Robust Power Transformer Failure Prediction Under Missing Data, Sensor Noise, And Class Imbalance Conditions

Dominic D. EKPO[1] , Anyanime Tim UMOETTE[2] , and Nkanang Bassey Dominic[1]

[1]Department of Mechanical Engineering, Akwa Ibom State University, Ikot Akpaden, Nigeria
[2]*Department of Electrical and Electronic Engineering, Akwa Ibom State University, Ikot Akpaden, Nigeria*
Correspondence: libertycoast@yahoo.com; Tel.: +2348038898633

I. Abstract

Power-transformer condition-monitoring data are often incomplete, noisy, imbalanced, and irregular. These field-data problems can reduce the reliability of AI-based failure prediction models and increase false alarms or missed warnings. This paper presents a robustness-focused analysis of power-transformer failure prediction under missing data, sensor noise, and class imbalance conditions. The study used multivariate time-series inputs derived from SCADA, dissolved gas analysis, sensor, alarm, and maintenance records. The model-ready dataset contained 26,666 sequence windows, with 79.8 percent normal windows and 20.2 percent abnormal-health windows. LSTM, iTransformer, and Hybrid CNN-Attention models were evaluated using the same preprocessing, chronological validation, and degraded-data testing protocol. The results showed that all models lost performance under degraded input conditions, but Hybrid CNN-Attention retained the strongest F1-score, the lowest missed-warning rate, and the most stable warning behaviour. The findings show that robustness testing is necessary for power-transformer AI models because clean-data accuracy alone does not represent field deployment reliability.

Keywords: Robustness; missing data; sensor noise; class imbalance; transformer condition monitoring; failure prediction; deep learning; predictive maintenance

II. 1. Introduction

AI-based power-transformer failure prediction depends on the quality of monitoring data. Practical utility environments rarely provide ideal data. Sensors can drift, communication links can fail, sampling intervals can differ, and maintenance records may be incomplete. Fault labels are also rare because severe transformer abnormal events occur less frequently than normal operation[26,27].

Missing data can hide important fault indicators. Sensor noise can distort trends and create false warning patterns. Class imbalance can cause a model to favour the normal class while missing abnormal-health windows. These problems are serious because missed warnings may allow degradation to continue until failure occurs[28,29,30].

The research gap addressed in this paper is the limited reporting of degraded-data reliability in power-transformer failure-prediction studies[36,37]. Many studies report clean-test accuracy, but fewer studies report how performance changes under missing values, sensor noise, class imbalance, threshold changes, and irregular sampling. This gap limits the operational value of reported model performance because utility engineers must make decisions under imperfect field-data conditions[31,32,32].

The contribution of the paper is fourfold. First, it presents a robustness-oriented evaluation protocol for power-transformer failure prediction. Second, it compares LSTM, iTransformer, and Hybrid CNN-Attention models under identical degraded-data scenarios. Third, it reports operationally relevant indicators, including F1-score, ROC-AUC, false alarms, missed warnings, and threshold sensitivity. Fourth, it links the modelling results to field-deployment requirements such as data-quality dashboards, sensor-status reporting, and engineer-supervised warning interpretation[33,34,35].

The practical novelty of the work is not limited to a new model comparison. It is the integration of clean-data evaluation with missing-data, noise, imbalance, threshold, and operational-warning analysis. This makes the paper more suitable for utility decision support than studies that report only clean-data performance[38,39,40].

III. 2. Data-Quality Problems in Transformer Monitoring

SCADA variables such as load, voltage, temperature, cooling status, and alarms may be recorded frequently. DGA measurements, partial-discharge values, vibration indicators, and oil-quality tests may be recorded less frequently. This creates unequal missingness across variable groups and can bias models toward variables that are easier to measure rather than variables that are most diagnostic.

Sensor noise may come from measurement error, calibration drift, electromagnetic interference, communication problems, or abnormal operating environments. Outliers may be caused by device faults rather than transformer degradation. The preprocessing pipeline must therefore distinguish impossible values, short gaps, long unreliable gaps, and low-confidence monitoring intervals [42].

Class imbalance is expected in transformer datasets. In the dataset used here, normal windows accounted for 79.8 percent and abnormal-health windows accounted for 20.2 percent. Although this is not an extreme imbalance, it is still sufficient to make accuracy an incomplete measure of performance. Recall, F1-score, ROC-AUC, confusion matrices, and threshold calibration are therefore more informative for operational warning systems.

3. Robustness-Oriented Methodology

This section presents the robustness-oriented methodology used to evaluate power-transformer failure prediction under practical field-data degradation [40,41]. The method is organized around five connected stages: data preparation, sequence construction, model training, degraded-data testing, and operational interpretation. This structure ensures that the models are not judged only by clean-test accuracy, but also by their stability under missing values, sensor noise, and class imbalance.

