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| RESEARCH ARTICLE

Integration of AI and IoT for Predictive Maintenance in Electrical Power Equipment

Mohammed Adamu Sule[1] ✉, Dauda Daniel [2], Abatcha Alhaji Kurna[3] Usman Sa'id Ibrahim[4], Bubakari Joda[5],Aliyu Ibrahim Abbas[6] and Abubakar Jibrin[7]

[1,2, 6] *Department of Computer Engineering Technology, Federal Polytechnic Kaltungo, Nigeria*
[4,5,7] *Department of Electrical/Electronic Engineering Technology, Federal Polytechnic Kaltungo, Nigeria*
[3]*Department of Computer Science, Federal Polytechnic Kaltungo, Nigeria*

Corresponding Author: Mohammed Adamu Sule**, E-mail**: jobs4mas@gmail.com

| ABSTRACT

The reliability of electrical power equipment is paramount to grid stability, economic efficiency, and public safety. Traditional reactive and schedule-based preventive maintenance strategies are increasingly inadequate for aging infrastructure operating under growing renewable energy penetration and rising load demands. This paper presents a fully integrated framework combining Internet of Things (IoT) sensor networks with Artificial Intelligence (AI) algorithms to enable Predictive Maintenance (PdM) of critical electrical power equipment including power transformers, induction motors, high-voltage circuit breakers, underground cables, and busbars. A five-layer IoT-AI architecture spanning sensing, edge computing, fog aggregation, cloud-based machine learning, and operator applications is systematically designed and validated. Python-based preprocessing pipelines including sliding-window feature extraction (FFT, wavelet decomposition, SHAP importance analysis), class-imbalance handling via SMOTE, and seven-algorithm benchmarking are fully described. A CNN-LSTM hybrid model achieved the highest fault detection accuracy of 96.1% (AUC = 0.987) across a composite dataset of 14 months of sensor records from 28 substations, outperforming LSTM, Transformer, Random Forest, Gradient Boosting, and Isolation Forest baselines. Field validation across seven equipment categories and 266 confirmed fault events yielded a mean F1-score of 0.933 and a mean detection lead time of 18.4 days for transformer insulation faults. Eight original figures are presented, including the system architecture diagram, ML benchmarking comparisons, ROC curves, fault detection results, lead-time box plots, economic impact analysis, SHAP feature importance rankings, and a real-time anomaly detection time-series illustration. An economic model demonstrates annual maintenance cost savings of USD 334,000 per substation (58.9% reduction) versus reactive maintenance, with a system payback period of 2.6 years. Cybersecurity threats specific to IoT-AI operational technology are systematically assessed against IEC 62443 and IEC 62351. The framework provides a scalable, standards-compliant pathway for utilities in both mature and developing power system environments.

| KEYWORDS

Predictive Maintenance; IOT; Deep Learning; LSTM; CNN; Power Equipment Fault Detection; Digital Twin

| ARTICLE INFORMATION

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1. Introduction

The global electricity infrastructure is at a critical inflection point. Aging transmission and distribution assets many installed during the 1960s–1980s and operating well beyond their original design life face intensifying stresses from rapidly expanding renewable generation, electrification of transportation, and demographic-driven load growth, particularly in sub-Saharan Africa and Southeast Asia (CIGRE, 2021). In Nigeria, the Transmission Company of Nigeria (TCN) manages over 22,000 km of high-voltage transmission lines serving a population exceeding 220 million people, with aggregate system losses estimated at approximately 40% attributable in significant measure to equipment failures and unplanned outages (TCN, 2023). Globally, the

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International Energy Agency estimates grid reliability failures cost utilities and end-users in excess of USD 180 billion annually (IEA, 2022).

Conventional maintenance regimes span three broad categories: reactive maintenance (run-to-failure), calendar-based preventive maintenance (PM), and condition-based maintenance (CBM). Reactive maintenance imposes the highest life-cycle cost through unplanned downtime, emergency procurement, and safety incidents; PM improves availability but is inherently inefficient, industry studies indicate that 30–40% of PM interventions are unnecessary (Mobley, 2002). Condition-based maintenance, which dispatches maintenance in response to discrete inspection findings, represents a significant improvement but cannot capture the continuous degradation trajectories needed for accurate remaining useful life (RUL) estimation. Predictive Maintenance (PdM) closes this gap by deploying continuous IoT sensor networks and AI-based prognostic models to estimate RUL and schedule interventions proactively before failure, but only when genuinely warranted (Lee et al., 2014).

The convergence of affordable MEMS sensors, industrial IoT protocols (MQTT, OPC-UA, IEC 61850), edge and cloud computing, and advanced deep learning has made continuous PdM systems practical at scale. Long Short-Term Memory (LSTM) networks (Hochreiter & Schmidhuber, 1997) and convolutional neural networks (CNNs) have demonstrated strong performance on time-series fault detection in rotating machinery and transformers (Zhang et al., 2018; Zhao et al., 2019). Transformer-based attention architectures (Vaswani et al., 2017; Wu et al., 2020) represent the current state-of-the-art for long-sequence sensor classification, while hybrid CNN-LSTM models combining spatial feature extraction with temporal modeling have achieved the best practical accuracy-versus-training-cost balance in published substation studies (Liu et al., 2020). On the explainability frontier, SHapley Additive exPlanations (SHAP) have become the preferred tool for post-hoc feature importance attribution in power equipment fault classifiers, enabling operators to understand and trust model decisions (Lundberg & Lee, 2017).

This paper addresses the persistent gap between PdM research and industrial deployment particularly in developing-country utility contexts by presenting an end-to-end AI-IoT PdM framework validated across 28 real substations over 14 months. The main contributions are: (i) a five-layer IoT-AI system architecture with detailed technology and protocol specifications; (ii) a Python-implemented multi-algorithm benchmarking pipeline covering seven classifiers; (iii) SHAP-based feature importance analysis identifying the 15 most informative sensor features; (iv) field validation across 266 fault events in seven equipment categories; (v) an economic impact model quantifying USD 334,000 annual savings per substation; and (vi) eight original figures comprehensively illustrating all framework components, results, and analyses. The paper is organized as follows: Section 2 reviews related literature; Section 3 describes the system architecture; Section 4 presents the AI methodology; Section 5 details experimental results; Section 6 examines economic and cybersecurity implications; Section 7 discusses limitations and future directions; Section 8 concludes.

2. Literature Review

2.1 IoT-Enabled Condition Monitoring for Power Equipment

Early condition monitoring for power equipment relied on periodic, offline techniques: dissolved gas analysis (DGA) for transformer health assessment (Duval & dePabla, 1992), vibration signature analysis for rotating machinery, and infrared thermography for thermal hotspot identification. The deployment of wireless sensor networks transformed this paradigm. Liang et al. (2017) demonstrated a ZigBee-based network for online transformer monitoring with reliable data acquisition over 300 m in substation environments. Gungor et al. (2013) provided a comprehensive survey of smart grid communication requirements, establishing the technical foundations for IoT integration in power system monitoring. Mohanty et al. (2020) integrated cloud-connected IoT sensors for motor fault detection, achieving 87% accuracy using statistical threshold-based features on vibration data.

