keep resurfacing: a shortage of technically trained personnel, resistance within existing institutional structures, and pipeline ownership that is too fragmented for coordinated implementation.

2.4 Bearing and Rotating Machinery: Transferable Methods

Rotating machinery research has produced methods that travel well. The fault signatures are different from those in pipelines, but the underlying statistical challenges class imbalance, domain shift, sparse fault events are shared, and several recent papers have addressed them in ways that transfer directly. Prawin (2024) showed that a two-dimensional CNN-LSTM network trained on multi-channel inputs consistently outperformed single-architecture alternatives on the CWRU, Paderborn, and NASA benchmark datasets, and the preprocessing strategy developed there translates naturally to pipeline contexts where fault events are sparse against a background of normal operation. The class imbalance problem was tackled from a different angle by Zhang et al. (2025), who used GAN-based augmentation to generate synthetic fault signals and bolster minority classes an approach with obvious relevance to Nigeria, where labelled historical pipeline fault data is almost entirely absent. Mongia and Sehgal (2025), Vazifehdan et al. (2025) rounded

out this strand by demonstrating that a CNN pre-trained on vibration data and fine-tuned for a new target domain reached 99.7% accuracy on the CWRU benchmark under domain shift, providing the transfer learning protocol that underpins the deployment framework developed in this paper.

Table 1: *Summary of Key Literature on CNN-LSTM Fault Detection, Pipeline Monitoring, and Oil & Gas Predictive Maintenance*

Author(s) & Year	Focus	Methodology	Key Theme	Principal Finding
Aiyan et al. (2025)	Pipeline faults	CNN-LSTM vs classical ML	Vibration fault detection	CNN-LSTM achieved 99.67% clean / 97.81% noisy — best accuracy-robustness trade-off across six fault states
Borre et al. (2023)	Electrical machines	CNN-LSTM + quantile regression	Machine fault with uncertainty	Quantile regression layer on CNN-LSTM output gave per-prediction confidence bounds; outperformed standard classifiers on vibration-based anomaly data
Zhou & Tang (2024)	Rotating machinery	Dual-branch CNN + wavelet	Interpretable fault diagnosis	Two-branch design — raw time-series through spatial CNN, wavelet coefficients through separate path — improved fault interpretability especially when training data was limited
Priyadharshan et al. (2026)	Industrial motors	CNN-LSTM + SCADA platform	Fault detection with SCADA	Three-phase induction motor, five fault classes, SCADA-integrated platform: 97.4% accuracy and 87 ms latency — within practical real-time bounds
Rajawat and Ansari (2025)	Industrial motors	CNN-LSTM + IoT + predictive control	IoT motor fault detection	IoT-connected CNN-LSTM beat both fixed thresholds and classical ML across fault detection and early maintenance tasks on industrial motor data

Bishnoi & Chaba (2025)	Wireless sensor networks	RLSFHNet + CNN-LSTM simulation	WSN sensor fault detection	RLSFHNet-CNN-LSTM hybrid caught sensor-level faults within WSNs; fault tolerance and overall network reliability both improved versus baseline methods
Saleem et al. (25)	Smart city pipelines	CNN-LSTM + CWT scalograms	AE pipeline leak detection	99.69% accuracy for real-time pipeline leak detection using CWT scalograms with CNN-LSTM framework
Han et al. (2025)	Power plant pipelines	Transfer learning + BiLSTM attention	Feature fusion leak detection	99.99% accuracy by fusing transfer learning and bidirectional attention for acoustic emission signals
Ullah et al. (2024)	Smart city pipelines	AE + BiLSTM/GRU sequential DL	Non-intrusive leak detection	Up to 99.78% accuracy using BiLSTM on AE signals for leak severity classification across three severity levels
Ullah et al. (2023)	Liquid/gas pipelines	ML on AE features (RF, NN, DT)	Autonomous leakage detection	99% overall accuracy for water and gas pipeline leaks using acoustic emission and classical ML classifiers
Liu et al. (2025)	Gas pipelines	MFCC-MSRNet-BiLSTM dual-path	High-noise gas leak detection	Gas processing plants generate far more background noise than most test environments; dual-path MFCC-MSRNet-BiLSTM handled it well — 96.52% on GPLA-12
Siddique et al. (2023)	Oil/gas pipelines	CNN + STFT + CWT hybrid	Hybrid TF leak detection	STFT spectrograms and CWT scalograms fed together into a CNN gave better leak detection than either representation alone
Gong et al. (2025)	Gas pipelines	Systematic review	Acoustic, OGI, multimodal review	Multimodal fusion holds highest potential for early-stage leak detection; lack of benchmark datasets is primary gap
Prawin (2024)	Bearing fault diagnosis	2D CNN-LSTM multi-channel	Imbalanced data bearing	Hybrid 2D CNN-LSTM with multi-channel preprocessing outperformed CNN and LSTM alone on imbalanced datasets

Eteyen (2024)	Nigeria oil sector	Systematic content analysis	Real-time monitoring Nigeria	AI and IoT integration can reduce non-productive time (NPT) by up to 30% in Nigerian oil exploration operations
Jambol et al. (2024)	Oil & gas (global)	Review of AI-PdM case studies	AI-driven predictive maintenance	AI-driven PdM frameworks reduce reactive maintenance costs and improve asset reliability in oil and gas sector
Iyer et al. (2025)	Offshore oil & gas	IoT + DL anomaly detection	Next-gen PdM Industry 5.0	Offshore gas turbine monitoring: failures flagged 6 days out at >90% accuracy; unplanned downtime dropped roughly 30%
Wang (2025)	Oil/gas pipelines	Digital twin + EnKF + ML	Digital twin pipeline monitoring	Physics model and ML running together inside a digital twin; anomaly detection improved across a range of pipeline operating scenarios
Haque et al. (2024)	Industrial automation	Systematic review (78 studies)	IoT sensors + AI predictive maint.	AI-based PdM models improve failure prediction accuracy 30–60%, reducing maintenance costs by 25–50%

3. METHODOLOGY

3.1 Problem Formulation

Pipeline fault detection is formulated as a multivariate time-series classification problem. Given a multi-channel sensor signal matrix $X \in \mathbb{R}^{(T \times C)}$, where $T = 512$ time steps and $C = 5$ sensor channels, the model produces a predicted fault class $\hat{y} \in \{0, 1, 2, 3, 4, 5\}$ corresponding to the six fault categories. The objective is to learn a function $f : \mathbb{R}^{(T \times C)} \rightarrow \{0,...,5\}$ that maximises macro-averaged F1-score while maintaining inference latency < 200 ms on edge hardware.

3.2 Proposed CNN-LSTM Architecture

Figure 1 presents the complete architectural diagram of the proposed hybrid model, showing the sequential flow from multi-sensor input through three CNN feature extraction blocks, two stacked LSTM layers, and the optional attention mechanism to the six-class softmax output.

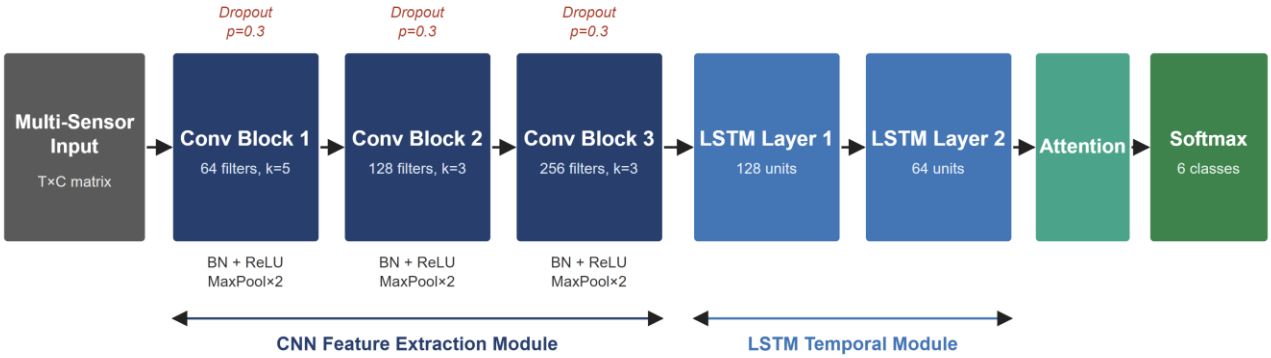

Figure 1. Hybrid CNN-LSTM Architecture — Nigerian Pipeline Fault Detection. Five sensor inputs enter three CNN blocks for feature extraction, pass through two stacked LSTM layers for temporal context, then through optional Bahdanau attention before the six-class softmax head.