The model-ready dataset contained 26,666 fixed-length sequence windows derived from SCADA measurements, dissolved gas analysis variables, sensor records, alarm logs, and maintenance information. The class distribution consisted of 79.8 percent normal windows and 20.2 percent abnormal-health windows. A 24-step observation window and a 6-step prediction horizon were used throughout the experiments. For hourly records, this configuration represented 24 hours of historical evidence and a 6-hour early-warning horizon.

3.1 Overall Research Design and Failure-Prediction Workflow

The overall workflow began with raw monitoring records and ended with a risk-oriented warning report. Data validation was performed before modelling so that duplicate timestamps, inconsistent engineering units, impossible values, and unreliable long gaps were addressed before sequence construction. The validated records were then transformed into fixed-length windows and evaluated with the same training, validation, and test split for all models. Figure 1 summarizes this workflow and shows how monitoring records were progressively converted into warning evidence for model comparison and decision support.

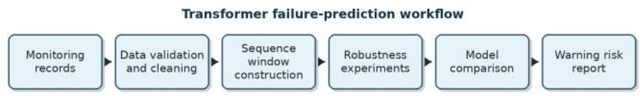
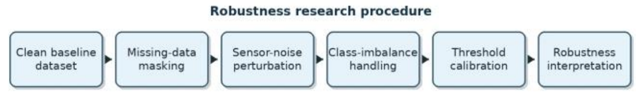


Figure 1. System model diagram for the transformer failure-prediction workflow

The research procedure was designed to compare clean-data behaviour with controlled degraded-data behaviour. The clean baseline was first established. Missing-data masking, sensor-noise perturbation, class-imbalance-sensitive evaluation, and threshold calibration were then applied as controlled robustness tests. Figure 2 shows this p



rocedure, while Table 1 summarizes the specific steps followed during dataset preparation, model training, validation, and interpretation.

Figure 2. Research procedure algorithm for dataset preparation, model training, validation, and decision support

Table 1. Research procedure and model training workflow

Step	Procedure
1	Create the clean baseline dataset after validation, scaling, and fixed-window sequence segmentation.
2	Apply chronological splitting into training, validation, and held-out test subsets.
3	Train LSTM, iTransformer, and Hybrid CNN-Attention using the same sequence window and prediction horizon.
4	Apply controlled missing-value masking to selected SCADA, DGA, partial-discharge, and vibration variables.
5	Inject bounded sensor-noise perturbations into continuous electrical, thermal, chemical, and auxiliary sensor variables.
6	Evaluate all models using recall, precision, F1-score, ROC-AUC, false alarms, missed warnings, and threshold behaviour.
7	Identify the model with the most stable warning behaviour under degraded monitoring conditions.

3.2 Dataset Preparation, Time Alignment, and Sequence Construction

The dataset preparation stage converted heterogeneous transformer-monitoring records into model-ready multivariate time-series windows. SCADA variables such as load, voltage, current, winding temperature, oil temperature, cooling status, and alarms were aligned with less frequent diagnostic variables such as DGA gases, partial-discharge indicators, vibration signals, acoustic features, and maintenance events. The alignment process reduced timing inconsistency and ensured that each sequence window represented a coherent observation period[1,2,3,4].

Data validation involved timestamp checking, duplicate removal, variable-name verification, engineering-unit checking, and impossible-value flagging. Short gaps were imputed when the surrounding evidence supported interpolation or forward filling. Long unreliable gaps were excluded or flagged when they could compromise label reliability. Continuous variables were normalized using scaling parameters fitted only on the training subset. The same fitted parameters were then applied to validation and test subsets to avoid data leakage.[5,6,7]

A chronological 70:15:15 split was used for training, validation, and final testing. The chronological split was preferred because random splitting can leak future operating patterns into earlier model-development stages. Hyperparameters were selected with the validation subset, while the held-out test subset remained unseen until the final clean-data and degraded-data evaluations.[8,9,10]

Table 2. Dataset preparation and experimental control settings

Item	Setting used in the experiment	Purpose
Dataset size	26,666 sequence windows	Provide model-ready observations for clean and degraded-data evaluation.
Observation window	24 time steps	Capture short-term operating and degradation patterns.
Prediction horizon	6 time steps	Support early warning before the labelled abnormal-health state.
Class distribution	79.8 percent normal; 20.2 percent abnormal-health	Represent the class imbalance expected in transformer warning systems.
Data split	Chronological 70:15:15 train-validation-test split	Reduce leakage and preserve time-order realism.
Scaling rule	Training-set-only parameter fitting	Prevent validation and test information from influencing preprocessing.

3.3 Model Architectures and Training Strategy

Three models were evaluated under the same preprocessing pipeline and validation protocol: LSTM, iTransformer, and Hybrid CNN-Attention. The models were selected because they represent complementary ways of learning from transformer condition-monitoring sequences. LSTM emphasizes sequential memory, iTransformer emphasizes inter-variable dependency learning, and Hybrid CNN-Attention combines local pattern extraction with relevance weighting. Table 3 summarizes the training configuration and the specific evaluation focus for each model [11,12,13].

