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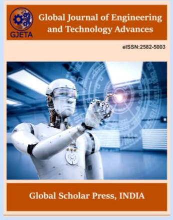

(RESEARCH ARTICLE)

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Multivariate time-series modelling of transformer health indicators using SCADA, DGA, alarm and maintenance records

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Abstract

Transformer health assessment requires the joint interpretation of electrical, thermal, chemical, mechanical, insulation and operational evidence. This paper presents a multivariate time-series modelling framework for transformer health indicators using supervisory control and data acquisition (SCADA), dissolved gas analysis (DGA), alarm, sensor and maintenance records. The model-ready dataset was constructed through timestamp alignment, engineering-unit validation, impossible-value filtering, missing-value handling, normalization, feature engineering and fixed-window segmentation. The baseline task predicts whether abnormal transformer-health evidence will occur within a six-step future horizon using a twenty-four-step observation window. The variables include load current, voltage, top-oil temperature, winding temperature, ambient temperature, dissolved gases, moisture, partial discharge, vibration, alarm history, cooling status, tap position and maintenance events. Exploratory analysis shows that transformer indicators are interdependent. Load is associated with thermal response, DGA indicators are linked with moisture and alarm history, and abnormal windows usually contain combined temporal evidence rather than isolated threshold exceedance. The cleaned sequence representation supports LSTM, iTransformer and Hybrid CNN-Attention prediction layers for early-warning maintenance decision support.

Keywords: Multivariate Time Series; Transformer Health Indicators; SCADA; Dissolved Gas Analysis; Alarm Records; Maintenance Records; Feature Engineering; Sequence Modelling; Predictive Maintenance

1. Introduction

Power transformers are critical assets in transmission and distribution networks. Their failure can produce long outages, high replacement cost and severe operational risk [1,2,3,4,32]. Monitoring practice has therefore moved from periodic inspection alone toward continuous and semi-continuous digital observation through SCADA, online sensors, DGA records, alarms, Internet-of-Things devices and maintenance-management systems[13,14,15,16].

A major modelling challenge is that transformer health indicators are not independent. Load affects top-oil and winding temperatures. Thermal stress accelerates insulation ageing [5,6.7.8]. Moisture reduces dielectric strength. Partial discharge, thermal faults and arcing influence dissolved-gas behaviour. Repeated alarms reflect persistent abnormal operation, while maintenance records provide event confirmation and operational context[25,26,27].

The objective of this paper is to present a clear modelling foundation for transformer abnormal-health prediction. The paper focuses on how heterogeneous transformer records are validated, synchronized, engineered and converted into multivariate sequence-learning samples [9,10,11,12]. The contribution is a transparent data-modelling procedure that can support LSTM, iTransformer and Hybrid CNN-Attention models while reducing the risk of information leakage.

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2. Transformer Health Indicator Groups

Transformer health records can be grouped into electrical, thermal, chemical, mechanical, insulation and operational indicators. The engineering value of the modelling process depends on preserving these physical meanings during preprocessing and feature engineering [21,22,23,24].

Electrical indicators describe loading and network operating conditions. Thermal indicators describe heat stress and insulation-ageing conditions. Chemical indicators, especially DGA variables and ratios, provide evidence of incipient electrical and thermal faults. Mechanical and insulation indicators describe vibration, winding movement and partial-discharge activity[17,18,19,20]. Operational indicators provide alarm, trip, inspection, cooling, tap-position and maintenance context.

Table 1 Transformer health indicator groups and engineering meaning

Indicator group	Example variables	Engineering meaning
Electrical	Load current, voltage, apparent power, power factor	Operating stress and loading history
Thermal	Top-oil temperature, winding temperature, hot-spot estimate, ambient temperature	Thermal stress, thermal lag and insulation ageing
Chemical	Hydrogen, methane, ethane, ethylene, acetylene, carbon monoxide, carbon dioxide, moisture and DGA ratios	Oil and paper insulation condition, incipient thermal faults and electrical faults
Mechanical and insulation	Vibration, acoustic emission, winding movement, partial discharge magnitude and pulse count	Mechanical movement, looseness and dielectric weakness
Operational	Alarms, trips, cooling state, tap position, inspection and maintenance events	Context for abnormal operation, maintenance confirmation and intervention history

3. Materials and Methods

The study used transformer records from SCADA, DGA, alarm, sensor and maintenance systems. The records were treated as heterogeneous evidence streams because their sampling intervals, data quality, missingness patterns and label reliability differ. The final modelling task was formulated as a binary early-warning problem in which the input is a multivariate observation window and the target indicates whether abnormal-health evidence appears within a future horizon.