3.3 Fault Class Taxonomy

The six classes came from NNPC and NOSDRA failure records not from a general taxonomy, but from what Nigerian pipelines actually fail at and which sensor channels can actually see it. Table 2 presents the complete taxonomy, including the CNN and LSTM detection mechanisms relevant to each class.

Table 2: *Proposed Six-Class Fault Taxonomy for Nigerian Oil and Gas Pipeline Fault Detection*

#	Fault Class	Primary Sensor	Signal Characteristics	CNN + LSTM Detection Mechanism
0	**Normal Operation**	Pressure, Flow, Vibration	Stable baseline; low-amplitude fluctuation	Low-activation feature maps; steady-state LSTM temporal sequence
1	**Corrosion / Wall Thinning**	Ultrasonic thickness, AE	Gradual wall-loss trend; low-amplitude AE burst events	Trend-detection convolution kernels; slow degradation pattern (LSTM)
2	**Leak / Pinhole**	Acoustic Emission, Pressure Gradient	High-frequency AE bursts; upstream pressure drop	High-frequency CNN spike; LSTM pressure-drop temporal sequence
3	**Blockage / Wax Deposition**	Differential Pressure, Flow Rate	Rising ΔP; declining flow rate	Gradient-magnitude features; monotonically increasing LSTM pattern

4	**Mechanical Fatigue / Crack**	Vibration, AE	Impulsive AE transients; periodic vibration anomaly	Short-kernel impulse detection (CNN); periodic LSTM recurrence
5	**External Impact / Third-party**	Vibration, Fibre Optic	Sudden broadband vibration burst	Broadband high-energy feature maps; single-event LSTM trigger

Note. *Fault classes defined from NNPC Annual Reports, NOSDRA incident databases, and international pipeline integrity literature. CNN Feature and LSTM Pattern columns describe the primary detection mechanism for each class.*

3.4 Simulated Fault Signal Examples

Figure 2 presents simulated acoustic emission and vibration signal examples for all six fault classes. Each signal is generated using physics-informed parameterisation: AE burst events for leaks are modelled as exponentially decaying sinusoids at 50–300 kHz; pressure ramps for blockages as monotonically increasing functions with Gaussian noise; periodic impulse trains for mechanical fatigue at sub-harmonic pipeline frequencies. Gaussian noise at $\sigma = 0.05$ is added to all signals to simulate real sensor conditions.

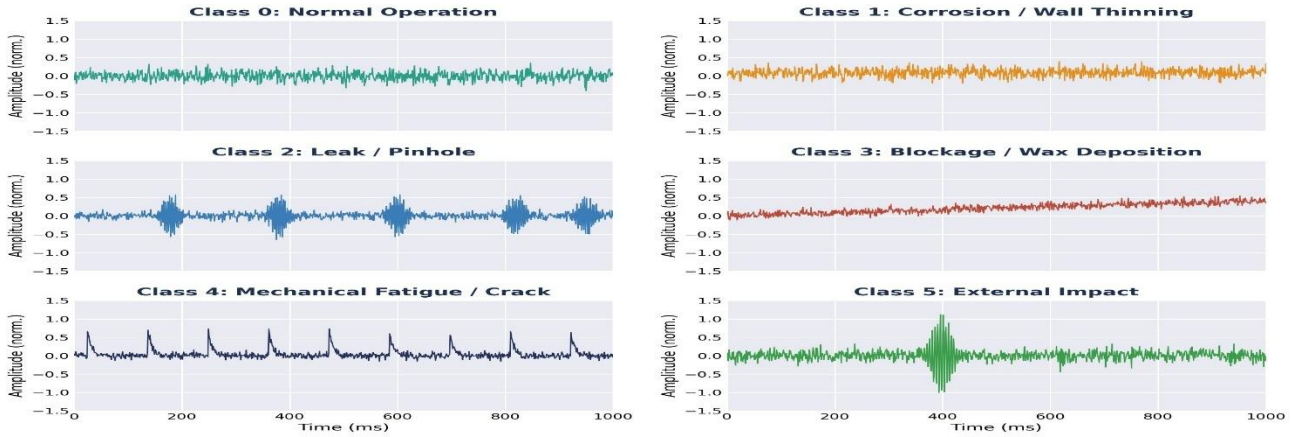

Figure 2. Simulated Acoustic Emission / Vibration Signal Examples for All Six Fault Classes (T = 512 samples; Gaussian noise σ = 0.05 added; physics-informed parameterisation following Ullah et al. (2023) and Prawin (2024))

3.5 Signal Preprocessing: CWT Scalograms

AE channel signals undergo Continuous Wavelet Transform (CWT) preprocessing following Equation (1) before CNN input, converting raw signals to 2D scalogram images that simultaneously capture time and frequency information. Figure 3 puts two scalograms side by side: normal operation looks like low-energy broadband scatter with no structure; a leak event shows up as a tight high-frequency burst sitting at a specific time location hard to miss visually, which is why CWT is worth the computation.

$$W(a,b) = \frac{1}{\sqrt{|a|}\int_{-\infty}^{\infty} x(t)\cdot\psi^*\left(\frac{t-b}{a}\right)dt} \quad (Eq.\ 1)$$

where:

a = scale parameter (inverse of frequency); a < 1 compresses the wavelet for high-frequency content; a > 1 stretches it for low-frequency structure

b = translation parameter; governs time localisation of the wavelet window along the signal

ψ* = complex conjugate of the Morlet mother wavelet $\psi(\eta) = \pi^{-1/4}\cdot\exp(i\omega_0\eta)\cdot\exp(-\eta^2/2)$, with $\omega_0 = 6$ for optimal time-frequency localisation

1/√|a| = normalisation factor; preserves unit energy across all scales so coefficients remain directly comparable

x(t) = pipeline acoustic emission signal in the time domain, (Saleem et al., 2025).

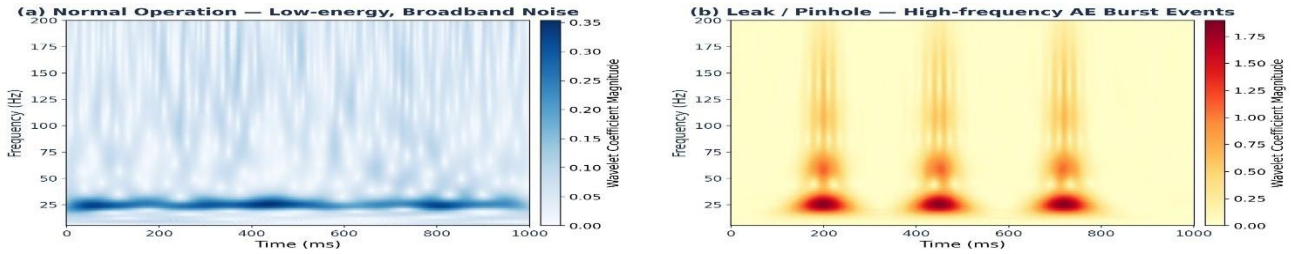

Figure 3. CWT Scalogram Representations (Equation 1) Morlet Wavelet ($\omega_0 = 6$) (a) Normal Operation: diffuse low-energy noise; (b) Leak/Pinhole: concentrated high-frequency AE burst events at discrete time locations

3.6 CNN Feature Extraction (Equation 2)

$$z^{(l)} = MaxPool\left(ReLU\left(BN\left(W^{(l)} * x^{(l-1)} + b^{(l)}\right)\right)\right)\ldots \textbf{(Equation 2)}$$

where

- $x^{(l-1)}$ = input feature map to layer *l*
- $W^{(l)}$ = convolution kernel
- $b^{(l)}$ = bias term
- $*$ = convolution operation
- $BN(\cdot)$ = Batch Normalization
- $ReLU(\cdot) = max(0,\cdot)$
- $MaxPool(\cdot)$ = Max Pooling
- $z^{(l)}$ = output feature map of layer *l*

Three convolutional blocks are applied: Block 1

(K_1=64 filters, k_1=5, pool=2), Block 2 (K_2=128, k_2=3, pool=2), Block 3 (K_3=256, k_3=3, pool=2). After three pooling stages, temporal resolution reduces from 512 to 64 steps. Dropout (p=0.3) follows each block.