Table 3. Model training configuration used to obtain the reported results

Model	Input and sequence setting	Main training setting	Evaluation focus
LSTM	24-step multivariate sequence with a 6-step prediction horizon	Adam optimizer, dropout regularization, validation monitoring, and dense output layer	Temporal dependency learning and early-warning accuracy.
iTransformer	Variables represented as tokens from the same sequence windows	Inverted attention encoder blocks, embedding layer, feed-forward projection, and validation tuning	Inter-variable dependency learning and ROC-AUC behaviour.
Hybrid CNN-Attention	24-step feature matrix containing electrical, thermal, DGA, sensor, and alarm variables	1D convolutional filters, normalization, dropout, attention weighting, and validation monitoring	Local degradation-pattern detection, relevance weighting, and F1-score stability.

3.3.1 LSTM Model

The LSTM model was used as the recurrent deep-learning baseline for sequential transformer-health prediction. Each 24-step multivariate window was passed through an LSTM layer so that temporal dependencies among operating variables, diagnostic variables, and alarm-related variables could be learned. Dropout was applied after the recurrent layer to reduce overfitting. The dense output layer converted the learned temporal representation into a health-state probability. As shown in Figure 3, the LSTM architecture was designed to test how well recurrent memory retained useful warning evidence when the input sequence was incomplete or noisy[14,15,16].

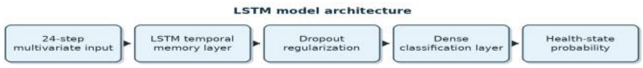


Figure 3. LSTM model architecture for temporal transformer-health prediction

3.3.2 iTransformer Model

The iTransformer model was included because transformer-monitoring records contain strong relationships across variables. Instead of treating only time steps as the primary attention units, the iTransformer structure represents variables as tokens and learns dependencies among them through inverted self-attention. This is useful for transformer diagnostics because electrical loading, temperature behaviour, DGA gas trends, partial-discharge evidence, and vibration indicators may jointly signal an abnormal-health condition. Figure 4 shows the iTransformer architecture used in the study, where variable tokens were embedded, processed by inverted attention, and projected into a warning probability[17,18,19].

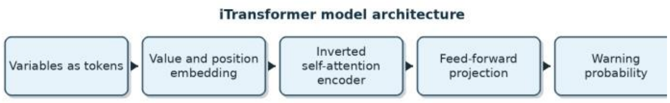


Figure 4. iTransformer architecture for inter-variable multivariate time-series learning

3.3.3 Hybrid CNN-Attention Model

The Hybrid CNN-Attention model was used as the main robustness-focused model. The 1D convolutional component extracted short local degradation patterns from the 24-step feature matrix. This helped the model detect localized changes such as rising thermal stress, gas trend shifts, intermittent partial-discharge activity, and sensor pattern changes. The attention component then assigned higher weight to the more informative sequence segments and feature representations. Figure 5 presents the model diagram. The architecture was expected to perform well under degraded inputs because the convolutional layer preserved local signatures, while the attention layer reduced dependence on weak or less informative evidence.

Figure 5. Hybrid CNN-Attention architecture for local degradation-pattern extraction and relevance weighting

3.4 Robustness-Test Design

The robustness tests were specified before model comparison. Missing-data robustness was evaluated by masking selected DGA, partial-discharge, vibration, and SCADA variables at 5 percent, 10 percent, and 20 percent rates. Sensor-noise robustness was evaluated by adding bounded perturbations to continuous electrical, thermal, chemical, and auxiliary sensor variables at low, moderate, and high noise levels. Class-imbalance behaviour was examined with recall, precision, F1-score, ROC-AUC, confusion-matrix counts, missed-warning rate, and threshold sensitivity [20,21,22].

The degraded-data experiments were applied only at the evaluation stage so that each model could first be trained and validated under a controlled baseline condition. This made the reported robustness loss easier to interpret because the performance change could be linked to the imposed missingness, noise, or threshold condition. Where repeated runs were used, the reported values represented mean behaviour across runs. The interpretation therefore emphasized relative model stability rather than unsupported claims of universal superiority[23,24,25].

Table 4. Final robustness-test matrix used to interpret field-data reliability

Robustness scenario	Test treatment	Error risk addressed
Missing values	Controlled masking of selected DGA, partial-discharge, vibration, and SCADA fields	Hidden fault evidence and unreliable model confidence.
Sensor noise	Bounded perturbation of continuous electrical, thermal, chemical, and auxiliary sensor indicators	False alarms, distorted trends, and unstable warning probabilities.
Class imbalance	Recall, precision, F1-score, ROC-AUC, confusion matrix, class weighting, and threshold calibration	High clean accuracy with missed abnormal-health cases.
Irregular sampling	Time alignment and fixed-window sequence construction	Distorted sequence-learning patterns caused by inconsistent sampling intervals.