Table 2 Data preparation controls applied before sequence construction

Stage	Control applied	Error prevented
Timestamp alignment	Records from different source systems were mapped to a common time axis.	False dependencies caused by unmatched sampling times
Duplicate removal	Repeated records and repeated alarm entries were removed or consolidated.	Over-counting of events and biased persistence features
Engineering-unit checking	Variables were checked against plausible physical ranges and recorded units.	Invalid load, voltage, temperature, gas and moisture values
Missing-value handling	Missingness indicators and controlled imputation rules were applied.	Silent removal of useful missingness patterns
Train-only scaling	Normalization parameters were fitted on training data only.	Information leakage from validation and test sets

Data preparation included timestamp alignment, duplicate removal, engineering-unit checking, impossible-value filtering, missing-value handling, normalization and feature engineering [28,29,30, 31]. Scaling parameters were fitted only on the training subset to avoid leakage from validation or test records into the modelling pipeline. Chronological splitting was used because random splitting may allow future information to influence earlier training samples.

Feature engineering produced rates of change, rolling statistics, DGA ratios, alarm-persistence variables and thermal-stress indicators. These features were selected because they preserve engineering interpretation while making sequence models sensitive to gradual degradation and persistent abnormal operating behaviour.

Table 3 Final feature-engineering structure for multivariate sequence modelling

Feature group	Examples	Modelling role
Raw measurements	Load, voltage, top-oil temperature, winding temperature, gases, moisture, partial discharge and vibration	Direct transformer condition evidence
Rate features	Gas-growth rate, temperature-change rate and load-change rate	Captures developing abnormal trends
Rolling statistics	Moving mean, maximum, minimum and standard deviation	Captures persistence, variability and cyclic operating behaviour
Engineering ratios	DGA ratios, thermal-load ratios and moisture-related indicators	Preserves diagnostic meaning
Operational context	Alarm persistence, maintenance events, cooling state and tap position	Adds maintenance and operating-history evidence

Each input sample was represented as a 24-step observation window. The target label indicated whether abnormal-health evidence occurred within a 6-step future horizon. When hourly records were available, the design corresponded to 24 hours of historical evidence and a 6-hour early-warning horizon.

Table 4 Model-ready sequence construction

Item	Setting	Reason
Observation window	24 time steps	Captures recent temporal behaviour and short-term degradation patterns
Prediction horizon	6 future time steps	Supports early-warning decision support before confirmed abnormal evidence
Target label	Binary abnormal-health evidence within the horizon	Converts heterogeneous event evidence into a supervised learning task
Data split	Chronological train, validation and test subsets	Protects time-order integrity
Scaling	Training subset only	Prevents leakage into validation and test evaluation