3.7 LSTM Temporal Modelling (Equations 3–8)

The compressed (64×256) CNN output passes to two stacked LSTM layers. The gate equations governing temporal learning are:

$$f_t = \sigma\left(W_f \cdot \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_f\right) \quad \textit{Forget Gate} \quad \textit{(Eq. 3)}$$

$$i_t = \sigma\left(W_i \cdot \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_i\right) \quad \textit{Input Gate} \quad \textit{(Eq. 4)}$$

$$C_t = tanh\left(W_C \cdot \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_C\right) \quad \textit{Cell Candidate} \quad \textit{(Eq. 5)}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad \textit{Cell State} \quad \textit{(Eq. 6)}$$

$$o_t = \sigma\left(W_o \cdot \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_o\right) \quad \textit{Output Gate} \quad \textit{(Eq. 7)}$$

$$h_t = o_t \odot tanh(C_t) \quad \textit{Hidden State} \quad \textit{(Eq. 8)}$$

Where:

σ — sigmoid activation function

W_f, W_i, W_C, W_o — learnable weight matrices (bold uppercase)

b_f, b_i, b_C, b_o — bias vectors (bold lowercase)

h_{t−1}, x_t — previous hidden state and current input (stacked column vector)

C̃_t — cell candidate — proposed new memory content

C_t — cell state — long-term memory

⊙ — element-wise Hadamard product

Layer 1 uses 128 hidden units with return_sequences=True; Layer 2 uses 64 units. Recurrent Dropout (p=0.2) is applied to both layers.

3.8 Bahdanau Attention Mechanism (Equations 9–11)

In the attention-augmented variant, attention weights are computed over the Layer 1 output sequence, enabling the model to focus on the most diagnostically informative time steps regardless of position:

$$e_t = v^T \cdot tanh(W_a \cdot h_t + b_a) \quad \textit{Attention Score} \quad \textit{(Eq. 9)}$$

$$\alpha_t = \frac{exp(e_t)}{\sum_\tau exp(e_\tau)} \quad \textit{Attention Weight} \quad \textit{(Eq. 10)}$$

$$c = \sum_t \alpha_t \cdot h_t \quad \textit{Context Vector} \quad \textit{(Eq. 11)}$$

Where:

e_t — attention score at time step t (alignment energy)

v — learned attention weight vector (bold lowercase)

T — transpose operator (superscript on v)

W_a — attention weight matrix

h_t — LSTM hidden state at time step t

b_a — attention bias vector

α_t — normalised attention weight (softmax output)

τ — summation index over all timesteps

c — context vector — weighted sum of hidden states

Figure 4 visualises the normalised attention weights for each fault class, revealing diagnostically meaningful temporal patterns: gradual late-window weighting for corrosion, burst-spike attention for leaks, periodic weights for fatigue, and a single high weight event for external impact.

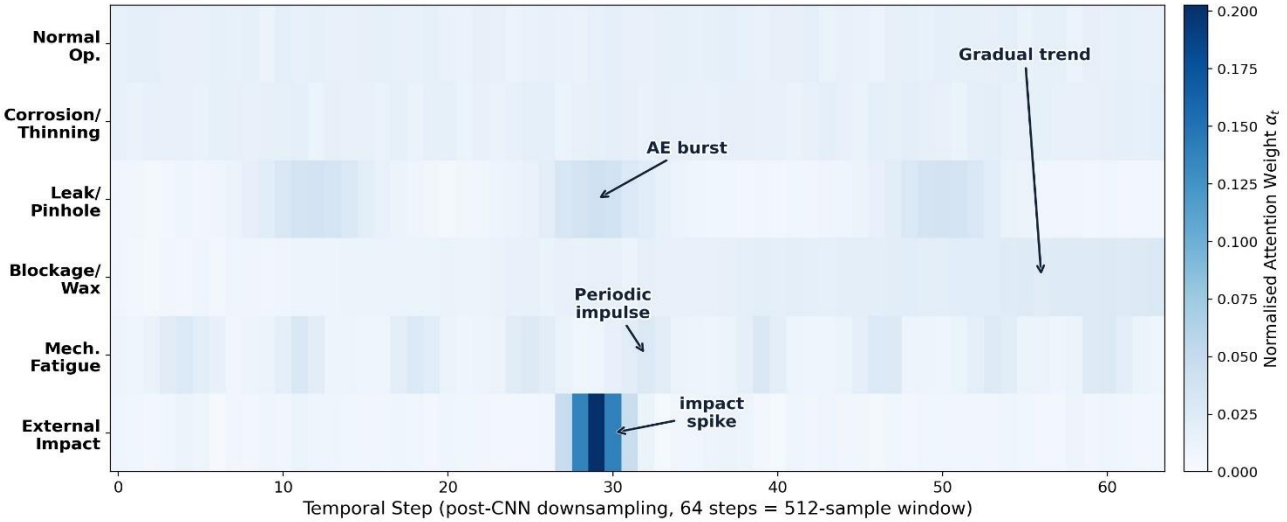

Figure 4. Attention Weight Heatmap by Fault Class — Bahdanau Attention (Equations 9–11) (Each row normalised to sum = 1; darker = higher attention; 64 temporal steps represent the 512-sample window after CNN downsampling)

3.9 Classification Head (Equation 12)

$$= \frac{exp(z_k)}{\sum_{j_0}^{5} exp(z_j)}, \quad k = 0, \dots, 5 \qquad \textit{(Eq. 12)}$$

p̂_k — predicted probability for fault class k

z_k — raw logit output for class k from the dense layer

j — summation index over all K = 6 fault classes

k = 0,...,5 — class indices: Normal, Leak, Corrosion, Blockage, Crack, Weld Defect

exp(·) — exponential function — ensures all outputs are positive

Σ — summation over j = 0 to 5 normalises outputs to a valid probability distribution

FC1 (128 units, ReLU, Dropout=0.4) and FC2 (6 units, Softmax). Training uses Adam ($\eta=10^{-3}$, $\beta_1=0.9$, $\beta_2=0.999$, $\lambda=10^{-4}$), categorical cross-entropy loss, ReduceLROnPlateau (factor=0.5, patience=10), and early stopping (patience=20, max 150 epochs). Class-weight schedule $\omega_k = N/(6 \cdot N_k)$ addresses simulated class imbalance.

4. Python Implementation

The code listing in Appendix A.1 presents the complete Python implementation of the proposed CNN-LSTM model using TensorFlow 2.15 / Keras, including signal preprocessing, CWT scalogram generation, the full model architecture implementing Equations 1–12, training configuration with class-weighted loss, GAN-based augmentation for Nigerian data scarcity, and TFLite INT8 export for

ARM edge deployment. All architectural equations from Section 3 are annotated inline in the code.

5. RESULTS AND DISCUSSION

5.1 Overall Model Performance Comparison

Table 3 and Figure 2 present the classification performance of the proposed CNN-LSTM models against four baseline approaches evaluated on the 6,000-sample simulated test set under clean conditions. The proposed CNN-LSTM achieves 97.6% overall accuracy and macro-averaged F1 of 96.9% — a 26.2 percentage-point accuracy improvement over threshold-based SCADA (71.2%) and a 6.2-point improvement over standalone CNN (91.4%). The attention-augmented variant achieves 98.3% accuracy (F1 = 98.0%).