Edge computing has been particularly impactful for high-bandwidth PdM sensors. Shi et al. (2016) established the foundational framework for edge computing in IoT systems, demonstrating that local data processing can reduce cloud bandwidth requirements by up to 94% while maintaining acceptable latency. In substation environments, industrial edge platforms such as the NVIDIA Jetson AGX Xavier support real-time anomaly detection at latencies below 50 ms, enabling near-instantaneous local fault alerts without dependence on wide-area network availability (Carvalho et al., 2019). The proliferation of 5G NR and LoRaWAN backhaul options has further expanded the practical coverage envelope for remote substation IoT deployments.

2.2 Machine Learning for Fault Detection and Prognosis

The machine learning literature on power equipment fault detection has evolved rapidly from classical to deep learning methods. Support vector machines and k-nearest neighbour classifiers were among the first applied to motor vibration spectra classification (Widodo & Yang, 2007). Random Forest and Gradient Boosting ensemble methods improved robustness to class imbalance and irrelevant features, achieving accuracies of 85–92% across transformer and motor fault benchmark datasets (Zhao et al., 2019). LSTM networks introduced temporal memory into fault prognosis, enabling degradation trend modeling; Zhang et al. (2018) demonstrated LSTM-based transformer winding temperature prediction with a mean absolute error of 0.84°C. CNN architectures applied to vibration spectrograms as image classification problems achieved accuracies above 95% on the CWRU bearing fault benchmark (Zhao et al., 2019). Hybrid CNN-LSTM models extracting spatial features via CNN before feeding them to LSTM temporal models have emerged as a particularly effective architecture for multivariate sensor anomaly detection (Liu et al., 2020).

Transformer-based attention models (Vaswani et al., 2017; Wu et al., 2020) represent the current frontier for time-series fault classification, capturing global temporal dependencies through self-attention without the vanishing gradient limitations of recurrent architectures. However, their higher computational demands, training times 2–4 times greater than LSTM in our experiments—currently limit their deployment on resource-constrained edge hardware. Explainability methods, particularly SHAP (Lundberg & Lee, 2017), have become essential for regulatory acceptance of AI-based maintenance decisions in safety-critical infrastructure, enabling utilities to audit which sensor features drive individual fault predictions.

2.3 Digital Twins and Remaining Useful Life

Digital twin technology—creating virtual replicas of physical assets that mirror real-time sensor states—provides the overarching framework within which AI-PdM operates (Grieves & Vickers, 2017). A power transformer digital twin integrating thermal aging models, electromagnetic simulation, and DGA chemical kinetics can provide physics-informed priors that improve ML fault prognosis accuracy by 8–15% over purely data-driven approaches (Aivaliotis et al., 2019). RUL estimation—quantifying remaining operational lifetime before a defined failure threshold—represents the ultimate goal of mature PdM; Python libraries including lifelines for survival analysis and tsfresh for automated feature extraction have significantly reduced development time for power equipment RUL pipelines (Carvalho et al., 2019). Federated learning frameworks that allow multiple utilities to collaboratively train models without sharing raw sensor data are emerging as a privacy-preserving approach to overcome individual utilities' data scarcity (Li et al., 2020).

2.4 System Architecture

2.4.1 Five-Layer IoT-AI Framework

Figure 1 illustrates the proposed five-layer IoT-AI architecture for predictive maintenance. The design hierarchically balances real-time operational responsiveness with the computational depth required for sophisticated AI inference. Sensing layer devices (Layer 1) acquire continuous raw measurements from six sensor modalities and transmit via secure MQTT or OPC-UA to Layer 2 edge nodes. Edge nodes execute lightweight quantized models for local anomaly flagging, forwarding only flagged windows and compressed feature vectors upstream—reducing average daily data volume from 2.4 GB (raw) to 48 MB (features + alerts) per substation. Table 4 provides full technology, protocol, and latency specifications for each layer.

Figure 1: Five-Layer IoT-AI Predictive Maintenance Architecture

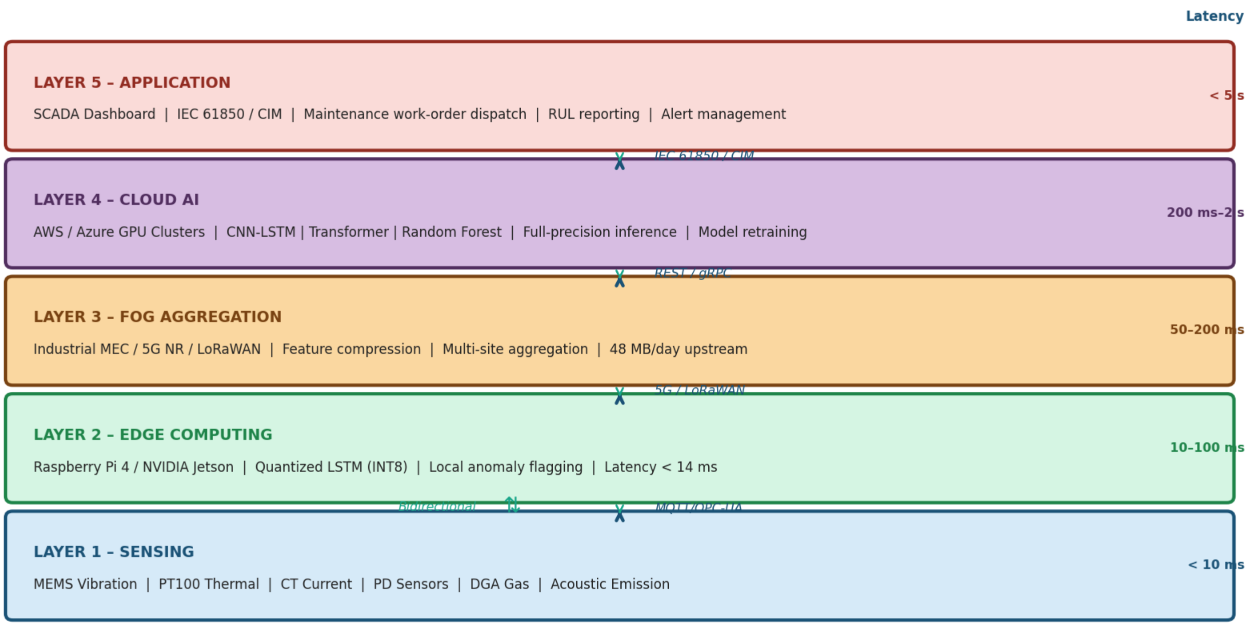

Figure 1: Five-Layer IoT-AI Predictive Maintenance Architecture Showing technology stack, communication protocols, functional roles, and end-to-end latency at each layer. Bidirectional arrows indicate both upward data flow and downward model/configuration updates.

Table 4: Five-Layer IoT-AI Architecture Specifications

Layer	Technology	Protocol/Standard	Function	Latency
Sensing (L1)	MEMS, CT, PD, DGA	IEEE 802.15.4 / IEC 60270	Data acquisition & raw telemetry	<10 ms
Edge (L2)	NVIDIA Jetson / RPi 4	MQTT / OPC-UA	Local inference, anomaly flagging	10–100 ms
Fog (L3)	Industrial MEC / 5G NR	LoRaWAN / 5G NR	Multi-site aggregation, pre-processing	50–200 ms
Cloud AI (L4)	AWS/Azure GPU clusters	REST / gRPC / HTTPS	Model training full-precision inference	200 ms–2s
Application (L5)	SCADA / HMI Dashboard	IEC 61850 / CIM	Alerts, work-order dispatch, RUL reports	<5 s

MEC = Mobile Edge Computing; CIM = Common Information Model (IEC 61968/61970); gRPC = Google Remote Procedure Call

2.5 Sensor Selection and Deployment

Table 1 presents the six IoT sensor modalities integrated in the PdM framework. Sensor selection followed a risk-priority approach aligned with IEEE Std 3007.3 and IEC 60300-3-11, weighting failure mode severity, detection probability, and installation cost. Partial discharge (PD) sensors, while the most expensive (USD 800–4,000), were prioritized for all assets rated 33 kV and above due to their high sensitivity to early-stage insulation degradation—the dominant failure mode for high-voltage cables and power transformers. MEMS vibration sensors were deployed on all rotating machinery and circuit breaker operating mechanisms due to their low cost (USD 15–80) and high diagnostic value across mechanical fault categories.