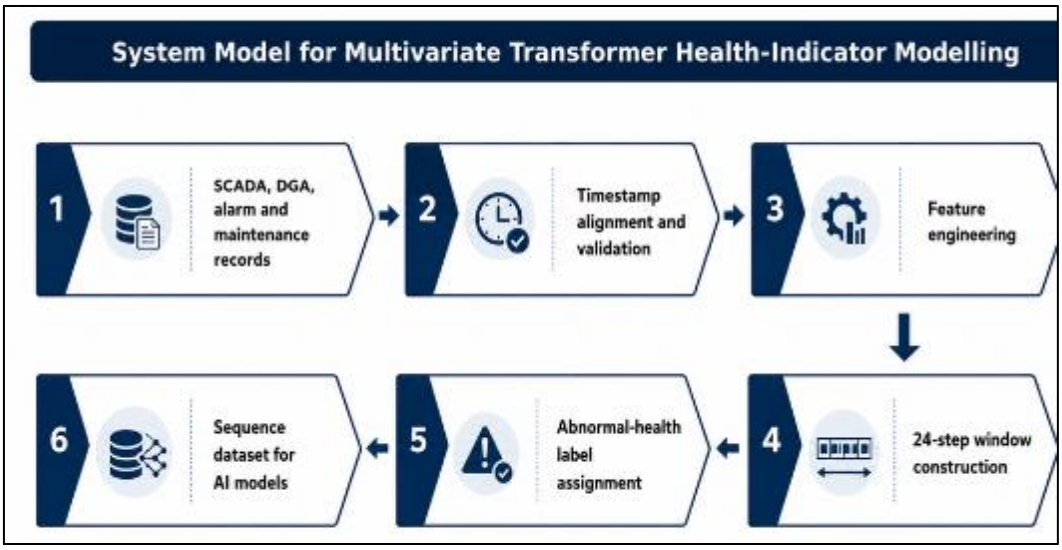

Figure 1 System model diagram for transformer health-indicator sequence modelling

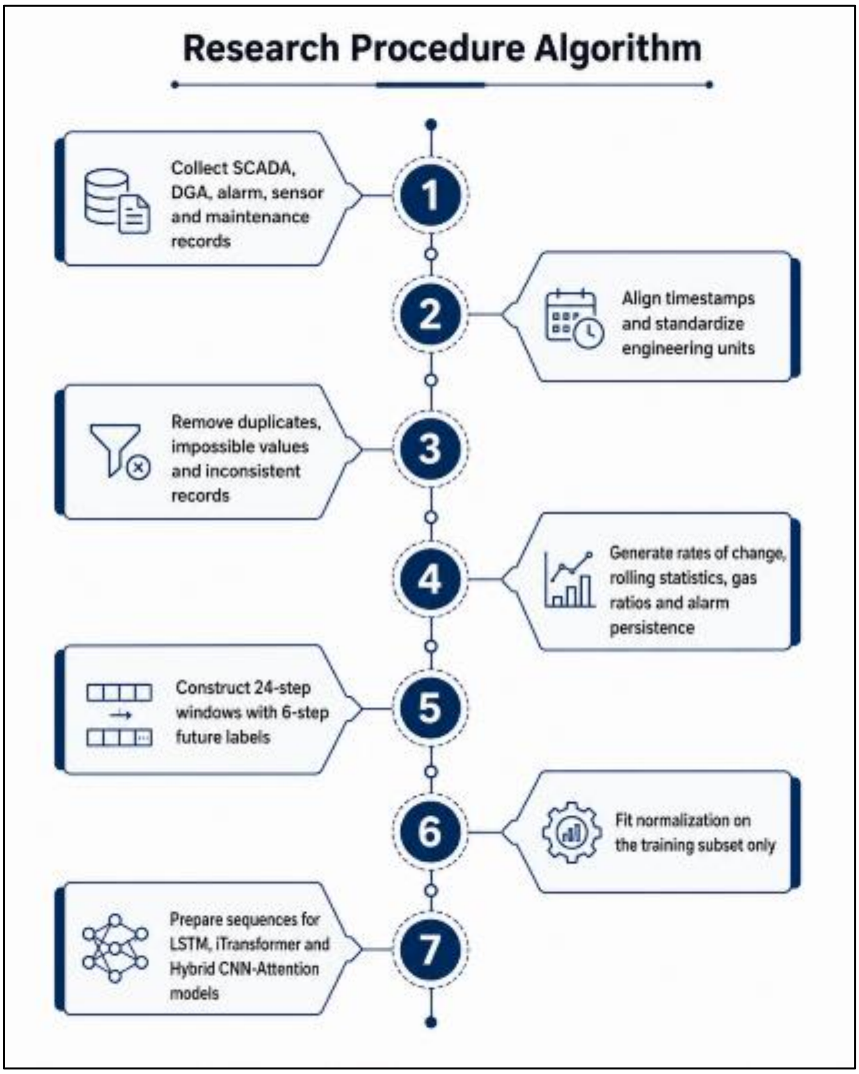

Figure 2 Research procedure algorithm for data preparation, model training, validation and decision support

