



AI-Based Power Transformer Failure Prediction Using Iot and Machine Learning: A Review

Navale Shrutika Jalindar¹, Bangar Abhishek Popat²,

Bhosale Sachin Bajirao³, Khatri Anand A.⁴

Dept. of Computer Engineering

Jaihind College of engineering, Pune, India

Abstract. Power transformers are essential parts of electrical power systems. Any failure in these transformers can cause power interruptions, equipment damage, and increased maintenance expenses. This paper reviews selected research on transformer monitoring, fault detection, machine learning, explainable AI, and remaining useful life estimation. The reviewed studies use different techniques, including IoT sensors, dissolved gas analysis (DGA), LightGBM, SHAP, LIME, and thermal modelling. These methods help monitor transformer conditions, identify faults, estimate their severity, and study equipment ageing. Although the reported results are encouraging, a direct comparison is difficult because the studies use different datasets and evaluation methods. The review also highlights issues related to data quality, model testing, fault identification, and practical use. Finally, it suggests possible improvements for future research.

Keywords: Power transformer, failure prediction, fault diagnosis, Internet of Things, machine learning, predictive maintenance, explainable AI, remaining useful life.

I. Introduction

Power transformers are widely used in electrical networks to transfer electricity from one voltage level to another. Their proper functioning is necessary for maintaining a reliable power supply. During operation, transformers are exposed to different types of stress, including electrical, thermal, mechanical, and environmental stress. Over time, these conditions may cause overheating, insulation deterioration, winding damage, and problems related to transformer oil. If such problems are not identified at an early stage, they can lead to unexpected failures, power outages, and expensive repairs.

Traditional protection systems help protect transformers against specific electrical faults. However, condition monitoring focuses on checking the health of equipment and identifying possible problems before they become serious. IoT sensors can collect operating information such as temperature, voltage, and current. Machine learning techniques can analyse this information and identify unusual patterns. Explainable AI methods can also help engineers understand the reasons behind the predictions made by a model.

This review discusses selected research papers based on their objectives, data sources, techniques, results, and limitations. It covers IoT-based monitoring, machine learning for fault diagnosis, explainable AI, and transformer ageing. It also explains



the difference between detecting an existing fault, identifying a fault category, predicting future failures, and estimating the remaining useful life of a transformer.

II. Review Methodology

This paper reviews the selected research publications provided for the study. Each paper was examined to understand its main purpose, the data or sensors used, the methods applied, the results obtained, and the limitations identified. The review mainly covers IoT-based transformer monitoring, machine learning techniques for fault diagnosis, explainable AI, and methods used to study transformer ageing and remaining useful life.

The review is based on the supplied research papers and does not cover every publication available on the topic. Four main questions guide the analysis: (1) What types of measurements and machine learning methods are used in the studies? (2) What results or predictions do the proposed methods provide? (3) What evidence is presented to support the reported results? (4) What problems remain and what improvements can be made in future research?

III. Literature Review

1. IoT-Based Transformer Monitoring and Fault Reporting

Nkinyam, Encho, and Mbaka [1] presented a monitoring system designed for a 100 kVA distribution transformer. The system uses sensors, a microcontroller, data storage, GSM-based SMS notifications, and the ThingSpeak IoT platform. It monitors transformer operating conditions and provides alerts for problems such as overloading, phase loss, and neutral-related faults. According to the authors, the measurements obtained from the system showed a Pearson correlation coefficient above 0.96 when compared with readings from conventional instruments. This study demonstrates how sensors and communication technologies can be used to monitor transformer conditions and send alerts remotely. However, the similarity between sensor readings and conventional instrument readings does not prove that a system can accurately predict future transformer failures. Further testing should examine sensor accuracy, alert response time, detection of uncommon faults, and the amount of warning provided before a failure occurs.

2. SHAP Feature Selection and Optimised LightGBM for DGA Diagnosis

Liu and Yang [2] developed a transformer fault-diagnosis method using dissolved gas analysis (DGA). Their approach applies SHAP to determine which gas-related features have a greater influence on the results. They also use the Bald Eagle Search optimisation algorithm to adjust the parameters of the LightGBM model. The study reports a test accuracy of 0.9509 and an F1-score of 0.9606, with 11 samples classified incorrectly. The study combines feature analysis with model optimisation to improve fault diagnosis. However, the results depend on the dataset, the distribution of fault categories, and the way the model is tested. Future studies should include a confusion matrix, precision and recall for each fault category, and clear details about the dataset and test procedure. Classifying faults from DGA measurements is different from predicting when a transformer will fail. Failure-time prediction requires suitable data showing how the equipment condition changes over time.