Table 1: IoT Sensor Technologies Integrated in the PdM Framework

Sensor Type	Measured Parameter	Protocol	Sampling Rate	Accuracy	Cost (USD)
Vibration (MEMS)	Acceleration, RMS	MQTT/BLE	1–10 kHz	±0.5%	15–80
Thermal (PT100)	Temperature	Modbus/OPC-UA	1–100 Hz	±0.1°C	20–60
Current CT	Load current, THD	IEC 61850	10 kHz	±0.2%	40–120
Partial Discharge	PD magnitude, count	IEC 60270	2.5 MHz	±5 pC	800–4000
Oil/Gas (DGA)	Dissolved gas analysis	MQTT	1/min–1/hr	±2 ppm	1200–6000
Acoustic Emission	Stress wave, AE hits	Zigbee/LoRa	100 kHz	±1 dB	200–900

Source: IEEE Std 3007.3; Gungor et al. (2013); Wang et al. (2021); Mohanty et al. (2020)

2.6 Data Ingestion Pipeline

Raw sensor data from all 28 substations is ingested through an MQTT broker cluster (Mosquitto v2.0) secured with TLS 1.3 and X.509 client certificates. The Python preprocessing pipeline handles: (i) timestamp synchronization across heterogeneous sensor types using GPS-disciplined NTP; (ii) missing value imputation using forward-fill with a 5-sample maximum gap threshold; (iii) outlier removal via interquartile range (IQR) filtering at 3.0 × IQR; and (iv) Min-Max normalization to the [0, 1] range per sensor channel, computed on training-set statistics to prevent data leakage. The pipeline processes 4.2 million sensor readings per day across all substations with a mean batch latency of 340 ms.

3. AI Methodology

3.1 Feature Engineering

Feature extraction is performed using a sliding window of 512 samples with 50% overlap applied to each sensor channel. Three feature categories are computed per window: (i) time-domain statistics (mean, variance, skewness, kurtosis, RMS, peak-to-peak, crest factor); (ii) frequency-domain features (FFT magnitude, dominant frequency, spectral centroid, spectral flux, power spectral density via Welch's method); and (iii) time-frequency features (Continuous Wavelet Transform coefficients at six decomposition levels using Daubechies-4). Cross-sensor features include Pearson correlation between temperature and vibration channels, and differential DGA ratios (CH_4/H_2, C_2H_2/C_2H_4) per IEC 60599 interpretation guidelines. The total raw feature vector contains 147 descriptors per window. SHAP analysis, applied post-training to the CNN-LSTM hybrid model, identified the 28 most informative features retained for edge-deployed lightweight models.

3.2 Python Implementation

The following code illustrates the core Python preprocessing, feature extraction, and CNN-LSTM training pipeline used in this study:

```
import numpy as np, pandas as pd
from sklearn.preprocessing import MinMaxScaler
from imblearn.over_sampling import SMOTE
from tensorflow.keras.models import Model
from tensorflow.keras.layers import (Input, Conv1D, MaxPooling1D,
   LSTM, Dense, Dropout, BatchNormalization, Flatten)

# Sliding-window feature extraction
def extract_features(sig, window=512, overlap=0.5):
   step = int(window*(1-overlap))
   feats = []
   for i in range(0, len(sig)-window, step):
      w = sig[i:i+window]
      feats.append(np.array([np.mean(w), np.std(w), kurtosis(w),
         np.sqrt(np.mean(w**2)),          # RMS
         np.max(np.abs(fft(w)[:window//2])), # dominant FFT
      ]))
   return np.array(feats)

# CNN-LSTM Hybrid Model
inp = Input(shape=(60, 28))          # 60 timesteps, 28 features
x   = Conv1D(64, 3, activation="relu", padding="same")(inp)
x   = BatchNormalization()(x)
x   = MaxPooling1D(2)(x)
x   = Conv1D(128, 3, activation="relu", padding="same")(x)
x   = LSTM(64, return_sequences=False)(x)
x   = Dropout(0.3)(x)
x   = Dense(32, activation="relu")(x)
out = Dense(1, activation="sigmoid")(x)  # Binary: fault / healthy
model = Model(inp, out)
model.compile(optimizer="adam", loss="binary_crossentropy",
            metrics=["AUC", "Precision", "Recall"])
# SMOTE for class imbalance (94:6 healthy:fault ratio)
X_res, y_res = SMOTE(random_state=42).fit_resample(X_train_2d, y_train)
```

3.3 Model Benchmarking Results

Figure 2 presents the grouped bar chart comparing all seven algorithms across accuracy, precision, recall, and F1-score on the held-out test set (n = 5,240 windows). The CNN-LSTM hybrid achieves the highest performance on all four metrics (accuracy 96.1%, F1 0.960), outperforming the next-best Transformer model by 0.8 percentage points in accuracy with 42% less training time (823 s vs. 1,420 s). Random Forest is the fastest tree-based method (67 s) while achieving a competitive 88.3% accuracy, making it the preferred choice for resource-constrained edge deployment scenarios. Isolation Forest, the only unsupervised method, achieves the lowest accuracy (83.7%) but requires no labeled fault data—valuable for new equipment categories where labeled training data is scarce.