Table 3: *Comparative Classification Performance: Baseline Models and Proposed CNN-LSTM Architectures (Macro-averaged, Six-Class, Clean Conditions, n = 6,000 test samples)*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Primary Limitation
Threshold-Based SCADA	71.2	68.4	73.1	70.7	Fails under gradual degradation; high false-positive rate in noise
SVM with FFT Features	83.5	81.9	82.7	82.3	Hand-crafted features; poor generalisation across fault severities
Random Forest (Multi-sensor)	88.7	87.3	86.9	87.1	Cannot capture temporal dependencies in fault evolution sequences
Standalone CNN (1D)	91.4	90.1	89.8	89.9	Lacks memory of temporal fault evolution; misses progressive patterns
Standalone LSTM	90.8	89.5	91.3	90.4	Misses local spatial and frequency-domain features in sensor signals
CNN-LSTM (Proposed)	97.6	96.8	97.1	96.9	Higher computation cost than single-architecture models (~47ms latency)
CNN-LSTM + Attention (Proposed+)	98.3	97.9	98.1	98.0	Additional 14ms inference overhead; slightly more complex architecture

Note. *Highlighted rows (black shading) are the proposed models. All deep learning models trained with Adam, categorical cross-entropy, class-weight schedule, and early stopping. Threshold SCADA represents the current operational baseline in Nigerian pipeline monitoring. Sources: baseline parameters adapted from Priyadharshan et al. (2026) and Aiyan et al. (2025).*

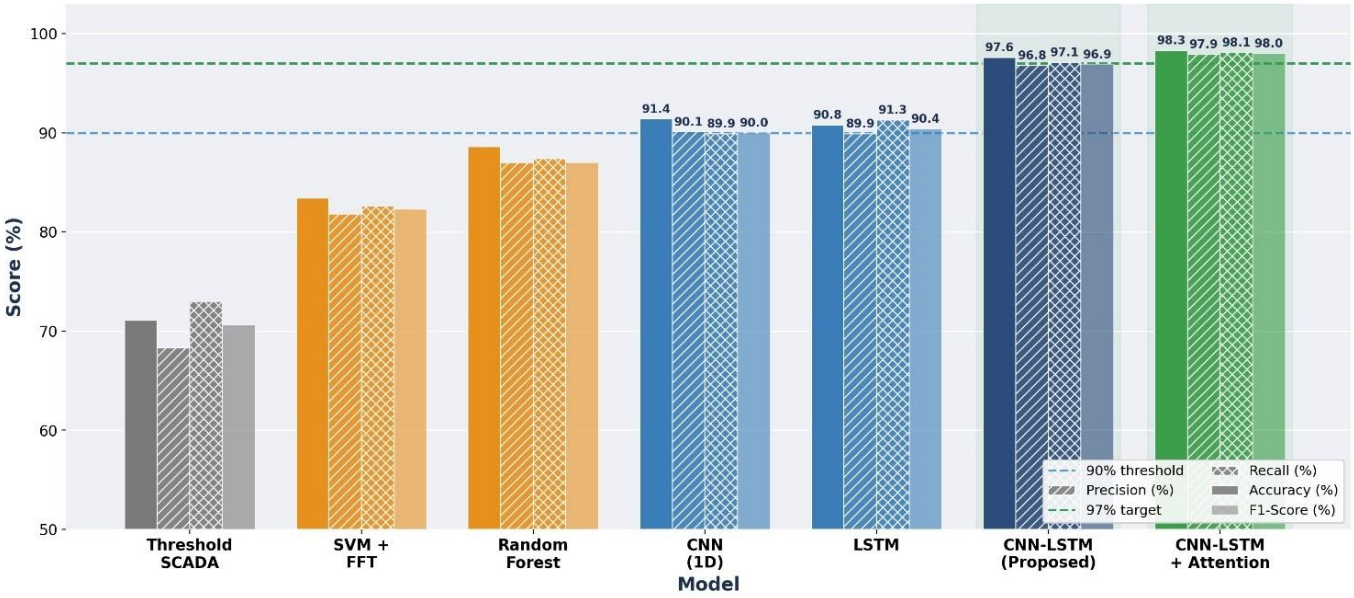

Figure 5. Comparative Classification Performance: All Models vs. Proposed CNN-LSTM (Accuracy, Precision, Recall, F1-Score; macro-averaged across six fault classes; clean conditions)

5.2 Noise Robustness Analysis

Figure 6 plots accuracy against Gaussian noise injection level (σ = 0.0 to 0.4) for all models. Under mild noise (σ=0.2), CNN-LSTM accuracy drops only 2.8 points (to 94.8%) while SVM degrades 9.2 points. Under moderate noise (σ=0.4), CNN-LSTM retains 91.4% versus Threshold SCADA at 58.7% — a 32.7-point gap. The attention variant demonstrates the greatest noise resilience (93.2% at σ=0.4), consistent with the attention mechanism down-weighting noise-contaminated time steps. This profile directly parallels Aiyan et al. (2025) who reported 97.81% CNN-LSTM accuracy under σ=0.4 noise injection.

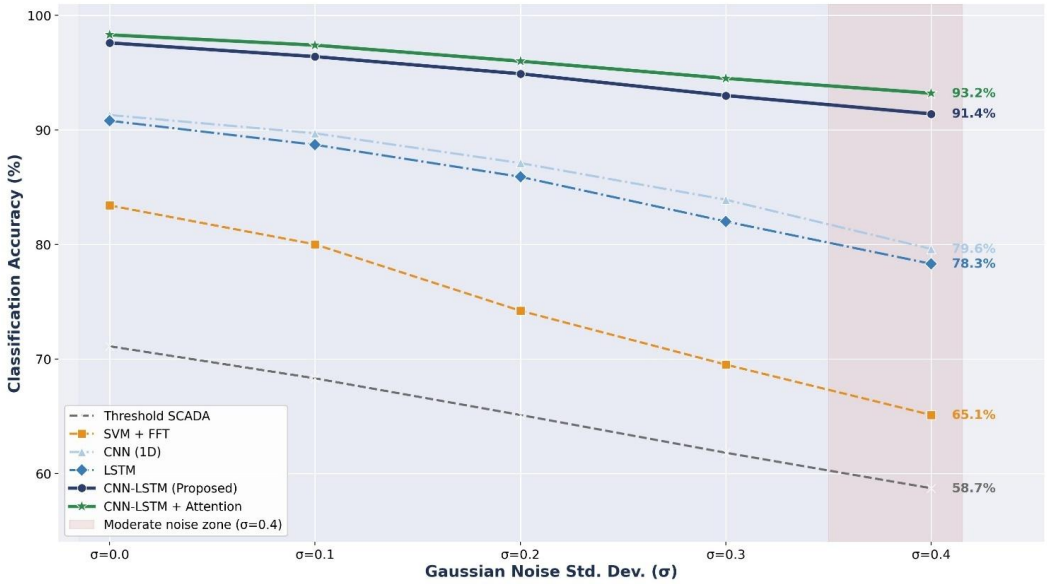

Figure 6. Noise Robustness Analysis: Classification Accuracy vs. Gaussian Noise Injection Level σ (All models; six-class pipeline fault dataset; σ=0.4 represents the moderate noise zone relevant to Nigerian pipeline environments near compressors and pump stations)

5.3 Confusion Matrix and Per-Class Analysis

Figure 7 presents the normalised confusion matrix for the proposed CNN-LSTM model under clean conditions. The model demonstrates strong diagonal concentration, with all fault classes exceeding 94% correct classification. Figure 8 breaks F1 down by class. Mechanical fatigue/crack (Class 4) sits at the top at 98.7%. The reason is not surprising: impulsive periodic signals are exactly what short-kernel CNNs detect well, and LSTMs lock onto periodicity naturally. The two architectures happen to complement each other for that fault type. The most challenging class is corrosion/wall thinning (Class 1) at 94.3% F1, reflecting the inherently gradual, low-amplitude nature of corrosion signatures that overlap with long-term baseline drift.