3. Multi-Grained Fault Diagnosis Using Enhanced DGA Features

Meng and co-authors [3] proposed a fault-diagnosis method that uses improved DGA features to examine transformer faults at different levels. The method identifies general conditions such as normal operation, overheating, and electrical discharge. It also examines different levels of fault severity. Gas concentration ratios are used to identify the fault category, while changes in gas concentrations are considered when estimating severity. The authors report better results than several existing machine



learning methods when tested on real-world datasets. An important feature of this approach is that it treats fault identification and fault severity estimation as separate tasks. This can provide more detailed information about transformer conditions. However, the results depend on the quality of gas measurements and the accuracy of the fault labels. The method cannot be directly compared with monitoring systems that use measurements such as temperature, voltage, and current because the input data and prediction targets are different.

4. IoT Monitoring with LightGBM, SHAP, and LIME

Aslan and co-authors [4] introduced a transformer monitoring approach that combines IoT measurements with LightGBM, GridSearch for parameter tuning, and SHAP and LIME for explaining model predictions. The dataset contains 19,352 observations collected at 15-minute intervals between 25 June 2019 and 14 April 2020. The recorded information includes phase voltages and currents, line-to-line voltages, neutral current, oil temperature, winding temperature, ambient temperature, oil level, and binary alarm signals. The authors report an accuracy of 99.91% and evaluate the model using accuracy, recall, and F1-score. This study is relevant to transformer condition monitoring because it combines operating measurements, machine learning, and methods for explaining predictions. However, high accuracy alone does not show how well the model identifies less frequent failures. Further evaluation should include a confusion matrix and precision and recall for the failure category. The data should also be divided carefully, preferably using chronological or transformer-wise testing, to reduce the risk of data leakage. Additional testing on different transformers and operating conditions would help determine whether the method performs consistently in practical situations.

5. TransformerSense: Sensor-Based Fault Analytics

The supplied TransformerSense paper [5] describes a transformer monitoring system that uses temperature, voltage, current, and oil-level sensors. The collected information is transmitted wirelessly and analysed to identify possible faults and generate warnings. The prototype shown in the paper includes an Arduino Uno, sensors, an LCD, and a Wi-Fi communication module. The main purpose of the system is to detect abnormal conditions early and support condition-based maintenance. This study provides a useful starting point for developing an affordable transformer monitoring prototype. However, the supplied document does not clearly present a complete evaluation of its machine learning model. Details such as the final algorithm, dataset size, class-wise performance, training and testing procedure, and prediction lead time are not clearly established. Claims about improved fault detection and reduced outages should therefore be supported by measurable results. The complete author list and publication details should also be checked against the original paper before submission.

6. Remaining Useful Life Estimation Using Thermal Modeling

Achour and co-authors [6] proposed an approach for studying transformer temperature and insulation ageing by combining thermal simulation with data-driven techniques. Their method uses a three-dimensional computational fluid dynamics model, a simplified model based on sparse Proper Generalized Decomposition, and techniques such as Neural Ordinary Differential Equations and Sparse Identification of Nonlinear Dynamics. The estimated hotspot temperature is used to study insulation ageing and remaining useful life (RUL). The authors report that their simplified model can calculate hotspot temperatures for a 50-year simulation in less than two seconds. Unlike methods that focus mainly on identifying existing faults, this study examines transformer ageing and estimates its remaining useful life. The reliability of the results depends on the assumptions used in the thermal model and the accuracy of the input data. The paper states that no datasets were generated or analyzed. Therefore, the reported results should not be considered sufficient proof of performance across transformers operating under real-world conditions. Implementing the complete thermal simulation may also be challenging for a student research project because of its technical complexity.



7. AI Application in Power – Electronic Systems

Zhao, Blaabjerg, and Wang [7] reviewed the use of artificial intelligence in power-electronic system design, control, and maintenance. Their review discusses different applications, including optimisation, classification, regression, and the analysis of data patterns. It also covers several techniques, such as expert systems, fuzzy logic, metaheuristic optimisation, and machine learning. This paper provides general information about the use of AI in electrical and power-electronic systems. It also helps explain the challenges associated with data quality, model interpretation, and practical implementation. However, its scope is broader than transformer failure prediction. Therefore, its findings should be used as background information rather than as a direct comparison with models developed specifically for transformer fault diagnosis. The study supports the importance of considering reliability, interpretability, and maintenance requirements alongside model performance.