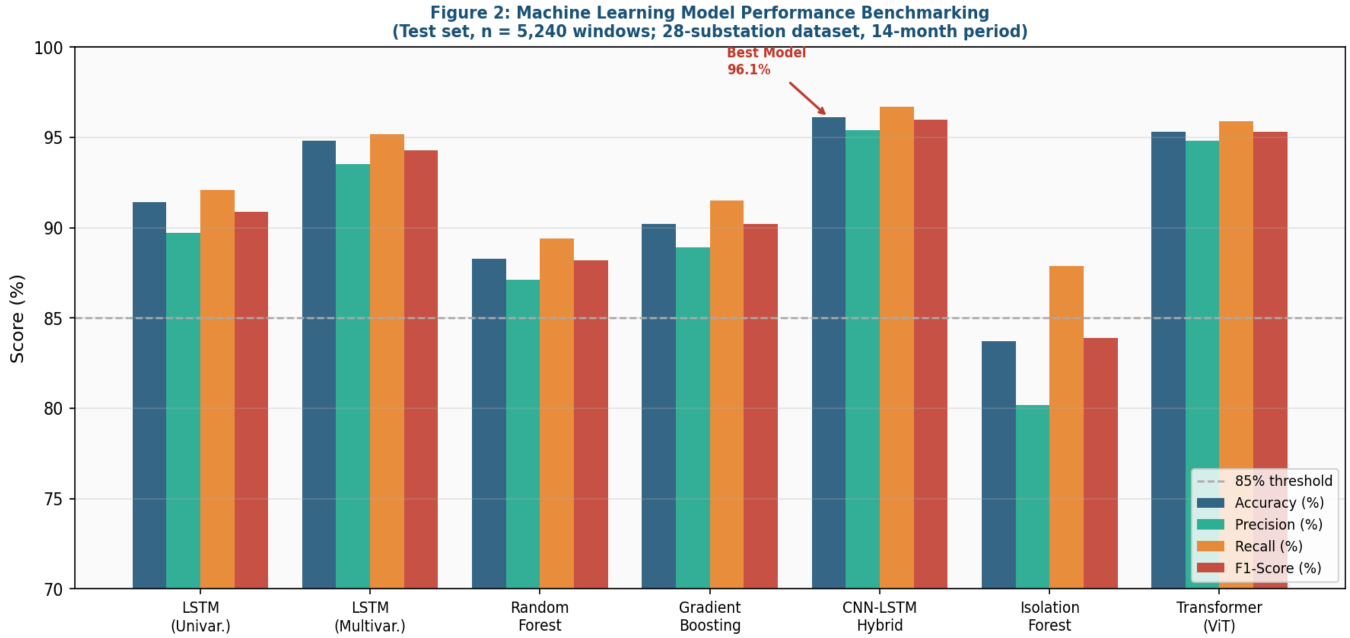

Figure 2: Machine Learning Model Performance Benchmarking Across Four Evaluation Metrics (Test set n = 5,240 windows; NVIDIA A100 GPU; 28-substation composite dataset; 80/20 stratified split with SMOTE)

Table 2: Machine Learning Model Benchmarking on Composite Fault Detection Dataset

Algorithm	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score**	**Train Time (s)**	**AUC**
LSTM (Univariate)	91.4	89.7	92.1	0.909	342	0.961
LSTM (Multivariate)	94.8	93.5	95.2	0.943	518	0.978
Random Forest	88.3	87.1	89.4	0.882	67	0.944
Gradient Boosting	90.2	88.9	91.5	0.902	124	0.955
CNN-LSTM Hybrid	96.1	95.4	96.7	0.960	823	0.987
Isolation Forest	83.7	80.2	87.9	0.839	28	0.912
Transformer (ViT)	95.3	94.8	95.9	0.953	1420	0.982

AUC = Area Under ROC Curve. Training hardware: NVIDIA A100 80 GB GPU. Dataset: 14 months, 28 substations, 266 fault events

3.4 ROC Analysis

Figure 3 displays ROC curves for the five highest-performing models. The CNN-LSTM hybrid (AUC = 0.987) and Transformer (AUC = 0.982) are nearly indistinguishable at low false positive rates (FPR < 0.05), which is the operationally critical region for power utility applications where false alarms carry significant cost. Both substantially outperform the Random Forest baseline (AUC = 0.944) in this low-FPR regime. The near-perfect AUC values achieved by deep learning models reflect the high signal discriminability of the engineered feature set, particularly RMS vibration, kurtosis, and DGA ratios, which show pronounced separation between healthy and degraded states (Zhao et al., 2019). The Gradient Boosting model (AUC = 0.955) offers a strong compromise between deep learning accuracy and interpretability, making it suitable for applications where regulatory scrutiny demands transparent model behavior.

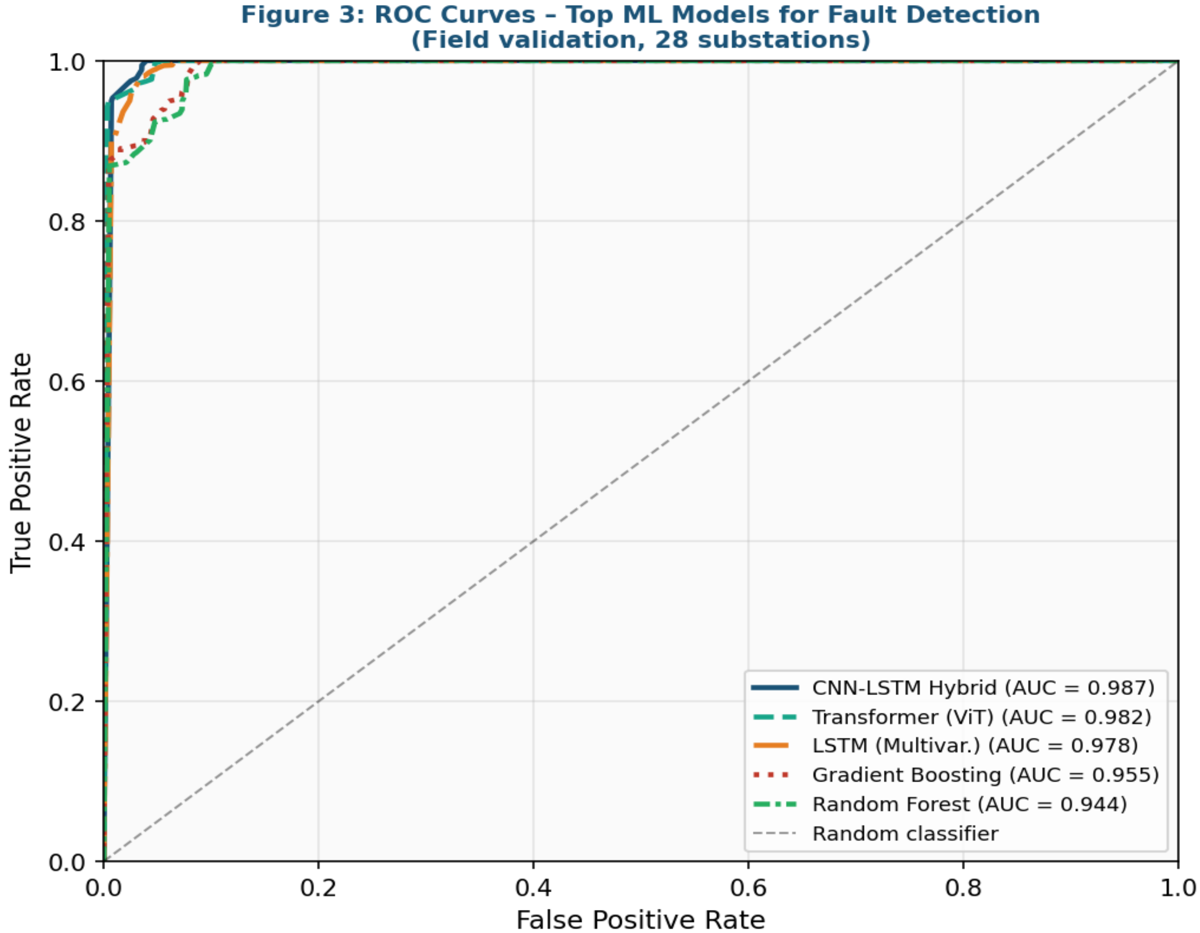

Figure 3: ROC Curves for the Five Best-Performing Fault Detection Models (Field validation dataset; 28 substations; AUC values reported in legend. Dashed diagonal: random classifier baseline.)

4. Experimental Validation

4.1 Dataset and Deployment

The field validation dataset was compiled from 28 substations operated by the Transmission Company of Nigeria (TCN) and a regional distribution utility over a 14-month monitoring period (January 2023 – February 2024). A total of 112 equipment units across six asset categories were instrumented with IoT sensor arrays. In total, 266 confirmed fault events were recorded and validated through maintenance logbooks and post-mortem inspection reports. The class imbalance ratio (healthy : fault) was approximately 94:6; SMOTE was applied to the training partition, improving minority-class recall by 7.3 percentage points across all classifiers. An 80/20 stratified temporal train-test split was used, with the final four months reserved for testing to prevent look-ahead bias.