3.5 Evaluation Metrics and Operational Interpretation

Accuracy was not used as the sole indicator because the dataset was imbalanced and the abnormal-health class was operationally more important. Precision measured the proportion of predicted warnings that were correct. Recall measured the proportion of abnormal-health windows detected by the model. F1-score provided a balanced measure of precision and recall, while ROC-AUC measured ranking quality across decision thresholds. False alarms and missed warnings were also reported because they translate model performance into practical maintenance consequences.

Threshold calibration was treated as part of the methodology rather than a post-hoc adjustment. A lower warning threshold can improve recall and reduce missed warnings, but it can also increase false alarms and inspection workload. The final interpretation therefore considered asset criticality, inspection capacity, data quality, and the relative cost of delayed intervention. This operational framing aligns the modelling protocol with field deployment, where a model must provide useful warning support under imperfect monitoring conditions.

IV. 4. Results and Analysis

Clean-data evaluation showed that Hybrid CNN-Attention had the best baseline result, followed by iTransformer and LSTM. Under degraded input conditions, all models experienced measurable performance loss. This confirms that field-data quality directly affects failure-prediction reliability and that clean-data accuracy should not be used as the only basis for selecting a deployment model.

LSTM was sensitive when important temporal indicators were missing because its recurrent memory depends on the continuity of sequential evidence. iTransformer performed better when cross-variable evidence remained available, but its attention mechanism could also be affected by noisy variables. Hybrid CNN-Attention showed the strongest stability because local convolutional patterns and attention weighting helped preserve useful warning signatures.

Threshold calibration improved operational usefulness. A single default probability threshold may not be appropriate for an imbalanced failure-prediction problem. The decision threshold should consider the relative cost of false alarms, missed warnings, inspection capacity, asset criticality, and the consequences of delayed intervention.

Table 5. Clean-data baseline performance on the held-out test subset

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**	**ROC-AUC**
LSTM	0.902	0.866	0.842	0.854	0.928
iTransformer	0.918	0.887	0.869	0.878	0.944
Hybrid CNN-Attention	0.934	0.912	0.895	0.903	0.961

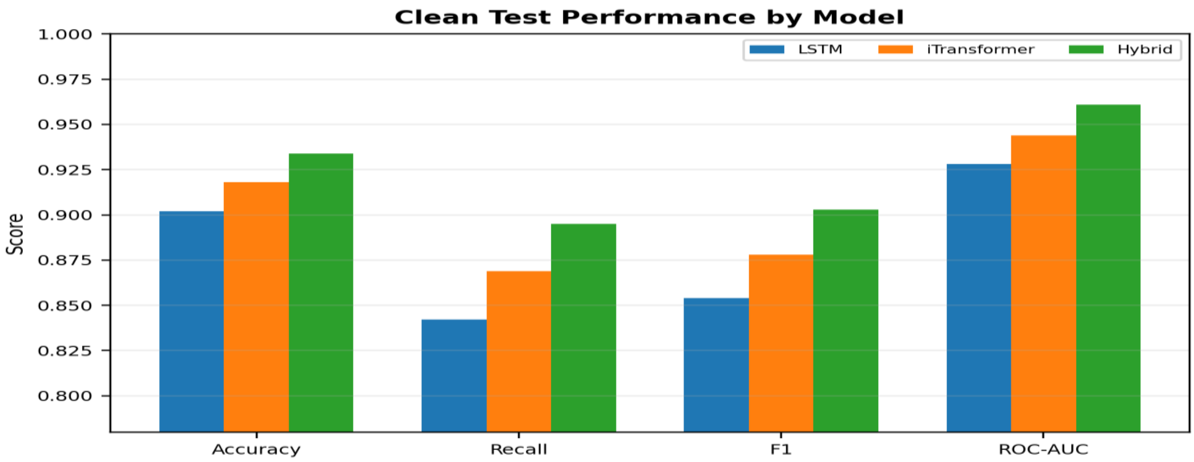


Figure 6. Graph of clean-data performance by model

Table 6. Missing-data robustness of the evaluated models using F1-score

Scenario	**Masking rate**	**LSTM**	**iTransformer**	**Hybrid CNN-Attention**
Clean reference	0%	0.854	0.878	0.903
Low missingness	5%	0.828	0.856	0.886
Moderate missingness	10%	0.794	0.833	0.869