IV. Comparative Analysis

Table 1. Comparative Analysis of Existing Research on Transformer Health Monitoring and Fault Diagnosis

Study	Input / approach	Main output	Key limitation
Nkinyam et al. [1]	Sensors, microcontroller, GSM, ThingSpeak	Monitoring and fault alerts	Sensor agreement is not ML prediction accuracy
Liu and Yang [2]	DGA, SHAP, optimised LightGBM	Fault classification	Needs clear class-wise and independent testing
Meng et al. [3]	Enhanced DGA features, multi-grained learning	Fault category and severity	Depends on reliable DGA labels
Aslan et al. [4]	IoT operational data, LightGBM, SHAP/LIME	Failure prediction/classification	High accuracy needs careful validation
TransformerSense [5]	Sensors, Arduino, Wi-Fi, ML framework	Monitoring and warning	Reproducible ML metrics not clear in supplied text
Achour et al. [6]	Thermal model, sPGD, Neural ODE, SINDy	Hotspot, ageing, RUL analysis	Complex model and limited field validation evidence

V. Research Gaps

The review of the selected research papers highlights several areas that need further improvement.

- Some studies discuss different prediction tasks together. Fault detection, fault classification, future failure prediction, and remaining useful life estimation should be treated as separate tasks.
- High accuracy does not always mean that a model can correctly identify rare transformer failures. Other evaluation measures, such as confusion matrix, precision, recall, F1-score, and PR-AUC, should also be considered.



- Dividing time-series data randomly may lead to data leakage, especially when readings collected close to each other are placed in both training and testing sets. Using time-based or transformer-wise data splitting can provide a more reliable evaluation.
- A model tested on one dataset or prototype may not perform equally well under different conditions. Factors such as transformer capacity, weather, load, sensor accuracy, and maintenance practices can affect its performance.
- Missing readings, changes in sensor performance, communication failures, and irregular data collection can reduce the reliability of a monitoring system. These issues should be considered during model development and testing.
- Methods such as SHAP and LIME help explain how a model produces its results. However, they cannot confirm that a particular feature is the actual cause of a transformer failure.
- The practical performance of a system depends on more than its accuracy. False alarms, undetected failures, alert delays, and the time available to take preventive action should also be evaluated.

VI. Proposed Improvements

For a student research project, it is better to select a specific prediction task and use a dataset that contains suitable information for that task. The following improvements are suggested for future development and testing.

- Define the prediction objective: Select a clear target, such as identifying normal and abnormal conditions, classifying transformer faults, or estimating the risk of failure within a specified time period.
- Understand the dataset: Record details such as the data source, number of samples, input features, data collection interval, distribution of fault classes, missing values, and the method used to assign labels.
- Test different machine learning models: Start with a basic model and compare its performance with suitable algorithms such as Decision Tree, Random Forest, or LightGBM.
- Use a proper testing method: Divide the data according to time or transformer units wherever possible. Data preparation and preprocessing should be performed using the training set to avoid information leakage.
- Evaluate model performance: Use a confusion matrix, precision, recall, F1-score, and accuracy to understand the model's performance. PR-AUC can also be used when the dataset contains an unequal number of samples across classes.
- Explain the predictions: Apply SHAP or another suitable explainable AI technique to understand which features influence the model's output. Feature importance should not be treated as proof of a direct cause of failure.
- Test the IoT system separately: If a hardware prototype is developed, check sensor accuracy, communication reliability, missing readings, alert response time, and machine learning performance individually.

VII. Proposed System Workflow

The proposed system aims to monitor transformer operating conditions and identify possible faults using sensor data and machine learning techniques. The workflow consists of the following steps:

- Data Collection: Operating parameters such as voltage, current, temperature, and oil level are collected using sensors or an available transformer dataset.
- Data Preprocessing: The collected data is checked for missing values, incorrect readings, and unnecessary information. The data is then prepared for analysis.
- Feature Selection: Important parameters that may indicate changes in transformer health are selected for further analysis.
- Machine Learning Model: The processed data is provided to a suitable machine learning algorithm, such as Random Forest or LightGBM, to identify abnormal operating conditions or classify possible faults.

- **Fault Prediction:** The trained model analyses the input data and classifies the transformer condition according to the selected prediction target.
- **Result Explanation:** Explainable AI techniques, such as SHAP, can be used to identify which input parameters influenced the model's prediction.
- **Alert Generation:** If the system detects an abnormal condition, it can generate a warning to inform the operator so that further inspection can be carried out.
- **Performance Evaluation:** The model is evaluated using measures such as accuracy, precision, recall, F1-score, and a confusion matrix to assess its performance.