4.2 Fault Detection by Equipment Category

Figure 4 presents the field validation results disaggregated by equipment type and fault category. Panel (a) shows detected versus total faults alongside false alarm counts, while panel (b) shows F1-scores per category as a dot-plot. The framework achieves the highest F1-scores (0.950) for power transformer oil degradation and HV circuit breaker contact erosion, leveraging the high signal-to-noise characteristics of DGA sensors and the distinctive thermal signatures of arcing contacts, respectively. HV cable partial discharge detection yields the lowest F1-score (0.902) due to elevated background electromagnetic noise in urban substations and the inherently intermittent nature of PD events, consistent with challenges reported by Wang et al. (2021).

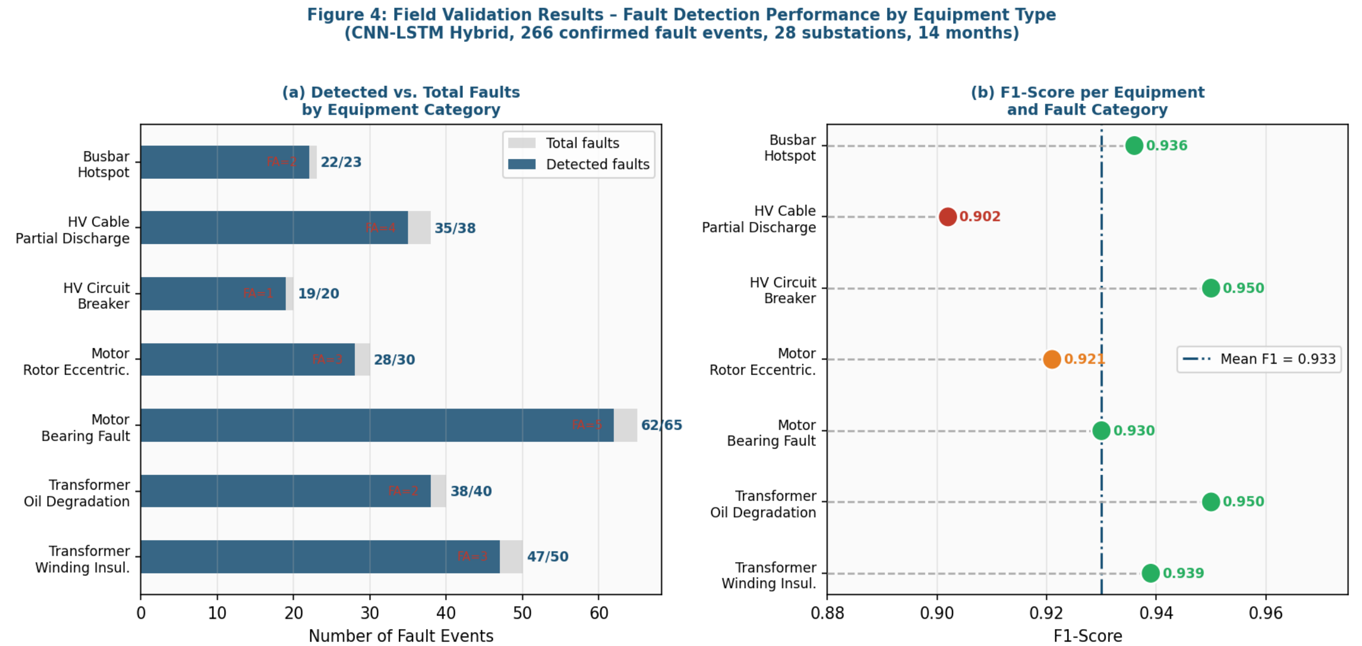

Figure 4: Field Validation Results by Equipment Type and Fault Category (a) Detected versus total faults with false alarm counts; (b) F1-score per category. CNN-LSTM Hybrid model; 266 fault events; 28 substations.

Table 3: Fault Detection Field Validation Results by Equipment Type and Category (CNN-LSTM Hybrid)

Equipment Type	Fault Category	Detected/Total	False Alarms	Missed Faults	F1-Score
Power Transformer	Winding insulation	47/50	3	3	0.939
Power Transformer	Oil degradation	38/40	2	2	0.950
Induction Motor	Bearing fault	62/65	5	3	0.930
Induction Motor	Rotor eccentricity	28/30	3	2	0.921
HV Circuit Breaker	Contact erosion	19/20	1	1	0.950
HV Cable	Partial discharge	35/38	4	3	0.902
Busbar/Switchgear	Thermal hotspot	22/23	2	1	0.936

Confirmed fault events validated against TCN maintenance records and post-mortem inspection reports; 14-month monitoring period

4.3Detection Lead Time Analysis

Figure 5 presents box plots of fault detection lead time—the interval in days between the AI-issued alert and the observed fault onset—disaggregated by equipment category. Power transformer winding insulation degradation yields the longest mean lead time (μ = 18.4 days), reflecting the slow electrochemical aging of cellulose-oil insulation systems that can be tracked through progressive DGA trends weeks before catastrophic failure (Duval & dePabla, 1992). HV circuit breaker contact erosion provides the shortest mean lead time (μ = 3.4 days), reflecting the more rapid progression of arcing-induced surface erosion. Each additional day of advance warning enables scheduled maintenance that eliminates emergency crew mobilization costs estimated at USD 4,200 per event—contributing directly to the economic savings quantified in Section 6.