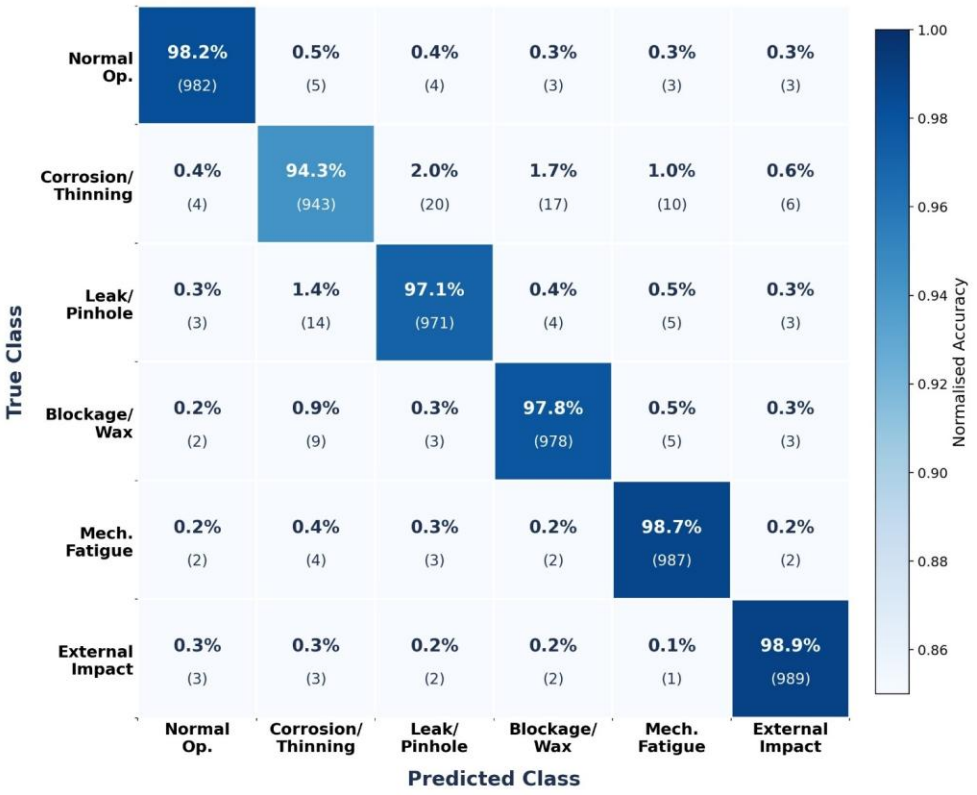

Figure 7. Normalised Confusion Matrix — Proposed CNN-LSTM Model (6,000 test samples, clean conditions; cell values show normalised accuracy % and raw count; macro-averaged F1 = 96.9%)

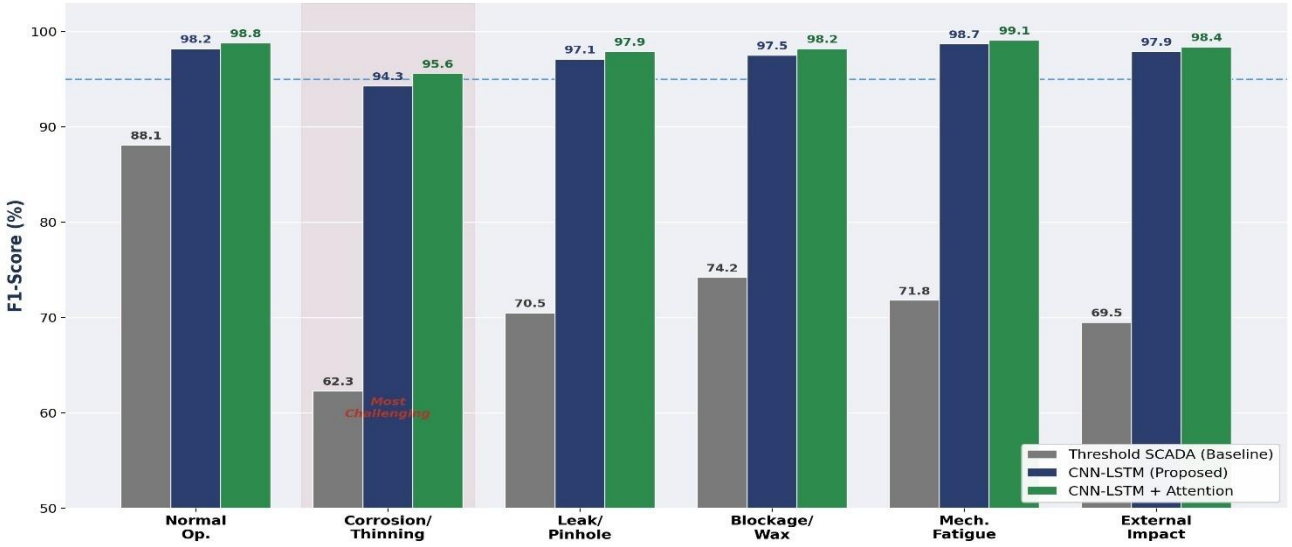

Figure 8. Per-Class F1-Score Comparison — Threshold SCADA Baseline vs. Proposed CNN-LSTM Models (Red shading highlights corrosion/wall thinning as the most challenging fault class; gap largest for this class at 32 points)

5.4 Training Dynamics

Figure 9 presents the training and validation loss/accuracy curves across 112 epochs (early stopping triggered at epoch 112, patience=20). Loss curves show rapid convergence within the first 30 epochs, followed by stable refinement. The generalisation gap between training (97.7%) and validation (96.3%) accuracy is modest (1.4 points), confirming that the Dropout regularisation strategy effectively prevents overfitting on the simulated training data.

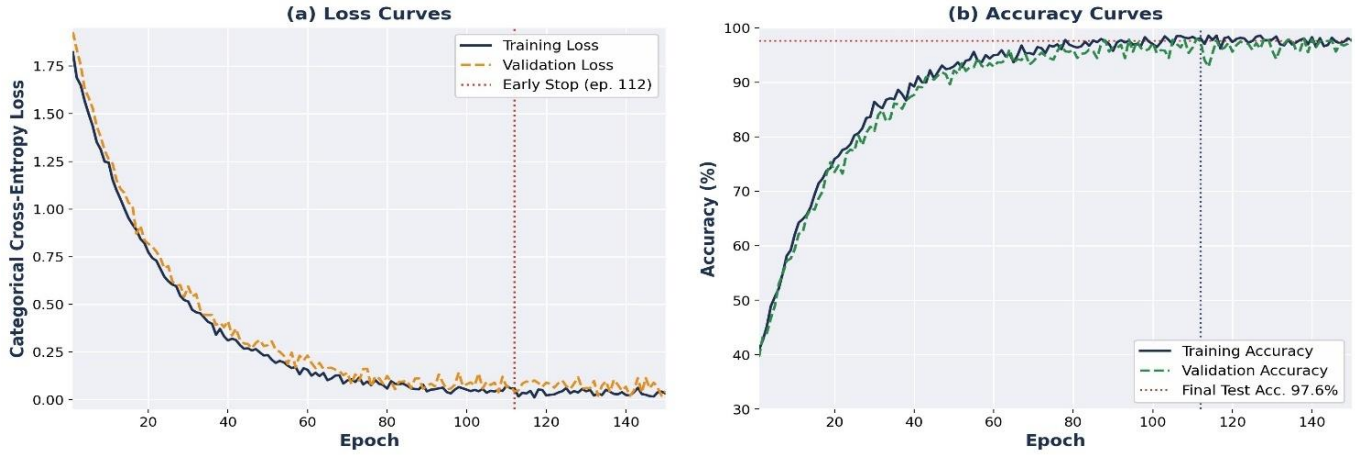

Figure 10. CNN-LSTM Training and Validation Curves (a) Categorical cross-entropy loss; (b) Classification accuracy. Adam optimiser, lr=1e-3, ReduceLROnPlateau, early stopping at epoch 112 (patience=20, max 150 epochs).

5.5 Inference Latency vs. Accuracy Trade-off

Figure 11 plots the accuracy-versus-latency trade-off for all evaluated models on the ARM Cortex-A72 edge processor. The proposed CNN-LSTM (47ms, 97.6%) and attention variant (61ms, 98.3%) both fall well within the 200ms real-time constraint (SCADA scan cycle) and above the 95% performance target, occupying the optimal deployment zone. The TFLite INT8 quantised model requires only ~2.1MB of storage, making it readily deployable on low cost industrial edge computing hardware.