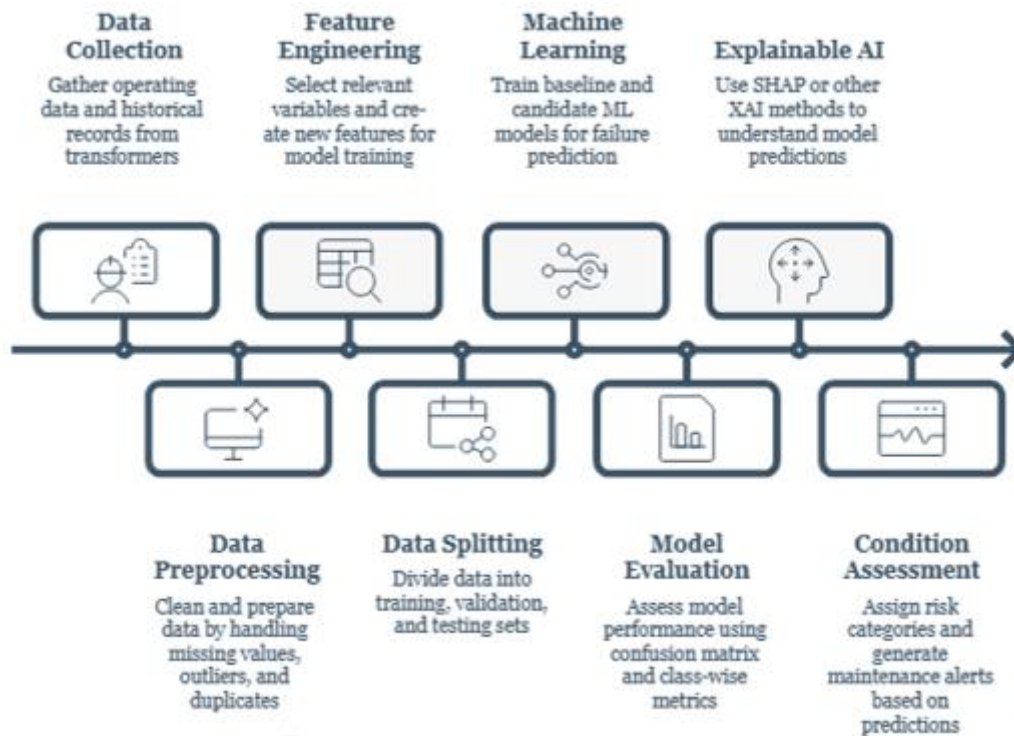


Fig. 1 presents a proposed conceptual architecture derived from the reviewed literature; it has not been implemented or validated.

The proposed workflow combines transformer monitoring, data analysis, machine learning, and result interpretation to support early fault identification and condition-based maintenance.

VIII. Conclusion

The research papers discussed in this review focus on different methods for monitoring transformer health and identifying possible faults. These methods include IoT-based monitoring, dissolved gas analysis, machine learning, explainable AI, fault severity analysis, and thermal modelling for studying transformer ageing and remaining useful life. Each approach has its own



purpose, data requirements, and evaluation methods. Therefore, the results reported in these studies cannot be compared directly.

For future student projects, it is important to select a clear research objective, use a proper testing method, and evaluate the model using suitable performance measures. Understanding the reasons behind model predictions and checking how the system performs under practical conditions are also important. Overall, the effectiveness of a transformer monitoring system should be judged by its actual test results rather than by expected improvements alone.

References

1. C. M. Nkinyam, L. T. Encho, and N. E. Mbaka, "Design and implementation of a 100 kVA transformer monitoring and fault detection system for distribution network," *Journal of Electrical Systems and Information Technology*, vol. 12,
2. C. Liu and W. Yang, "Transformer fault diagnosis using machine learning: a method combining SHAP feature selection and intelligent optimization of LGBM," *Energy Informatics*, vol. 8, article 52, 2025, doi: 10.1186/s42162-025-00519-3.
3. C. Meng, D. Fan, M. Wu, T. Yu, B. Xue, and Y. Lu, "Multi-grained power transformer fault diagnosis based on enhanced features of dissolved gas," *Applied Intelligence*, vol. 56, article 396, 2026, doi: 10.1007/s10489-026-07424-6.
4. E. Aslan et al., "A hybrid machine learning approach for predicting power transformer failures using Internet of Things-based monitoring and explainable artificial intelligence," *IEEE Access*, 2025, doi: 10.1109/ACCESS.2025.3583773.
5. "TransformerSense: An Intelligent Fault Analytics Framework for Predictive Protection of Power Transformers," *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, vol. 14, issue VI, June 2026, doi: 10.22214/ijraset.2026.83781. Verify the full author list and bibliographic details against the original publication.
6. L. Achour et al., "Remaining useful life of power transformers using efficient surrogates and deep learning techniques," *Advanced Modeling and Simulation in Engineering Sciences*, vol. 13, article 9, 2026, doi: 10.1186/s40323-026-00329-6.
7. S. Zhao, F. Blaabjerg, and H. Wang, "An overview of artificial intelligence applications for power electronics," *IEEE Transactions on Power Electronics*, vol. 36, no. 4, pp. 4633–4658, 2021, doi: 10.1109/TPEL.2020.3024914.