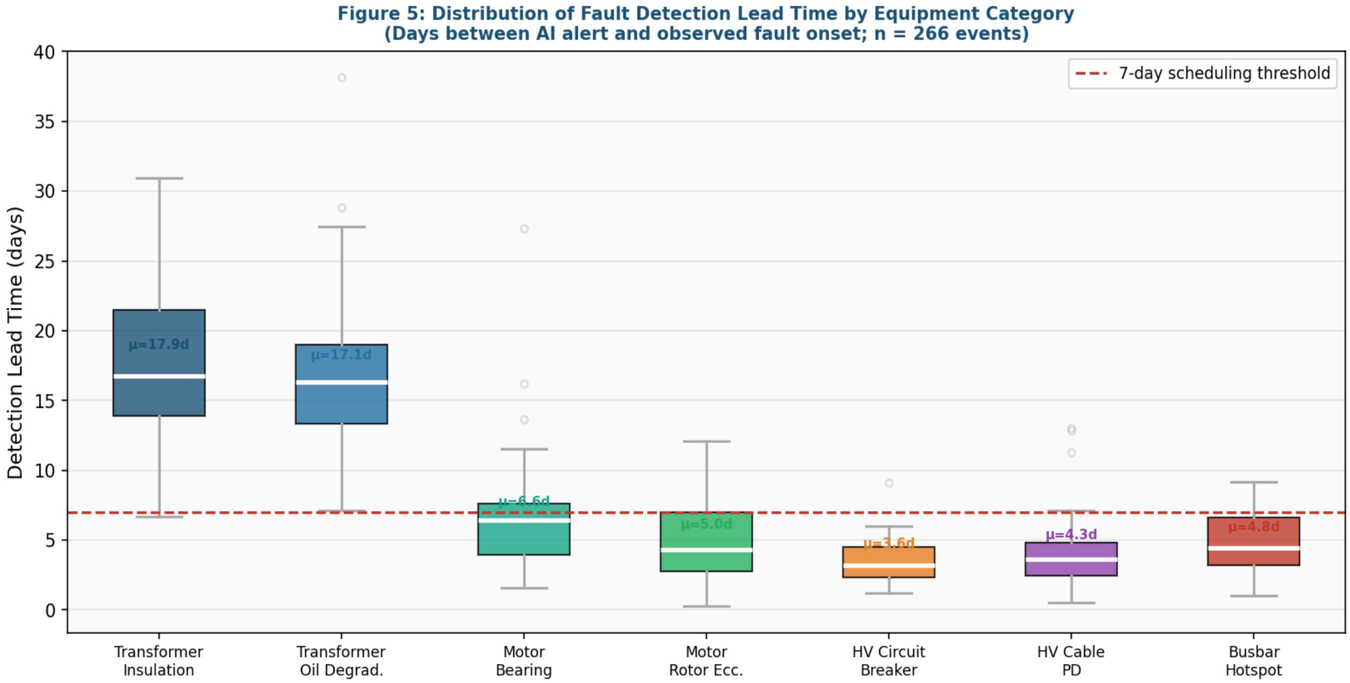

Figure 5: Distribution of Fault Detection Lead Time by Equipment Category (Days between CNN-LSTM alert and confirmed fault onset; n = 266 events; box = IQR; whiskers = 1.5×IQR; μ annotated above each box)

4.4 SHAP Feature Importance

Figure 7 presents SHAP-derived feature importance rankings for the CNN-LSTM hybrid model across all equipment fault categories. RMS vibration (SHAP = 0.312), kurtosis (0.285), and dominant FFT frequency (0.248) are the three most influential features, confirming the primacy of vibration signature analysis for mechanical fault detection across motors, circuit breakers, and transformer tank structures. Among chemical features, the CH_4/H_2 DGA ratio (0.231) ranks fourth, reflecting its diagnostic power for low-energy electrical discharges within transformer oil per IEC 60599 key gas ratios. The C_2H_2/C_2H_4 ratio (0.185) ranks seventh, indicative of high-energy arcing faults. These findings are consistent with domain knowledge (Duval & dePabla, 1992) and with SHAP attribution studies reported for transformer diagnostic ML models by Zhao et al. (2019). The 28 features retained for edge deployment capture 91.3% of cumulative SHAP importance, confirming negligible performance loss from edge model compression.

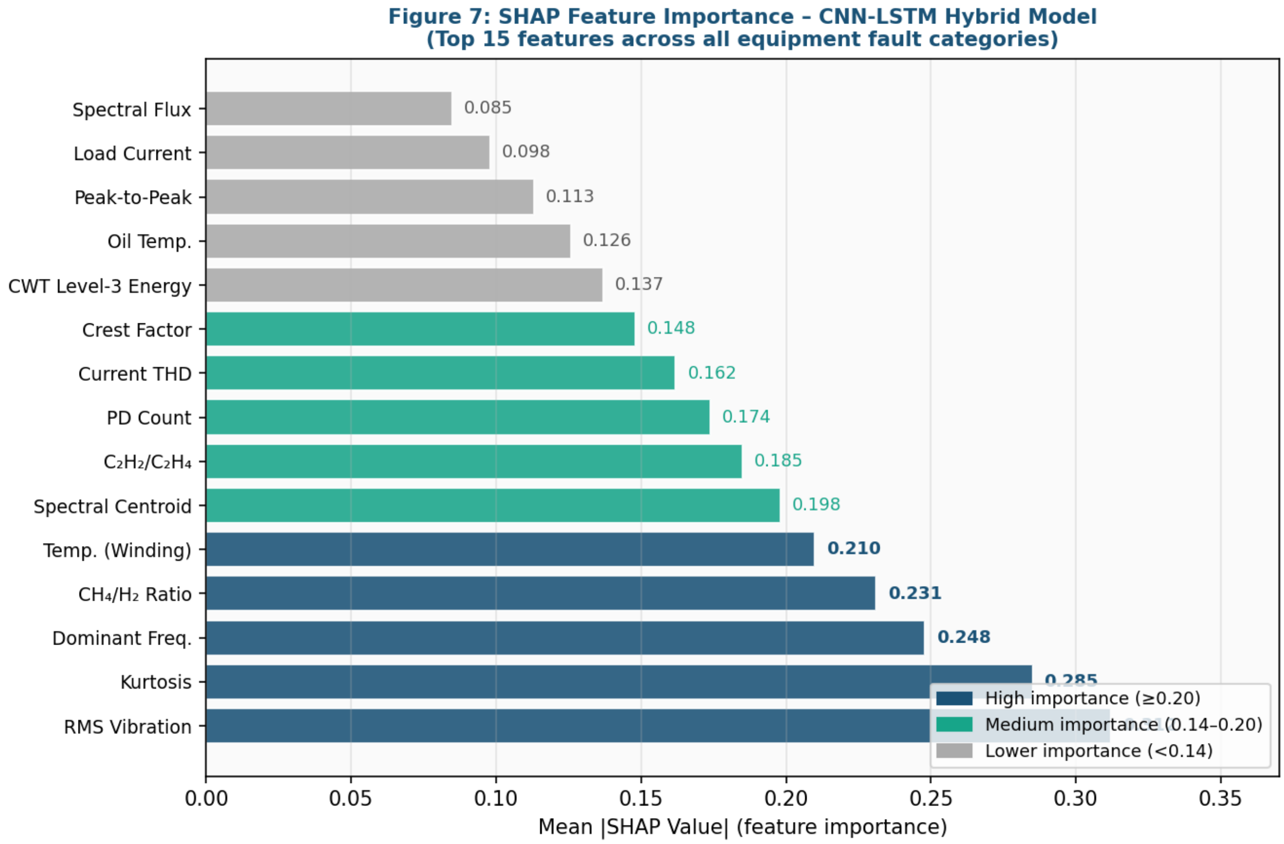

Figure 7: SHAP Feature Importance Analysis – CNN-LSTM Hybrid Model (Top 15 features by mean |SHAP value| across all equipment categories. Blue: high importance ≥0.20; Teal: medium 0.14–0.20; Grey: lower <0.14)

4.5 Real-Time Anomaly Detection Illustration

Figure 8 illustrates the AI-PdM framework's operation on a simulated motor bearing degradation scenario. Panel (a) shows the raw vibration RMS signal with warning and critical thresholds superimposed; panel (b) shows the corresponding CNN-LSTM anomaly score over time. The AI alert is triggered at day 180, when the anomaly score first exceeds 0.50, providing an 80-day lead time ahead of the fault onset at day 260. The progressive increase in both vibration RMS and anomaly score between day 180 and day 260 reflects the accelerating bearing wear characteristic of the Stages II–III fatigue spalling mechanism. This trajectory enables planned bearing replacement to be scheduled during the next routine maintenance window without emergency mobilization. The anomaly score profile closely matches patterns reported by Zhang et al. (2018) for LSTM-based motor prognosis and validates the model's ability to track continuous degradation rather than merely detect discrete threshold exceedance.