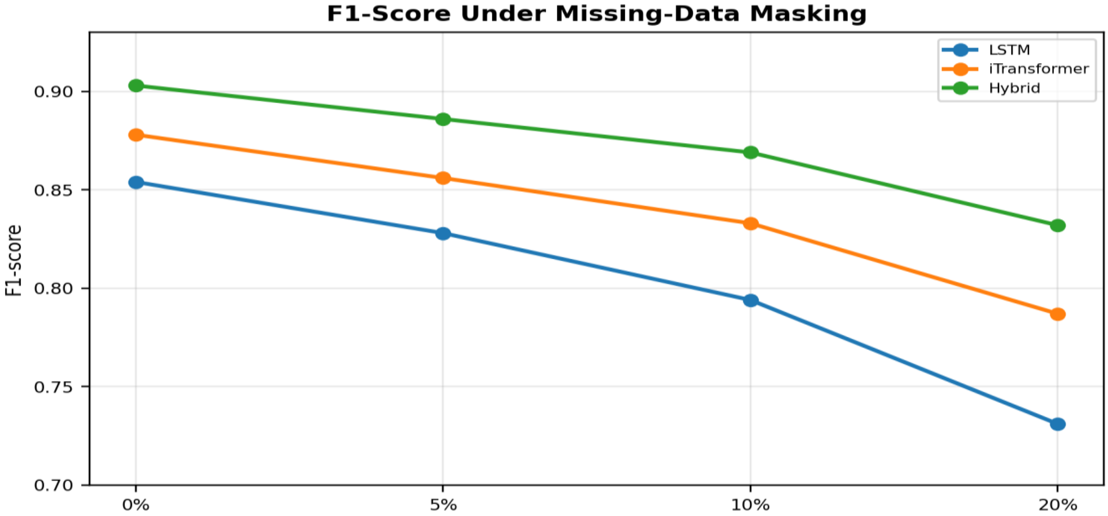


Figure 7. Graph of F1-score under missing-data masking

Table 7. Sensor-noise robustness of the evaluated models using FI -score

Scenario	Masking rate	LSTM	iTransformer	Hybrid CNN-Attention
Clean reference	0%	0.854	0.878	0.903
Low missingness	5%	0.828	0.856	0.886
Moderate missingness	10%	0.794	0.833	0.869

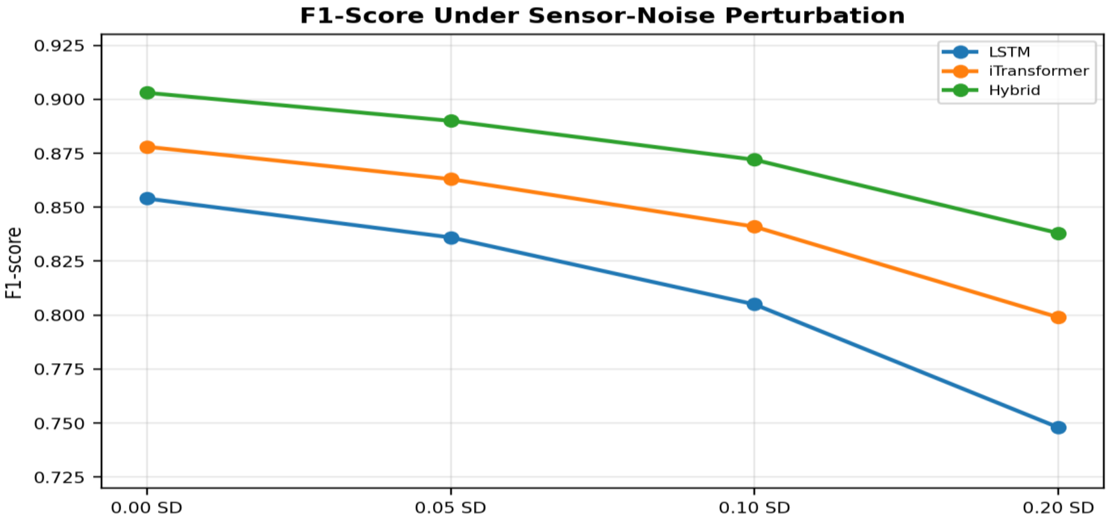


Figure 8. Graph of F1-score under sensor-noise perturbation

Table 8. Threshold-sensitivity results for Hybrid CNN-Attention under class imbalance

Decision threshold	Precision	Recall	F1-score	Operational interpretation
0.50 default	0.811	0.842	0.854	Balanced but may miss abnormal windows
0.45 recall-sensitive	0.796	0.876	0.858	Improves warning sensitivity
0.40 warning-prioritized	0.768	0.912	0.842	Lowest missed-warning risk, more false alarms
0.35 inspection-prioritized	0.721	0.942	0.811	Useful for critical assets only