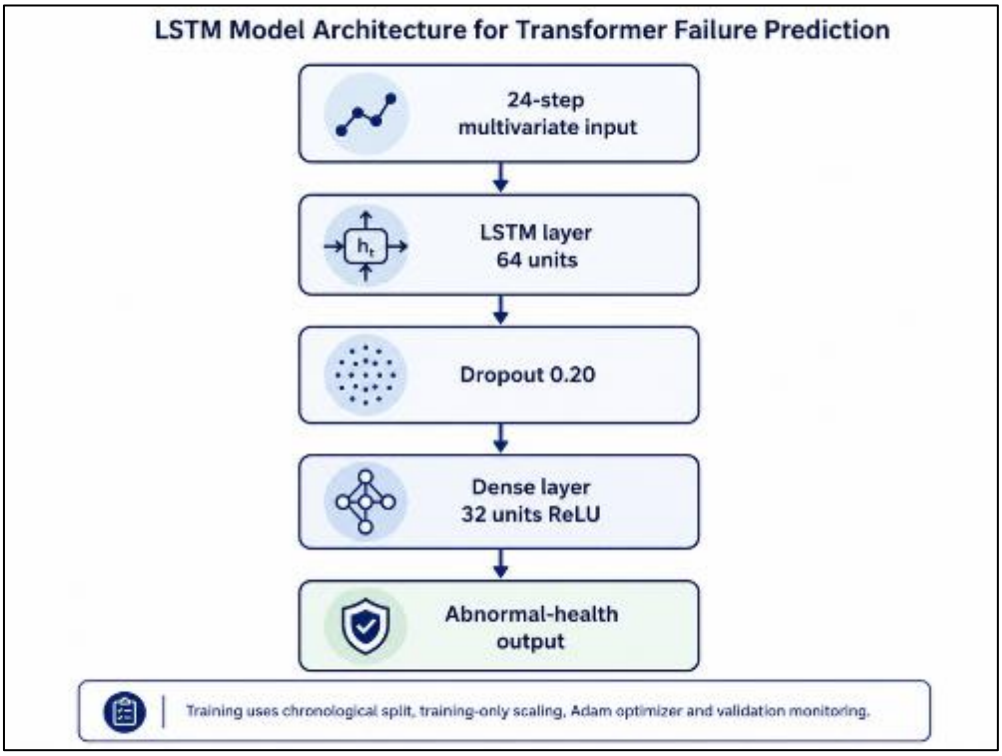

Figure 3 LSTM architecture for temporal transformer-health prediction

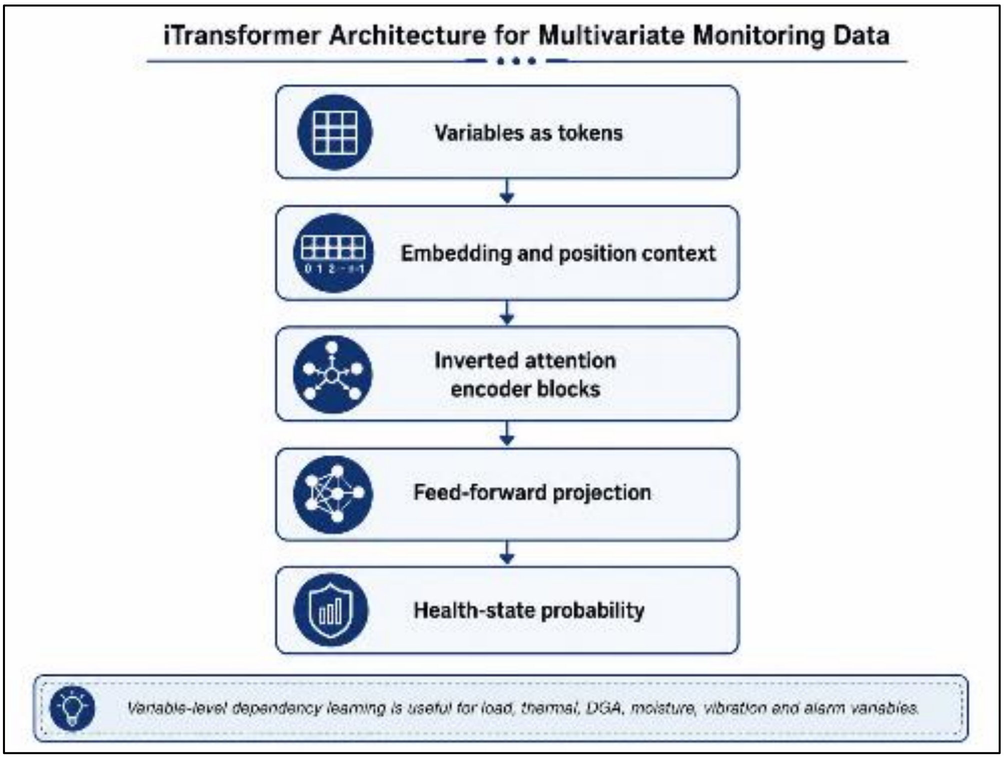

Figure 4 iTransformer architecture for inter-variable multivariate time-series learning