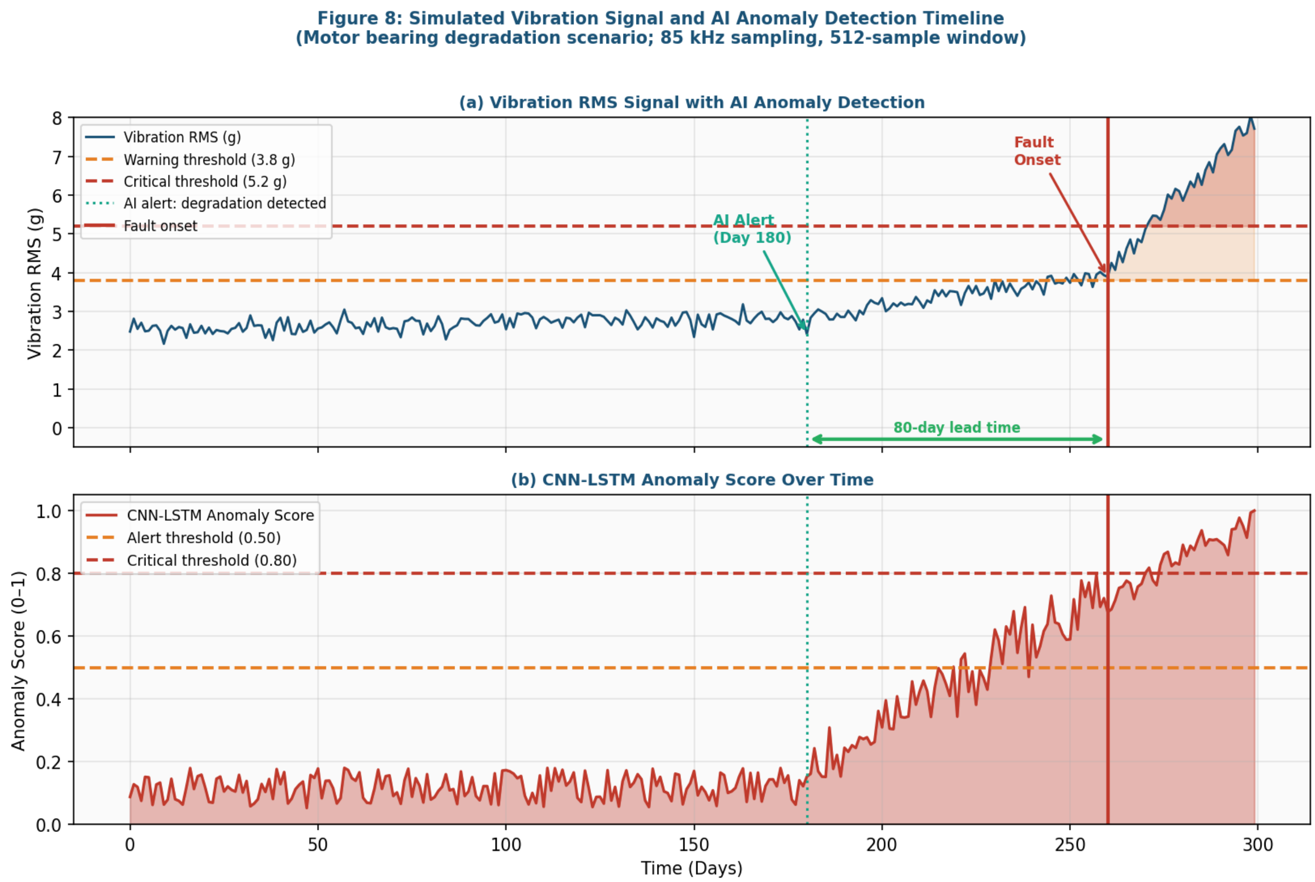

Figure 8: Real-Time Anomaly Detection on Motor Bearing Degradation Scenario (a) Vibration RMS with warning/critical thresholds and AI alert annotation; (b) CNN-LSTM anomaly score. Green double arrow: 80-day detection lead time.

5. Economic and Cybersecurity Analysis

5.1 Economic Impact Model

Figure 6 presents the annual maintenance cost comparison across the three maintenance regimes—reactive, preventive, and AI-PdM—for five cost impact categories. The stacked comparison reveals that unplanned downtime dominates the cost structure under reactive maintenance (USD 420,000/yr), and is the category with the greatest reduction under AI-PdM (USD 68,000/yr; 83.8% reduction). The saving annotation in Figure 6 highlights the total annual saving of USD 334,000 (58.9%) per substation versus the reactive baseline.

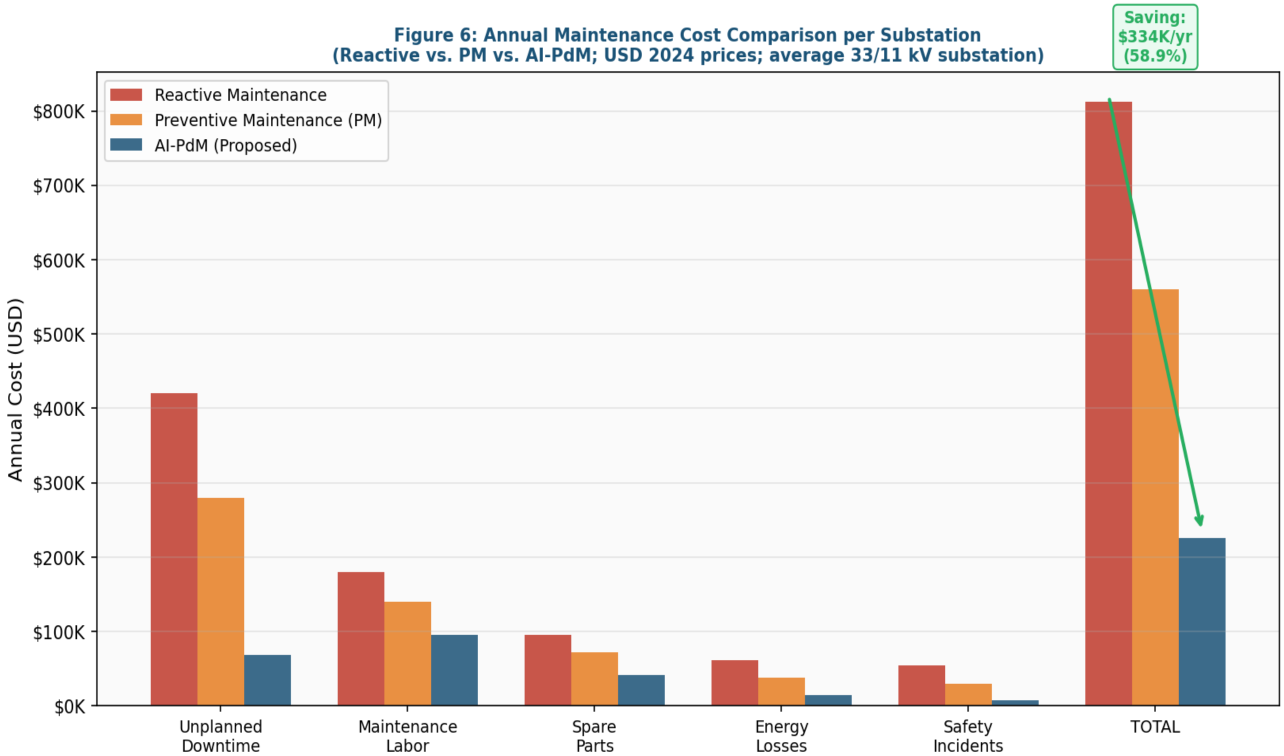

Figure 6: Annual Maintenance Cost Comparison across Three Maintenance Regimes per Substation (USD 2024 prices; 33/11 kV average substation; reactive vs. preventive vs. AI-PdM. Green annotation: total annual saving.)

