Proceedings of CONF-SPML 2027 Symposium: Intelligent Network Security and Machine Learning for Communication Systems
DOI: 10.54254/2755-2721/2027.MELB39062

Review of Research on Operating Condition Monitoring and Fault Early Warning of Electrical Equipment Based on Machine Learning

Yuchen Zhu

School of Electrical and Automation Engineering, Nanjing Normal University, Nanjing, China
1428164934@qq.com

Abstract. In constructing the new type of power system, the installed capacity of various electrical equipment such as transformers, motors, distribution terminals, and switchgears keeps expanding. Challenges including variable operating conditions of equipment, scarce early-fault samples, and heterogeneous mixed multi-source monitoring data have become increasingly prominent. Traditional manual inspection and fixed-threshold early-warning modes can hardly realize advance identification and accurate localization of minor faults. Boasting advantages such as powerful nonlinear fitting, autonomous feature extraction, and small-sample adaptability, machine learning has become a core technical approach for intelligent monitoring and early fault warning of electrical equipment. Based on 17 relevant literatures, this paper systematically sorts out existing research achievements from five dimensions: data preprocessing, feature engineering, diagnosis and early-warning models, lightweight deployment, and engineering application. It compares applicable scenarios and performance of Random Forest, Support Vector Machine, LSTM, CNN, Dynamic Graph Convolutional Neural Network (DGCNN), lightweight MobileNet, and intelligent optimization ensemble algorithms. This paper summarizes key bottlenecks: insufficient generalization ability under small-sample conditions, low fusion degree of multimodal data, edge-end deployment constraints and poor model interpretability. Combined with digital twin and edge computing, this paper prospects future research directions, providing theoretical and technical support for constructing a full-lifecycle intelligent operation-maintenance system of electrical equipment.

Keywords: Machine learning, electrical equipment, condition monitoring, fault early warning, edge computing

1. Introduction

The safe and stable operation of power systems relies heavily on core electrical equipment. User-side electrical faults account for 43.1% of total grid faults, and motor mechanical faults occupy 61.5% of motor-related faults, bringing heavy operation-maintenance pressure [1, 2]. Traditional manual inspection and fixed threshold alarms are vulnerable to seasons, loads, and equipment aging, leading to 15%-20% fault false alarm rate and an 8.2% missing detection rate for internal hidden

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2755-2721/2027.MELB39062

defects, such methods can only capture obvious faults instead of incipient anomalies like insulation deterioration [3]. Benefiting from intelligent sensing and distribution IoT technologies, multi-source monitoring data, including vibration, oil chromatography, infrared images, and electrical parameters, can be collected synchronously. Nevertheless, scarce fault samples, category imbalance and feature redundancy restrict traditional statistical analysis methods [4, 5]. Machine learning automatically mines multi-dimensional fault features from time-series, image, and structured data, improving fault identification accuracy and early-warning timeliness [6, 7]. Domestic and foreign scholars have carried out extensive research. Hybrid DGCNN-MobileNet models are proposed for small-sample fault diagnosis, ISMOTE combined with optimized Random Forest solves transformer imbalanced-sample problems, CNN-LSTM hybrid models realize time-series fault feature mining, digital-twin simulation and lightweight model compression strategies support model engineering verification and edge-side deployment [4, 5, 8-10]. Still, existing models suffer poor small-sample generalization, insufficient multi-modal data fusion, high network computation cost, and black-box interpretability defects [5, 8, 10].

This paper reviews the whole technical workflow of machine-learning-based equipment monitoring, compares mainstream models, summarizes bottlenecks, and proposes future research trends.

2. Preprocessing and feature engineering of electrical monitoring data

Field-collected electrical data usually contains missing values, outliers, dimension inconsistency, and fault-sample imbalance. Data preprocessing and feature engineering are critical prerequisites for machine-learning model performance [2, 9, 11].

2.1. Cleaning of abnormal and missing data

Sensor failures and transient equipment disturbances produce missing values and outliers. Common industrial processing approaches contain the 3σ criterion, box-plot anomaly elimination, linear interpolation, and sliding-window smoothing [2, 11]. Min-Max normalization eliminates dimension difference, whose formula is:

$$x^{*}=\frac{x-x_{min}}{x_{max}-x_{min}} \tag{1}$$

where x is the original monitoring parameter, x_{max} and x_{min} denote feature maximum and minimum, x^{*} is normalized feature vector [12]. Wang adopted this normalization for current and temperature preprocessing to obtain standardized model inputs [11].

2.2. Imbalanced-sample enhancement algorithm

Transformer oil chromatography faults and motor-bearing wear produce severely skewed sample distribution, with far fewer fault samples than normal samples, which biases model training toward majority classes. Traditional SMOTE generates samples via simple linear interpolation without distinguishing boundary samples. Zhao proposed an improved ISMOTE algorithm, introducing a neighborhood boundary index B_i and an information-entropy index H_i to build a composite index for screening key minority samples [9].