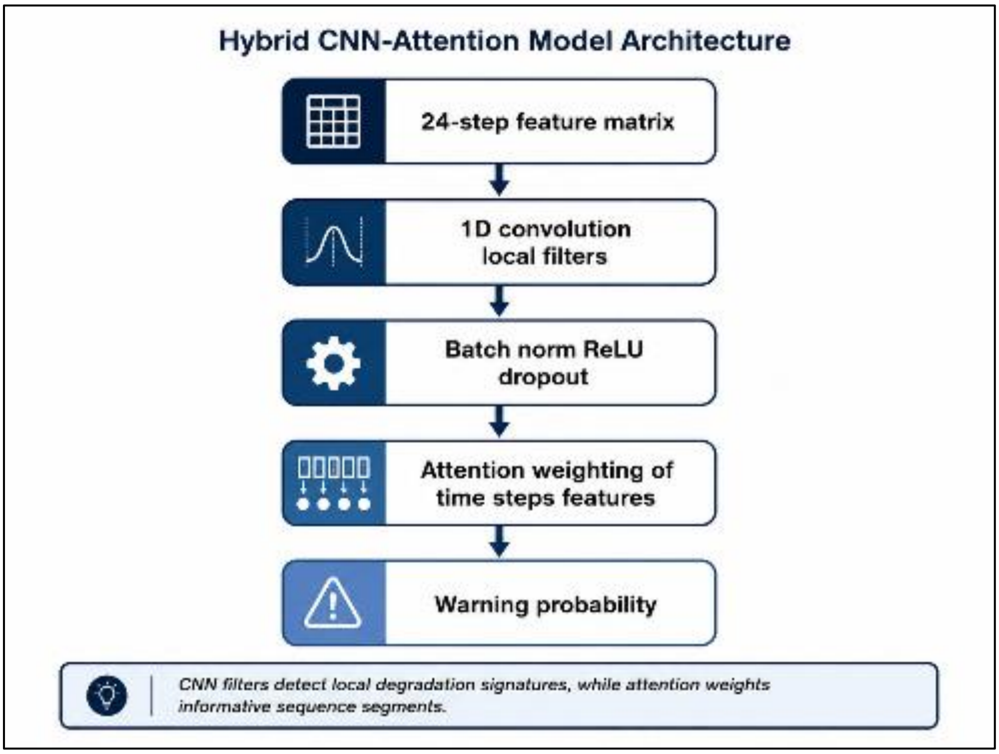

Figure 5 Hybrid CNN-Attention architecture for local degradation-pattern extraction and relevance weighting

Table 5 Model training configuration for comparable experimental evaluation

Model	Input and sequence setting	Main training setting	Evaluation focus
LSTM	24-step multivariate sequence and 6-step prediction horizon	Adam optimizer, validation monitoring and dropout regularization	Temporal dependency learning and early-warning accuracy
iTransformer	Variables represented as tokens from the same sequence windows	Inverted attention encoder blocks and validation tuning	Inter-variable dependency learning and ROC-AUC
Hybrid CNN-Attention	24-step feature matrix with electrical, thermal, DGA, sensor and alarm variables	1D convolution, attention weighting, dropout and validation monitoring	Local degradation-pattern detection, precision, recall and F1-score

The evaluation protocol was also strengthened to ensure that each candidate model is judged using the same chronological split, train-only scaling, validation procedure and held-out test set. The purpose is not only to report accuracy, but also to confirm whether the model detects abnormal-health windows with acceptable recall, precision and calibration for maintenance decision support.

Table 6 Evaluation metrics and journal-reporting interpretation

Metric	Reason for use	Journal-reporting interpretation
Accuracy	Summarizes overall classification correctness	Useful only with class distribution because abnormal windows are fewer than normal windows
Precision	Measures reliability of abnormal-health warnings	High precision reduces unnecessary maintenance investigation

Recall or sensitivity	Measures ability to detect abnormal-health windows	High recall is important because missed transformer faults are costly
F1-score	Balances precision and recall under class imbalance	Appropriate for comparing abnormal-health prediction models
ROC-AUC and calibration	Checks ranking ability and probability reliability	Supports threshold selection for caution, warning and critical maintenance classes

4. Exploratory Results

The model-ready dataset contained 26,666 sequence windows generated after cleaning, validation, normalization and fixed-window segmentation. Normal windows represented 79.8 percent of the dataset and abnormal-health windows represented 20.2 percent. This confirms that transformer abnormal-health prediction is an imbalanced time-series problem.