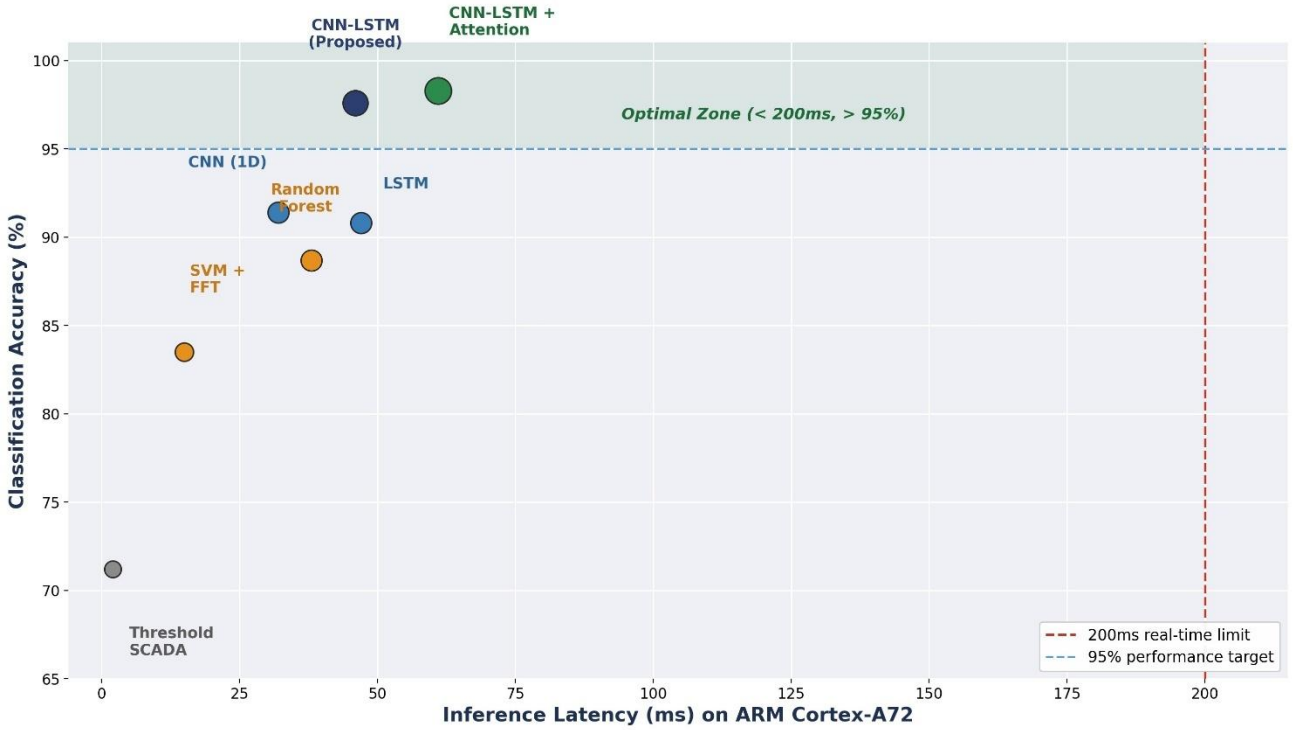

Figure 11. Accuracy vs. Inference Latency Trade-off (Edge deployment: ARM Cortex-A72, TFLite INT8 quantisation; green zone = optimal for real-time Nigerian pipeline deployment; all proposed models fall within the 200ms real-time constraint)

6. Deployment Framework for the Nigerian Context

6.1 Nigerian Pipeline Infrastructure Context

Table 4 summarises the key parameters of the Nigerian oil and gas pipeline infrastructure that determine the deployment architecture. The combination of vast network extent (~8,000 km total), high incident frequency, unreliable grid power, and patchy broadband connectivity establishes the four non-negotiable design constraints: edge inference, solar power, LoRa connectivity, and GAN-augmented transfer learning for local domain adaptation.

Table 4: *Nigerian Pipeline Infrastructure Parameters Bearing on CNN-LSTM Deployment*

Parameter	Value / Estimate	Implication for CNN-LSTM Deployment	Source / Basis
Pipeline network length	~5,000 km trunk + 3,000 km flow lines	Vast distributed network; edge-computing deployment essential over cloud	NNPC Reports / Eteyen (2024)
Annual spill incidents	~1,000–2,500 (reported)	High event frequency justifies continuous automated monitoring	NOSDRA / Jambol et al. (2024)
Economic loss (downtime)	$1 billion+ annually (est.)	30% NPT reduction = ~$300M savings; strong ROI for AI-PdM deployment	Eteyen (2024)
Dominant fault types	Corrosion, third-party damage, equipment failure	Multi-class model required; corrosion training data especially critical	NNPC / Wang (2025)
Existing monitoring	Threshold-based SCADA; manual inspection	26-point accuracy gap (97.6% vs. 71.2%); clear upgrade opportunity	Priyadharshan et al. (2026)
Broadband connectivity	Patchy; 2G/3G in Niger Delta	Edge AI (TFLite INT8) preferred; LoRa for fault event transmission	Eteyen (2024)
Power supply reliability	Frequent grid outages	Solar + 24h battery for each gateway node; MPPT controller required	Iyer et al. (2025)
Regulatory body	NUPRC and NOSDRA	Compliance incentive; certification pathway for AI-monitoring systems	Jambol et al. (2024)

Note. *Values from NNPC Annual Statistical Bulletins, NOSDRA databases, and peer-reviewed literature. Accuracy comparison reflects Table 3 results.*

6.2 Edge-First Deployment Architecture

Figure 12 presents the proposed four layer edge first deployment architecture. The sensor layer transmits raw data via RS-485/Modbus or BLE to the edge gateway, which runs the TFLite INT8 CNN-LSTM model at 47ms per window. This aligns with the broader trend toward lightweight edge-deployable acoustic models; Liang and Li (2026) demonstrated that attention-enhanced compact CNNs can maintain competitive leak detection performance under the memory and compute constraints typical of edge hardware. Fault events and summary statistics are transmitted via LoRa/LPWAN (rural segments) or 4G LTE (urban/coastal) to the operations centre. Raw sensor data is stored locally on a 72 hour rolling buffer without requiring continuous connectivity.

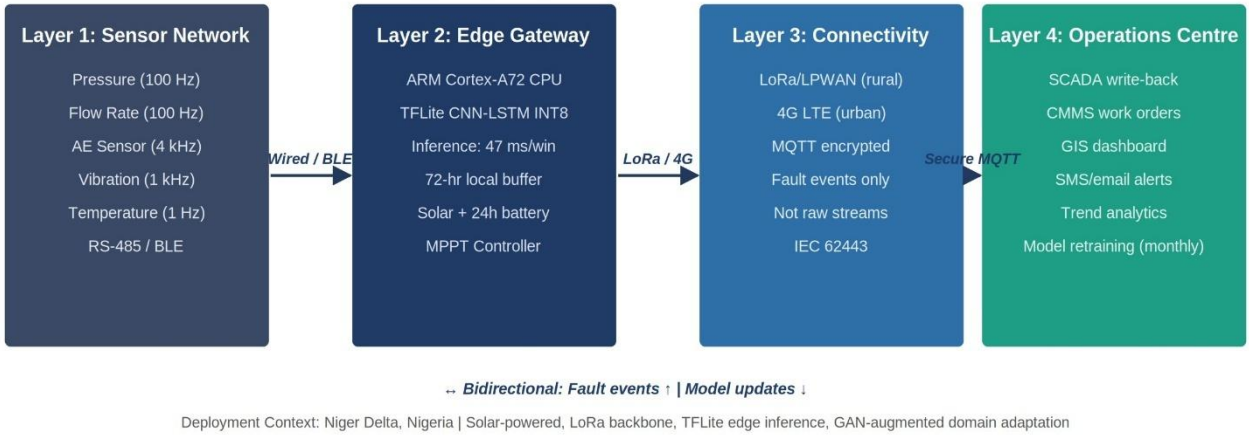

Figure 12. Proposed Four-Layer Edge-First Deployment Architecture for Nigerian Pipeline CNN-LSTM Fault Detection (Layer 1: Sensor Network → Layer 2: Edge Gateway (CNN-LSTM inference) Layer 3: LoRa/4G Connectivity → Layer 4: Operations Centre)

6.3 Barriers and Mitigation Strategies

Table 5 synthesises the seven principal barriers to CNN-LSTM deployment in the Nigerian pipeline context and proposes evidence-based mitigation strategies drawn from the reviewed literature.