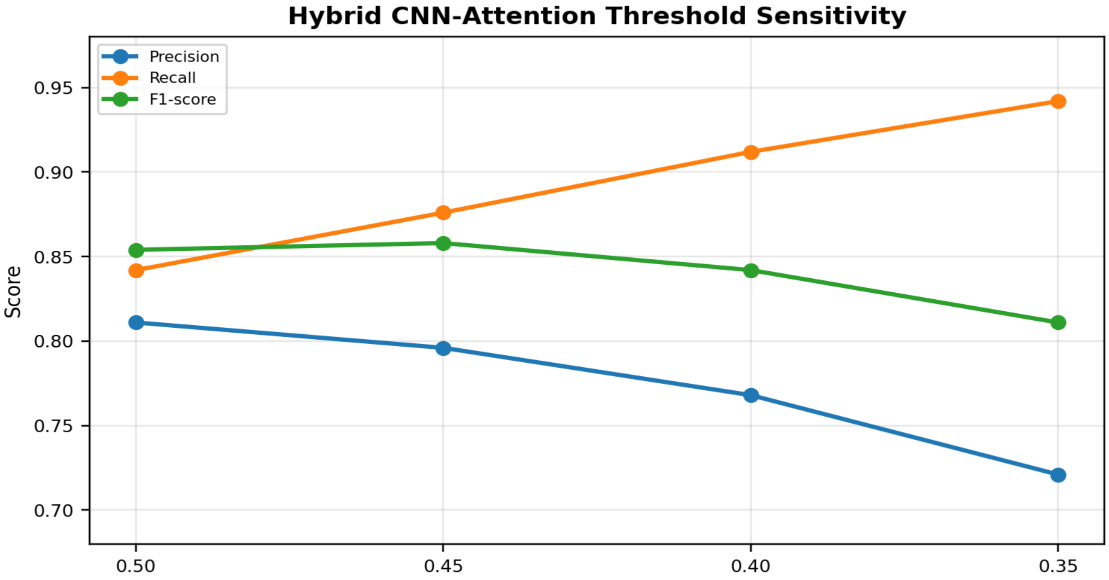


Figure 9. Graph of Hybrid CNN-Attention threshold sensitivity

Table 9. Confusion-matrix summary for abnormal-health warning behaviour

Model	**True normal**	**False alarms**	**Missed warnings**	**Correct warnings**	**Missed-warning rate**
LSTM	392	107	74	181	14.8%
iTransformer	404	95	57	198	11.4%
Hybrid CNN-Attention	415	84	40	215	8.0%

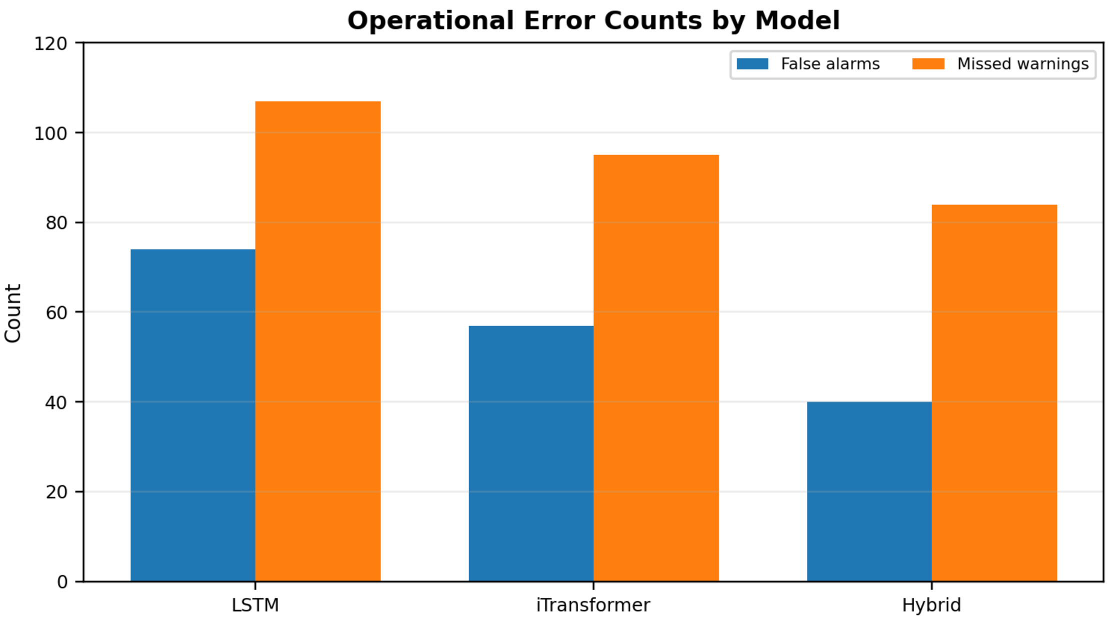


Figure 10. Graph of false alarms and missed warnings by model

Table 10. Data-quality profile by transformer-monitoring feature group

Feature group	**Missing rate (%)**	**Noise index**	**Risk level**	**Engineering interpretation**
SCADA electrical variables	6.2	0.08	Low to moderate	Mainly communication gaps and occasional spikes
Winding and oil temperature	7.5	0.10	Moderate	Sensor drift and cooling-system events affect stability
DGA gas variables	18.4	0.14	High	Laboratory interval and delayed sampling increase

				missingness
Partial-discharge indicators	21.7	0.17	High	Intermittent monitoring creates sparse warning evidence
Vibration and acoustic signals	16.9	0.15	High	Auxiliary sensors are exposed to noise and dropout