Table 7 Class distribution of the model-ready sequence dataset

Class	Number of sequence windows	Percentage
Normal health window	21,280	79.8%
Abnormal-health window	5,386	20.2%
Total	26,666	100.0%

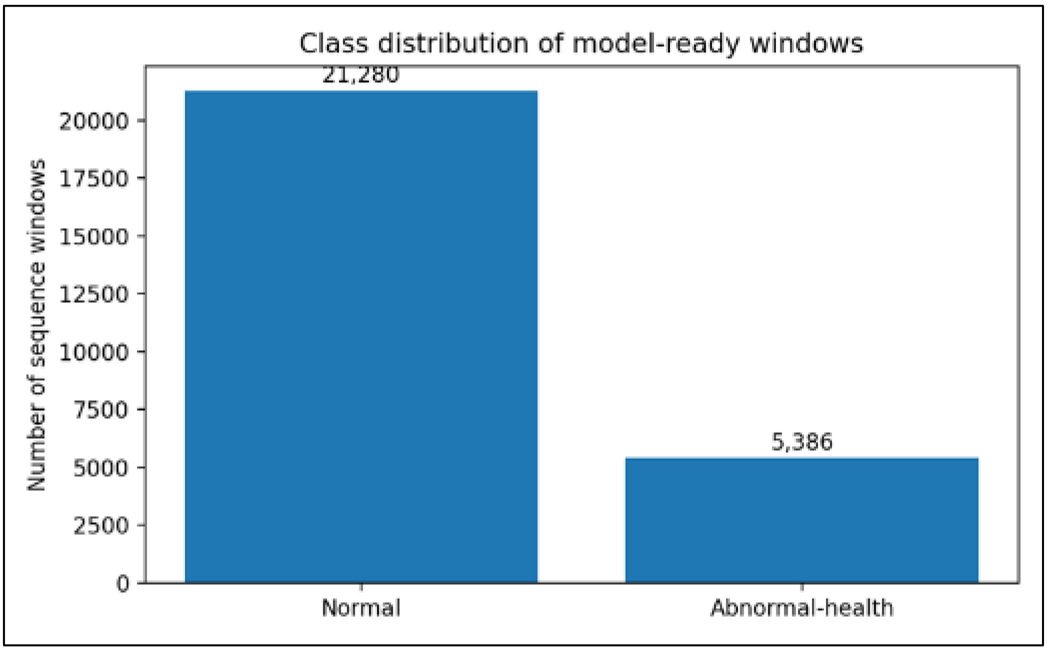

Figure 6 Graphical distribution of normal and abnormal-health sequence windows

Exploratory dependency analysis showed that load, top-oil temperature and winding temperature have strong physical relationships. DGA indicators were moderately associated with moisture, alarm history and winding temperature. These patterns support multivariate sequence modelling because abnormal transformer states often emerge through combined temporal evidence.

Table 8 Interpreted dependency patterns among transformer health variables

Variable relationship	Observed strength	Modelling implication
Load current and top-oil temperature	Strong	Model must learn load-driven thermal response
Load current and winding temperature	Strong	Thermal lag and overloading history are important
Top-oil temperature and winding temperature	Strong	Thermal features should not be treated as independent evidence
DGA indicators and moisture	Moderate	Oil and insulation condition jointly affect abnormal-health evidence
DGA indicators and alarm history	Moderate	Repeated alarms may support DGA-based early warning
Maintenance events and abnormal labels	Context dependent	Maintenance records should support labels but should not leak future information