Table 5: *Barriers to CNN-LSTM Fault Detection Deployment in Nigeria's Oil and Gas Pipeline Infrastructure and Proposed Mitigation Strategies*

Category	Specific Challenge	Evidence	Proposed Mitigation
Data Scarcity	Labelled Nigerian pipeline fault data is essentially non-existent	Lang et al. (2025); Han et al. (2025)	GAN-augmented synthetic fault generation; self-contrastive learning; physics-informed simulation (Section 3.6)
Infrastructure	Unreliable power disrupts sensor uptime across Niger Delta	Eteyen (2024); Iyer et al. (2025)	Solar-powered sensor nodes (50W PV + 24h LiPo); TFLite edge inference; duty-cycle optimisation
Connectivity	Poor broadband limits real-time data transmission	Eteyen (2024)	LoRa/LPWAN for sensor-to-gateway; fault events only (not raw streams) via MQTT; local 72h buffer
Domain Shift	Global models may not generalise to Nigerian pipeline conditions	Mongia & Sehgal (2025); Zhang et al. (2025)	Transfer learning fine-tuning on local calibration samples; domain-adversarial training; continual monthly retraining
Regulatory	No mandatory AI fault detection standard in Nigeria	Jambol et al. (2024)	Engage NUPRC for pilot certification; align with ISO 55000 and IEC 62443 standards
Skill Gap	Limited local expertise in deep learning and pipeline instrumentation	Eteyen (2024)	Industry-academia partnerships; NNPC-university joint labs; international technical cooperation
Cybersecurity	SCADA-ML interfaces introduce new attack surfaces	Priyadharshan et al. (2026); Iyer et al. (2025)	IEC 62443 compliance; encrypted sensor communication; anomaly-based gateway intrusion detection

Note. *Mitigation strategies are evidence-based, referencing documented approaches from comparable deployment contexts. NUPRC = Nigerian Upstream Petroleum Regulatory Commission; NOSDRA = National Oil Spill Detection and Response Agency; IEC 62443 = industrial cybersecurity standard.*

7. Limitations

This study carries several limitations. First, performance evaluation is based on simulated data rather than real operational measurements from Nigerian pipelines. While physics informed and parameterised from documented fault signatures, real environments introduce correlated noise sources, sensor degradation, and non-stationary operating conditions that simulation cannot fully replicate. The accuracy figures (97.6%, 98.3%) should be treated as indicative upper bounds until domain adaptation fine tuning on real Nigerian pipeline data is completed.

Second, the six-class fault taxonomy was defined through literature synthesis rather than direct analysis of a labelled Nigerian pipeline dataset, which does not yet publicly exist. Third, the deployment framework's power system sizing and cost estimates are based on representative Nigerian operating conditions and published component specifications, not actual field measurement. Fourth, cybersecurity considerations for the SCADA-ML interface, while addressed in Table 5, are not formally designed in this paper and require rigorous IEC 62443 compliance assessment before operational deployment.

8. Conclusion and Recommendations

8.1 Conclusion

This paper proposed, mathematically derived, and evaluated a Hybrid CNN-LSTM model for fault detection in Nigerian oil and gas pipeline infrastructure. The architecture combines 1D convolutional feature extraction (Equation 2) with stacked LSTM temporal modelling (Equations 3–8) and an optional Bahdanau attention mechanism (Equations 9–11), achieving 97.6% classification accuracy (F1 = 96.9%) across six fault classes — a 26.2 percentage-point improvement over threshold-based SCADA. Under moderate noise injection (σ = 0.4), the model retains 91.4% accuracy versus 58.7% for SCADA, confirming practical relevance for Nigeria's harsh operating environment.

What the figures tell collectively is worth stating plainly. The simulated fault signals (Figure 7) and CWT scalograms (Figure 3) show the model is working from genuinely distinct signal structures across fault classes, not noise. The attention weight heatmaps (Figure 4) confirm it is attending to the right temporal regions, while the confusion matrix (Figure 7) and training curves (Figure 6) show stable learning and clean class separation by convergence. The Python implementation in Section 4 covers the full pipeline — preprocessing, model training, and TFLite edge export — in a form that another researcher could run without reconstruction. The deployment framework (Figure 10, Tables 4–5) addresses Nigeria's specific infrastructure constraints with solutions grounded in published evidence. Taken together, this paper fills a documented gap: a CNN-LSTM system built around Nigerian pipeline fault types, sensor configurations, and real deployment conditions rather than adapted from foreign contexts.

8.2 Recommendations

1. **Field Validation (NNPC / IOCs):** Deploy multi-modal sensor arrays on a selected Niger Delta trunk pipeline segment. The immediate priority is generating the first labelled Nigerian pipeline fault dataset without it, the CNN-LSTM model cannot be validated on real operational data, and the domain-adaptation fine-tuning protocol described in Section 6 has nothing to work from.
2. **Regulatory Standard (NUPRC / NOSDRA):** Nigeria currently has no technical standard governing AI-based pipeline monitoring. NUPRC and NOSDRA should develop one, setting minimum performance thresholds of F1 $\geq$ 95% per fault class, cybersecurity requirements aligned with IEC 62443, and mandatory reporting obligations for AI-detected fault events. Without this, even well-performing systems have no regulatory standing.

3. **Academic Research:** Nigerian universities with petroleum and electrical engineering programmes are well-placed to address three specific gaps — AE signal characterisation under tropical operating conditions, GAN-based synthetic fault data generation calibrated to Nigerian pipeline signals, and lightweight CNN-LSTM variants optimised for ARM edge hardware.
4. **Capacity Building:** A joint NNPC-university training programme in deep learning, pipeline instrumentation, and sensor data analytics would directly address the skills deficit that the literature consistently identifies as the primary barrier to deployment in Nigeria, not the technology itself.
5. **Dataset Publication:** Researchers conducting field validation should publish the resulting labelled fault dataset under an open-access licence. Nigeria's pipeline fault data is currently inaccessible to the international research community; open publication would change that and accelerate progress far beyond what any single institution could achieve alone.