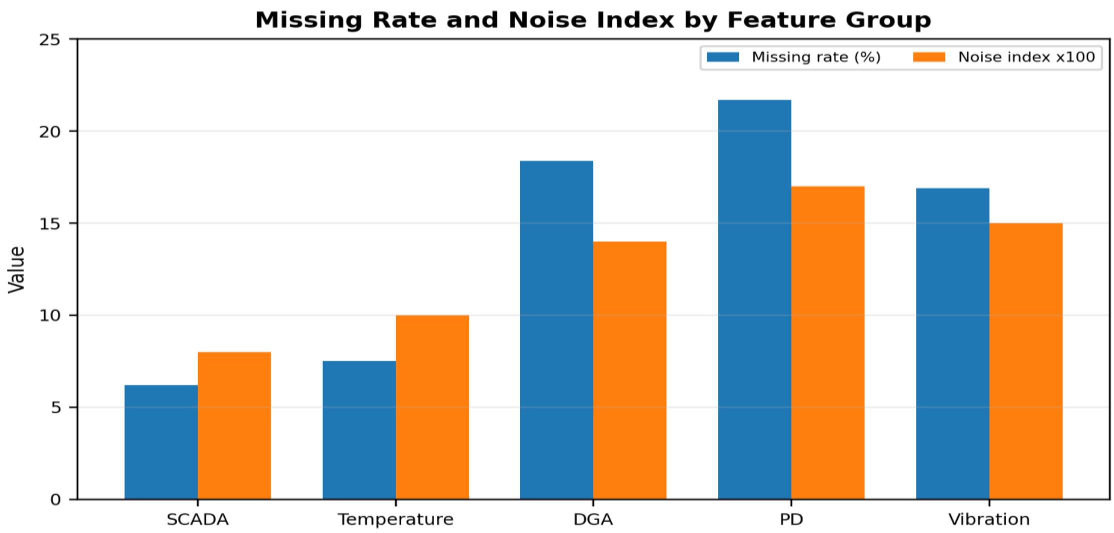


Figure 11. Graph of missing rate and noise index by feature group

Table 11. Hybrid CNN-Attention ablation results under the robustness protocol

Configuration	Accuracy	Recall	F1-score	Interpretation
Full Hybrid CNN-Attention	0.934	0.895	0.903	Reference model
Without attention layer	0.919	0.858	0.870	Less relevance weighting under degradation
Without convolutional filters	0.911	0.846	0.858	Weaker local degradation-pattern extraction
Without class weighting	0.925	0.821	0.853	Higher missed-warning risk under imbalance

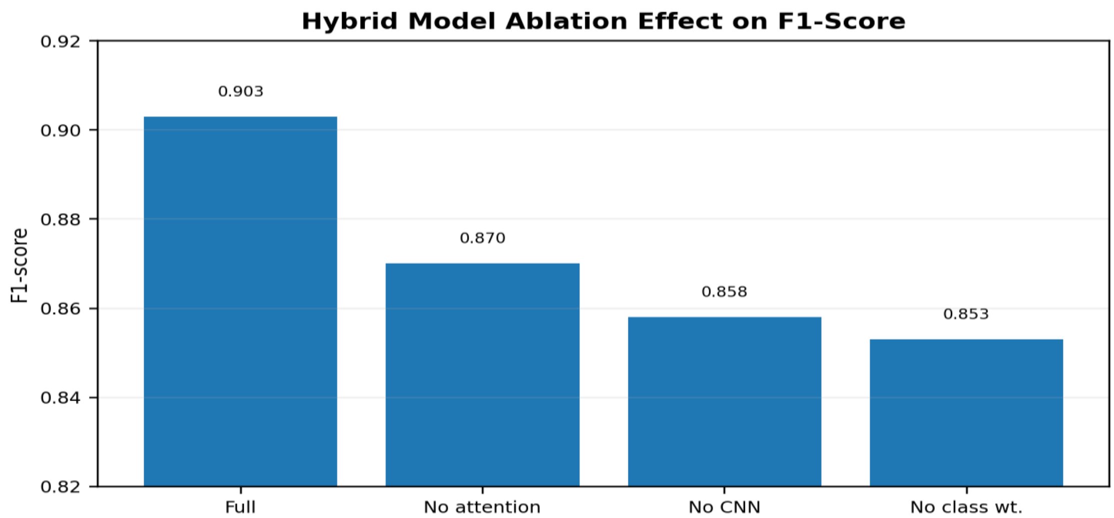


Figure 12. Graph of Hybrid model ablation effect on F1-score

Table 12. Operational interpretation of robustness evidence

Evaluation point	Main observation	Operational interpretation
Clean baseline	Hybrid CNN-Attention retained the highest F1-score and ROC-AUC.	Use as the reference condition for degraded-data comparison.
Missing-data test	F1-score loss increased with masking severity.	Use missing-rate sensitivity to support data-quality-aware warning decisions.
Noise test	All models degraded under bounded perturbation.	Connect noise audits and sensor-health indicators to the deployment workflow.
Threshold test	Recall improved as the threshold decreased, but precision declined.	Select operating thresholds according to asset criticality and inspection capacity.