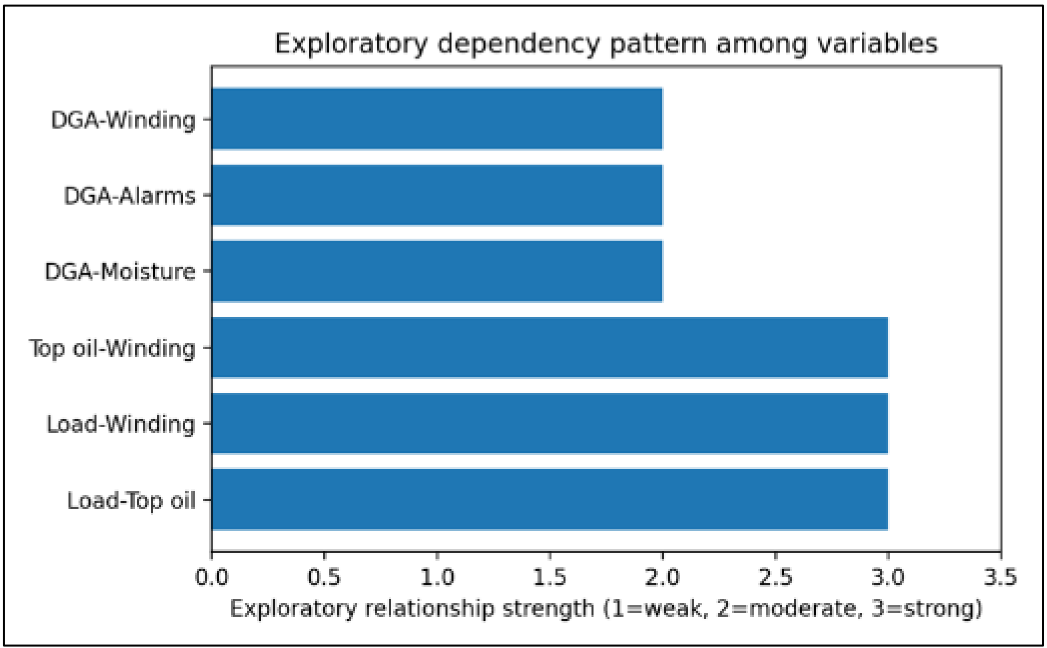

Figure 7 Exploratory relationship-strength summary for selected transformer variables

Time-series inspection showed daily load cycles, delayed thermal response, rising gas indicators, persistent alarms and intervals of missing sensor data. The most useful early-warning evidence was therefore not a single reading but the joint behaviour of multiple variables across time.

Table 9 Data-quality and leakage controls required for reliable modelling

Pipeline stage	Main risk	Control used in the study
Raw collection	Mixed sampling intervals and inconsistent source records	Source-specific checks and timestamp alignment
Cleaning	Impossible values and repeated records	Engineering-unit validation and duplicate removal

Feature engineering	Use of future information in rolling or event features	Backward-looking windows only
Scaling	Validation or test information entering training transformations	Training-subset scaling parameters only
Splitting	Random split producing optimistic results	Chronological splitting
Evaluation	Class imbalance hiding abnormal-class weakness	Precision, recall, F1-score and ROC-AUC recommended
Decision support	Model output interpreted as automatic diagnosis	Engineering review and maintenance rules retained