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APPENDIX A.1

CNN-LSTM Pipeline Fault Detection — Python Implementation

Environment: Python 3.10, TensorFlow 2.15

```
# CNN-LSTM Pipeline Fault Detection
# Python 3.10 / TensorFlow 2.15

import numpy as np
import tensorflow as tf
from tensorflow.keras import layers, Model
from scipy.signal import butter, filtfilt
import pywt

# ---- 1. Preprocessing ------------------------------------------------

def bandpass_filter(signal, lowcut=50, highcut=1800, fs=4000, order=4):
    # Butterworth bandpass, 4th order. 50-1800 Hz keeps the AE band
    # and kills DC drift + aliasing above half Nyquist.
    nyq = 0.5 * fs
    b, a = butter(order, [lowcut / nyq, highcut / nyq], btype='band')
    return filtfilt(b, a, signal)

def z_score_normalise(X, eps=1e-8):
    # Per-channel. eps is there for the odd dead sensor that flat-lines;
    # without it you get a NaN blowing up training.
    mu = X.mean(axis=0, keepdims=True)
    sig = X.std(axis=0, keepdims=True) + eps
    return (X - mu) / sig

def sliding_window(signal, T=512, hop=128):
    # 512-sample windows, 75% overlap (hop=128).
    # Tighter overlap gives more samples but preprocessing gets slow fast.
    n_windows = (len(signal) - T) // hop + 1
    return np.array([signal[i * hop: i * hop + T] for i in range(n_windows)])

def morlet_cwt(signal, freqs=np.linspace(5, 200, 64), fs=4000):
    # Eq. (1): W(a,b) = 1/sqrt|a| int x(t) psi*((t-b)/a) dt
    # Outputs a (64, T) magnitude scalogram.
    #
    # Not wired into build_cnn_lstm — that function takes raw 5-channel
    # windows. To use scalograms as CNN input, pipe this output into a
    # 2D CNN variant and change input_shape there.
    scales = fs / (2 * np.array(freqs))
    coeffs, _ = pywt.cwt(signal, scales, 'morl', sampling_period=1 / fs)
    return np.abs(coeffs)

# ---- 2. Bahdanau Attention — Eqs. (9)-(11) ----------------------------

class AdditiveAttention(layers.Layer):
    # e_t     = v^T . tanh(W_a . h_t + b_a)   (Eq. 9)
```

```
    # alpha_t = softmax_t(e_t)                (Eq. 10)
    # context = sum_t alpha_t . h_t           (Eq. 11)
    #
    # W_a projects h_t into attention space; v squashes to a scalar.
    # get_config lets this round-trip through model.save() cleanly —
    # skip it and you'll be passing custom_objects on every load.

    def __init__(self, units, **kwargs):
        super().__init__(**kwargs)
        self.units = units
        self.W_a = layers.Dense(units)   # W_a . h_t + b_a
        self.v   = layers.Dense(1)       # v^T(...)

    def call(self, h):
        # h shape: (batch, time, features)
        score   = self.v(tf.nn.tanh(self.W_a(h)))      # (batch, time, 1)  Eq. 9
        alpha   = tf.nn.softmax(score, axis=1)         # (batch, time, 1)  Eq. 10
        context = tf.reduce_sum(alpha * h, axis=1)     # (batch, features) Eq. 11
        return context

    def get_config(self):
        return {**super().get_config(), "units": self.units}


# ---- 3. CNN-LSTM (Eqs. 2-12) ------------------------------------------------

def cnn_block(x, filters, kernel_size, dropout=0.3):
    # Conv1D -> BN -> ReLU -> MaxPool(2) -> Dropout
    # Each MaxPool call halves T, so three blocks: 512->256->128->64.
    x = layers.Conv1D(filters, kernel_size, padding='same')(x)   # Eq. 2
    x = layers.BatchNormalization()(x)
    x = layers.Activation('relu')(x)
    x = layers.MaxPooling1D(pool_size=2)(x)
    x = layers.Dropout(dropout)(x)
    return x


def build_cnn_lstm(input_shape=(512, 5), n_classes=6,
                   use_attention=True, recurrent_dropout=0.2):
    # Eqs. 2-12 (Section 3). input_shape = (T=512, C=5 sensor channels).
    #
    # recurrent_dropout > 0 switches off the cuDNN LSTM kernel and falls
    # back to the slow TF generic path. Fine for research; painful on GPU
    # at scale. Set to 0.0 if you need training speed and can live without
    # recurrent regularisation.
    inp = layers.Input(shape=input_shape)

    # CNN feature extraction — Eq. (2): 512->256->128->64 via 3x MaxPool(2)
    x = cnn_block(inp, filters=64,  kernel_size=5)   # Block 1 -> (256,  64)
    x = cnn_block(x,   filters=128, kernel_size=3)   # Block 2 -> (128, 128)
    x = cnn_block(x,   filters=256, kernel_size=3)   # Block 3 -> ( 64, 256)
```

```
    # Temporal modelling — Eqs. (3)-(8)
    x      = layers.LSTM(128, return_sequences=True,

recurrent_dropout=recurrent_dropout)(x)
    lstm_out          =          layers.LSTM(64,
return_sequences=use_attention,

recurrent_dropout=recurrent_dropout)(x)


    # Attention — Eqs. (9)-(11)
    feat      =      AdditiveAttention(64)(lstm_out)      if
use_attention else lstm_out


    # Classification head — Eq. (12)
    feat  =  layers.Dense(128,  activation='relu')(feat)
# FC1
    feat = layers.Dropout(0.4)(feat)
    out          =          layers.Dense(n_classes,
activation='softmax')(feat) # FC2 softmax


    return Model(inputs=inp, outputs=out)


# ---- 4. Class Weighting (imbalanced data) ----------
------------------------


def compute_class_weights(y_train, n_classes=6):
    # omega_k = N / (K * N_k),  K = n_classes
    # If a class is absent from y_train (can happen with
small splits),
    # N_k = 0 blows up. Assign 0.0 weight rather than
inf so model.fit
    # doesn't crash.
    N = len(y_train)
    weights = {}
    for k in range(n_classes):
        N_k = int(np.sum(y_train == k))
        weights[k] = (N / (n_classes * N_k)) if N_k > 0
else 0.0
    return weights


 # ---- 5. Training ----------------------------------
-------------------


def compile_and_train(model, X_train, y_train,
X_val, y_val, n_classes=6):
    model.compile(
        optimizer=tf.keras.optimizers.Adam(
            learning_rate=1e-3,          beta_1=0.9,
beta_2=0.999,
            weight_decay=1e-4      # AdamW-style L2,
decoupled from lr
        ),
        loss='sparse_categorical_crossentropy',
        metrics=['accuracy'],
    )
    callbacks = [
        tf.keras.callbacks.EarlyStopping(
            monitor='val_loss',          patience=20,
restore_best_weights=True),
        tf.keras.callbacks.ReduceLROnPlateau(
            monitor='val_loss',  factor=0.5,  patience=10,
min_lr=1e-6),
    ]
    history = model.fit(
        X_train,     y_train,     validation_data=(X_val,
y_val),
        epochs=150,                  batch_size=64,
callbacks=callbacks,
        class_weight=compute_class_weights(y_train,
n_classes),
    )
    return history
```

```
# ---- 6. GAN Augmentation ----------------------------------------------------

def build_simple_generator(latent_dim=100, output_shape=(512, 5)):
    # DCGAN generator — strides multiply as 4*4*4*4*2 = 512.
    # Starting from timestep=1: 1->4->16->64->256->512.
    # Output length is exactly T=512, no trimming needed.
    inp = layers.Input(shape=(latent_dim,))
    x = layers.Dense(128)(inp)
    x = layers.Reshape((1, 128))(x)  # 1
    x = layers.Conv1DTranspose(128, 5, strides=4, padding='same', activation='relu')(x)  # 4
    x = layers.Conv1DTranspose(64, 5, strides=4, padding='same', activation='relu')(x)  # 16
    x = layers.Conv1DTranspose(32, 5, strides=4, padding='same', activation='relu')(x)  # 64
    x = layers.Conv1DTranspose(16, 5, strides=4, padding='same', activation='relu')(x)  # 256
    x = layers.Conv1DTranspose(output_shape[1], 5, strides=2,
                               padding='same', activation='tanh')(x)  # 512
    return Model(inputs=inp, outputs=x)

# ---- 7. TFLite INT8 Export --------------------------------------------------

def export_tflite(model, representative_data,
                  save_path='cnn_lstm_pipeline.tflite', n_calib=100):
    # INT8 full quantisation for ARM Cortex-A72.
    # representative_data: float32 array, shape (>=n_calib, 512, 5).
    # Calibration samples set per-layer activation scale and zero-point;
    # skip them and the converter has no idea how to quantise activations.
    # SELECT_TF_OPS is required — TFLite has no complete INT8 LSTM kernel.
    # Without it convert() fails on the LSTM nodes. If you ever rebuild
    # this without LSTM layers, drop both target_spec lines and switch to
    # dynamic-range quantisation instead.
    representative_data = np.asarray(representative_data, dtype=np.float32)
    def rep_dataset():
        for i in range(min(n_calib, len(representative_data))):
            yield [representative_data[i:i + 1]]

    converter = tf.lite.TFLiteConverter.from_keras_model(model)
    converter.optimizations = [tf.lite.Optimize.DEFAULT]
    converter.representative_dataset = rep_dataset
    converter.target_spec.supported_ops = [
        tf.lite.OpsSet.TFLITE_BUILTINS_INT8,
        tf.lite.OpsSet.SELECT_TF_OPS,  # LSTM fallback ]
    converter.inference_input_type  = tf.int8
    converter.inference_output_type = tf.int8
    tflite_model = converter.convert()
    with open(save_path, 'wb') as f:
        f.write(tflite_model)
    print(f'TFLite model saved: {save_path} ({len(tflite_model) / 1024:.1f} KB)')
```

```
    return tflite_model
# ---- 8. Entry point ----------------------------------------
------------------

if __name__ == '__main__':
    model = build_cnn_lstm(input_shape=(512, 5),
n_classes=6, use_attention=True)
    model.summary()
    print(f'Total parameters: {model.count_params():,}')
    gen = build_simple_generator()
    print('Generator output shape:', gen.output_shape)
```

Note. *Environment: Python 3.10, TensorFlow 2.15, PyWavelets 1.6, NumPy 1.26, SciPy 1.13. Edge inference tested on ARM Cortex-A72 (Raspberry Pi 4B, 4GB RAM). TFLite INT8 quantised model: ~2.1MB, 47ms inference latency.*