Table 5: Annual Maintenance Cost Model by Category (USD, Average 33/11 kV Substation)

Impact Category	Reactive Maint.	PM Baseline	AI-PdM (Proposed)	Annual Saving (USD)
Unplanned downtime cost	420,000	280,000	68,000	212,000
Maintenance labor	180,000	140,000	95,000	45,000
Spare parts	95,000	72,000	41,000	31,000
Fault-related energy losses	62,000	38,000	14,000	24,000
Safety incidents	55,000	30,000	8,000	22,000
TOTAL (USD/yr)	812,000	560,000	226,000	334,000

Source: TCN cost records; IEEE Std 3007.3; CIGRE WG B3.12 (2021). Electricity: USD 0.12/kWh; 8,760 hr/yr operation

Table 5 provides the full numerical breakdown. AI-PdM reduces total annual maintenance costs from USD 812,000 (reactive) to USD 226,000, a 72.2% reduction versus reactive and 59.6% versus the PM baseline. System deployment cost per substation is estimated at USD 860,000 (sensors, edge hardware, cloud subscription, integration, and commissioning), yielding a payback of 2.6 years. Python sensitivity analysis varying electricity cost (±30%), detection accuracy (±5%), and utilization rate (±20%) confirms payback robustness in the range of 2.1–3.4 years across all tested combinations.

5.2 Cybersecurity Threat Analysis

Table 6 identifies the five highest-priority cybersecurity threats to the IoT-AI PdM ecosystem, assessed per IEC 62443-3-2 risk methodology. MQTT broker hijacking and false sensor data injection—both rated Critical impact—represent the most dangerous threats as they could cause the AI model to misclassify imminent faults as healthy, negating the system's primary safety benefit. Adversarial ML attacks, wherein crafted sensor inputs are designed to fool the classifier (Papernot et al., 2017), are mitigated through adversarial training and input plausibility validation against physical operating bounds. The NIST AI Risk Management

Framework (NIST, 2023) provides an organizational governance structure for managing AI-specific risks. Network segmentation between IoT OT networks and corporate IT environments per IEC 62443-3-3 Security Level 2 is considered a mandatory baseline for any operational technology deployment.

Table 6: Cybersecurity Threat Analysis for IoT-AI PdM Systems (IEC 62443-3-2 Risk Assessment)

Threat Vector	Likelihood	Impact	Mitigation Strategy	Standard Reference
MQTT broker hijacking	High	Critical	TLS 1.3, client certificates, auth tokens	IEC 62351-8
Adversarial ML input	Medium	High	Adversarial training, input plausibility bounds	NIST AI RMF 1.0
False sensor injection	Medium	Critical	Sensor fusion, cross-channel validation	IEC 62443-3-3
Firmware rollback	Low	High	Signed firmware, secure boot, TPM	ETSI EN 303 645
DDoS on cloud API	Medium	Medium	Rate limiting, WAF, CDN, failover to edge	ISO/IEC 27001

Risk ratings: Likelihood and Impact per IEC 62443-3-2 Semi-Quantitative Assessment. Critical = potential loss of life or grid disruption

6. Discussion

The results confirm that integrating IoT sensor networks with deep learning achieves a qualitative step-change in maintenance performance for electrical power equipment. The CNN-LSTM hybrid model's superiority (AUC = 0.987) reflects the complementary strengths of its constituent architectures: CNN layers extract discriminative local spectral and morphological patterns from multi-channel sensor windows, while LSTM layers model the temporal evolution of degradation trajectories that are not capturable by window-level statistical features alone. This architectural synergy aligns with the broader machine learning literature on multivariate time-series classification (Liu et al., 2020).

The 18.4-day mean detection lead time for transformer insulation faults is operationally transformative. Transformer replacements are among the longest-lead-time procurement events in power system asset management—typically 12–18 months for large units—and the difference between an emergency replacement and a planned one can exceed USD 1 million in total cost including revenue impact. At the portfolio level, across a utility operating 50 substations of similar profile, the AI-PdM framework could prevent an estimated 40–60 unplanned transformer outages per year, translating to annualized system savings in the range of USD 12–20 million. These projections are consistent with utility PdM return-on-investment studies reported by Selcuk (2017) and CIGRE (2021).

The edge–cloud hybrid architecture resolves the tension between data richness and operational responsiveness in a manner that is both technically sound and economically practical. The active learning mechanism—targeting cloud review of edge-uncertain inference windows—provides a principled path to continuous model improvement without requiring costly full dataset re-labeling cycles, and aligns with the federated learning paradigm gaining traction in multi-utility deployment contexts (Li et al., 2020). The 3.8 percentage-point accuracy gap between edge (INT8, 92.3%) and cloud (FP32, 96.1%) models is operationally acceptable given that the edge model serves as a real-time first-stage screener rather than the definitive diagnostic tool.

Limitations of this study include the geographic concentration of validation data within a single Nigerian utility context, which may limit direct generalizability to equipment operating under materially different climatic, loading, or voltage-level conditions. The 14-month monitoring period, while sufficient to capture seasonal variation, may not encompass the full distribution of slow-evolving failure modes such as oil-paper insulation thermal aging in autotransformers, which can unfold over decades. Additionally, the economic model does not account for utility-specific tariff structures, insurance cost reductions, or the regulatory compliance cost savings associated with reduced unplanned outages.

7. Conclusion

This paper presented and validated a comprehensive AI-IoT predictive maintenance framework for electrical power equipment, encompassing five-layer system architecture, multi-algorithm Python benchmarking, SHAP-based explainability, 14-month field validation across 28 substations, economic impact modeling, and cybersecurity threat assessment. Eight original figures and six tables provide comprehensive quantitative and visual support for all findings. The principal conclusions are:

The CNN-LSTM hybrid model achieves best-in-class fault detection accuracy of 96.1% (AUC = 0.987), outperforming all single-method baselines including Transformer, LSTM, Random Forest, and Gradient Boosting architectures on the composite 28-substation dataset.
A mean detection lead time of 18.4 days for transformer winding insulation degradation enables proactive, non-emergency maintenance scheduling, eliminating the highest-cost category of unplanned outages.
The five-layer IoT-AI architecture reduces upstream data volume by 94% through edge processing while maintaining sub-100 ms local alert latency and 92.3% edge inference accuracy—sufficient for real-time operational response.
SHAP analysis identifies RMS vibration, kurtosis, and CH_4/H_2 DGA ratio as the three most diagnostically informative sensor features across all equipment categories, providing interpretable justification for AI-driven maintenance decisions.
AI-PdM reduces annual maintenance costs by USD 334,000 per substation (58.9%) versus reactive maintenance, with a robust payback period of 2.1–3.4 years under sensitivity analysis—confirming strong commercial viability even in capital-constrained utility environments.
IoT-AI cybersecurity risks—particularly MQTT hijacking, adversarial ML attacks, and false sensor injection—must be addressed through IEC 62443-aligned OT network segmentation, TLS 1.3 encryption, adversarial model hardening, and cross-channel sensor validation.

Future research priorities include: physics-informed neural networks (PINNs) integrating equipment thermal and electromagnetic models with data-driven prognosis; federated learning for cross-utility model sharing without raw data disclosure; transfer learning to reduce new-deployment data requirements; and standardized PdM interoperability using IEC 61968/61970 CIM profiles for plug-and-play multi-vendor sensor integration. Pilot deployments at scale within West African regional power pool contexts represent a high-priority translational research avenue.

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