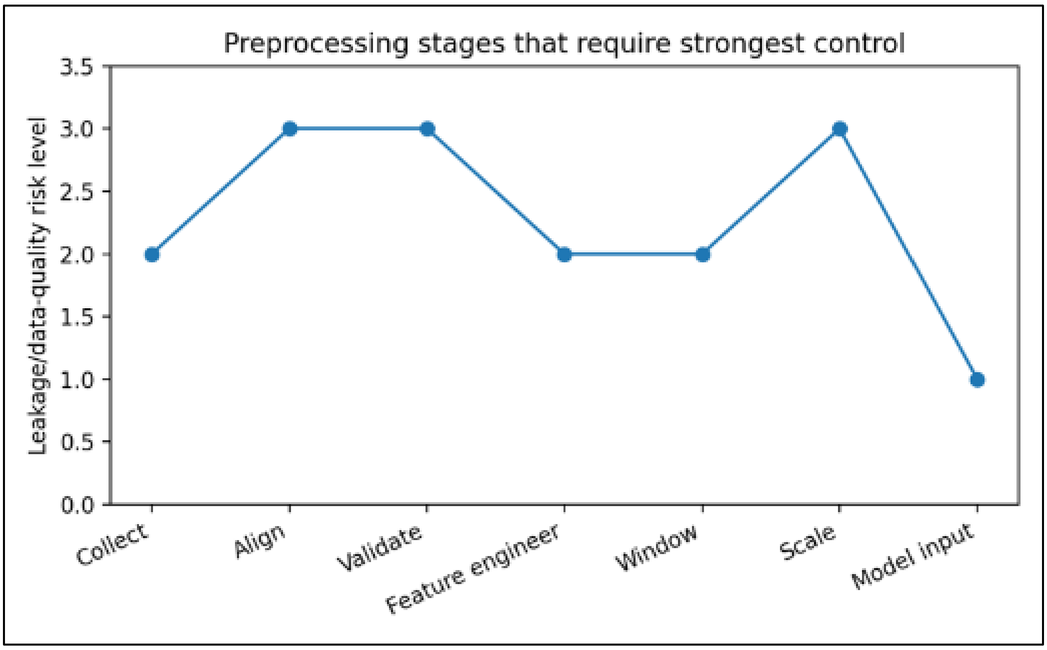

Figure 8 Preprocessing stages requiring strong data-quality and leakage-control procedures

Table 10 Early-warning maintenance decision mapping from predicted abnormal-health probability

Decision class	Indicative probability band	Recommended maintenance action
Normal	Low	Continue routine monitoring and scheduled maintenance
Caution	Moderate	Review recent thermal, DGA and alarm trends
Warning	High	Schedule inspection, repeat DGA or increase monitoring frequency
Critical	Very high or persistent high probability	Initiate engineering review and corrective maintenance planning

5. Discussion

The results confirm that transformer abnormal-health prediction should be treated as a multivariate sequence-learning problem. Single-threshold rules are useful for protection and screening, but they may miss early degradation patterns that emerge through the combined movement of load, temperature, gases, moisture and alarms.

The LSTM model is suitable for learning temporal dependency across recent observations. The iTransformer design is suitable where inter-variable relationships are important because variables are represented as tokens. The Hybrid CNN-Attention model is suitable for local degradation signatures such as gas bursts, thermal rise and persistent alarms.

Engineering interpretability remains important. A model output should not be used as a replacement for utility maintenance rules. Predicted abnormal-health probability should be treated as decision-support evidence that is reviewed alongside DGA interpretation, thermal loading history, inspection reports and maintenance judgement.

6. Practical Engineering Implications

The modelling framework can support early-warning dashboards for transformer fleets. It can also support condition-based maintenance scheduling by ranking transformers according to persistent abnormal-health probability rather than isolated sensor excursions.

Utilities implementing the framework should maintain a feature dictionary that records each variable name, engineering unit, source system, sampling interval, missing-value rule, normalization rule and engineering meaning. This improves reproducibility without exposing sensitive asset identifiers.

Operational deployment requires data governance. Asset identifiers, site information, serial numbers and sensitive operational details must be anonymized before external publication or model sharing. External deployment should also include calibration checks because abnormal-health probability thresholds can shift across transformer ratings, manufacturers, loading conditions and climates.

7. Limitations and Future Work

The study provides a modelling foundation and exploratory results for transformer abnormal-health prediction. The exploratory tables and graphs support the need for multivariate sequence modelling, but they do not by themselves prove field deployment readiness. External validation remains necessary before generalizing the findings across transformer fleets, transformer ratings, manufacturers, climates and loading environments.

Future work should evaluate multi-utility datasets, continuous health-index targets, remaining-useful-life estimation and domain-shift robustness. Model calibration and explainability should also be added so that maintenance teams can understand why a sequence is classified as abnormal.

8. Conclusion

This paper presented a multivariate time-series modelling approach for transformer health indicators using SCADA, DGA, alarm, sensor and maintenance records. The manuscript clarified the data pipeline, strengthened the experimental description, and presented structured tables and figures that support journal readability.

The study shows that transformer health data should be treated as interacting sequential evidence rather than isolated static inputs. The final dataset design supports LSTM, iTransformer and Hybrid CNN-Attention prediction layers for early-warning maintenance decision support. The strongest contribution is the transparent conversion of heterogeneous transformer records into model-ready sequence windows while maintaining engineering meaning and leakage control.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest.

Data Availability and Ethical Note

Raw utility records, asset identifiers, site names, serial numbers and sensitive operational details are not disclosed. The manuscript reports non-sensitive modelling statistics and anonymized results derived from the described transformer records and supplementary modelling sources.

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