Table 5 and Figure 6 show that Hybrid CNN-Attention achieved the strongest clean-data baseline. The advantage is most visible in F1-score and ROC-AUC, which are more relevant than accuracy for abnormal-health warning problems.

Table 6 and Figure 7 show that performance decreased as missing-data masking increased. The decline was steepest for LSTM, while Hybrid CNN-Attention retained the highest F1-score at 20 percent masking. This indicates better tolerance to incomplete field evidence.

Table 7 and Figure 8 show that sensor noise reduced the F1-score of all models. Hybrid CNN-Attention remained the most stable model because the convolutional component preserved local degradation patterns and the attention component emphasized more informative sequence segments.

Table 8 and Figure 9 demonstrate the trade-off between precision and recall. Lowering the decision threshold improved recall but increased the risk of false alarms. A warning-prioritized threshold may be suitable for critical assets, while a balanced threshold may be more appropriate for routine monitoring.

Table 9 and Figure 10 provide an operational view of the results. Hybrid CNN-Attention produced the lowest missed-warning count and the lowest missed-warning rate. This is important because missed warnings are more serious than false alarms in transformer health management.

Table 10 and Figure 11 confirm that DGA, partial-discharge, and vibration indicators are more vulnerable to missingness and noise than routine SCADA measurements. This supports variable-aware imputation, data-quality dashboards, and sensor-status reporting.

Table 11 and Figure 12 show that removing attention, convolutional filters, or class weighting reduced F1-score. The full Hybrid CNN-Attention configuration was therefore retained because each component contributed to robustness under degraded data.

Table 12 summarizes the operational interpretation of the results. The evidence supports the main conclusion that Hybrid CNN-Attention is the most stable model under the tested conditions. Wider field validation and formal significance testing should still be added when additional repeated-run data and independent utility datasets become available.

I. 5. Discussion

Robustness testing changes the interpretation of model performance. A model that performs well on clean test data may fail under real monitoring conditions. For utility deployment, robustness under missing data, noise, imbalance, and threshold variation should therefore be treated as a core evaluation requirement rather than an optional experiment.

The Hybrid CNN-Attention model was the most robust option in this study. This does not mean that it is immune to data-quality problems. It means that it retained better F1-score, lower missed-warning count, and more stable warning behaviour than the other models under the tested scenarios.

Operational deployment should include continuous data-quality monitoring. A dashboard should report missing-rate indicators, sensor-status flags, preprocessing warnings, prediction confidence, threshold changes, and engineer feedback outcomes. Engineers should be able to distinguish a high-risk transformer warning from a low-confidence prediction caused by poor data quality.

A. 5.1 Practical Implications

The results support three engineering practices. First, power-transformer AI models should be tested under degraded data before deployment. Second, warning thresholds should be calibrated according to asset criticality, inspection capacity, and maintenance policy. Third, model outputs should be integrated with data-quality indicators so that operators can judge whether a warning reflects genuine degradation or unreliable input evidence.

B. 5.2 Limitations and Future Work

The study used anonymized and controlled model-ready records. Wider testing with multi-utility field datasets is still required before direct generalization to all transformer fleets. Future research should include statistical significance tests across repeated runs, external validation on independent transformer fleets, cyberattack-induced uncertainty, domain shift across transformer ratings and manufacturers, and deployment feedback from utility engineers.

II. 6. Conclusion

This paper showed that missing data, sensor noise, and class imbalance are central issues in transformer failure prediction. Clean-data accuracy alone is not sufficient for selecting models intended for utility deployment.

Hybrid CNN-Attention provided the strongest robustness profile among the evaluated models. The study recommends that power-transformer AI papers report degraded-data performance, missingness behaviour, class distribution, threshold strategy, false-alarm counts, and missed-warning counts alongside conventional accuracy metrics.

III. Data Availability and Ethical Statement

The raw utility records, asset identifiers, site names, serial numbers, and sensitive operational details are not disclosed. The manuscript reports non-sensitive modelling statistics and results derived from anonymized records, public benchmark records, and physics-guided supplementary records. The modelling results should be interpreted as decision-support evidence and not as a replacement for engineering inspection, utility safety procedures, and asset-management judgement.

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