DOI: 10.54254/2755-2721/2027.MELB39062

$$C_i=\alpha\cdot B_i+\beta\cdot H_i \tag{2}$$

$$H_i=-\sum_{e\in\{M,m\}} p(c|x_i)\cdot\log p(c|x_i) \tag{3}$$

where α, β are equilibrium weights, B_i represents heterogeneous sample proportion within local neighborhood, H_i characterizes category mixing degree, and M and m correspond to majority and minority samples. This algorithm only interpolates boundary high-mixed fault samples to avoid invalid synthetic samples. After ISMOTE enhancement, the transformer dataset achieves a balanced sample quantity for each fault category [9].

2.3. Construction and screening of high-dimensional features

Oil-chromatography gas ratios and multi-channel vibration signals generate high-dimensional redundant features, raising computation burden and triggering overfitting [9, 11]. Correlation coefficient and gradient-boosting feature importance ranking are widely applied for feature screening. The correlation-coefficient formula reads:

$$r=\frac{\mathrm{cov}(X,Y)}{\mathrm{std}(X)\cdot\mathrm{std}(Y)} \tag{4}$$

where $\mathrm{cov}(X,Y)$ means covariance between features and fault labels, $\mathrm{std}(\cdot)$ denotes standard deviation. Larger absolute r represents stronger feature-fault correlation [11]. According to experiments on 32-dimensional oil-chromatography candidate features, selecting the top 16 features obtains the highest diagnosis accuracy of 91.92%, extra redundant features degrade model performance [9, 11].

3. Mainstream machine-learning models for fault monitoring and early warning

Existing machine-learning models fall into three categories: traditional ensemble-learning models, deep-neural-network models and intelligent-optimization hybrid models [4, 8, 9, 12].

3.1. Traditional ensemble machine-learning models

3.1.1. Random Forest (RF)

Random Forest adopts a Bagging strategy, training multiple decision trees in parallel and outputting classification results by majority voting. Its prediction formula is:

$$\hat{y}=\frac{1}{n}\sum_{i=1}^{n} f_i(x) \tag{5}$$

where n is number of decision trees, $f_i(x)$ denotes prediction output of single tree, $\hat{y}$ is final fault category [12].

DOI: 10.54254/2755-2721/2027.MELB39062

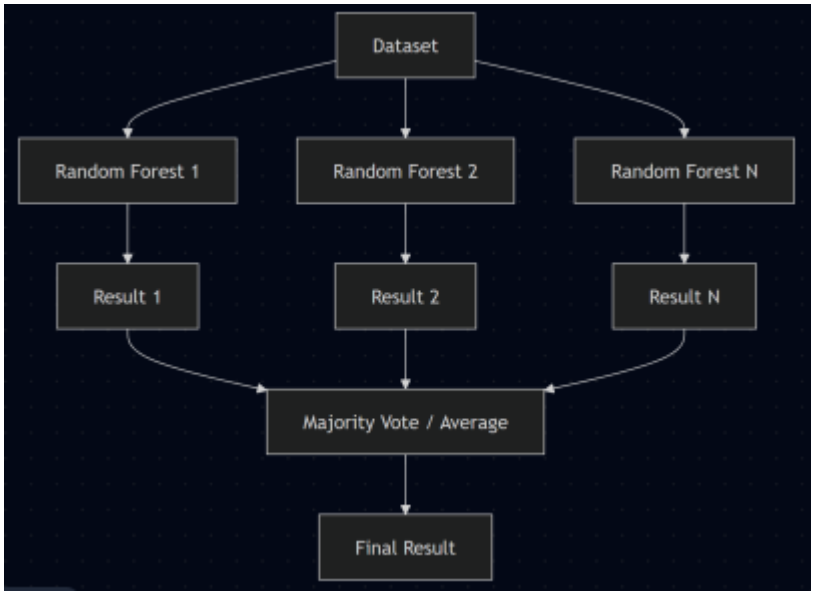


Figure 1. Network structure of Random Forest [12]

The network structure of Random Forest is shown in Figure 1. RF exhibits strong anti-noise capacity and adapts to structured tabular data such as oil-chromatography data. However, its hyperparameters rely on manual tuning and tend to local optima [6, 12]. ICPO optimization can realize automatic hyper-parameter searching for RF to boost overall performance [9].

3.1.2. Support vector machine (SVM)

SVM maps low-dimensional fault features into high-dimensional space by kernel functions to construct optimal hyperplanes. It performs well under small-sample scenarios for early weak motor-fault identification, yet shows limited performance for multi-classification and large-scale datasets [6, 7]. SVM fits simple linearly-separable faults, while its performance degrades for complex multi-modal faults [6].

3.2. Deep-neural-network diagnosis models

3.2.1. LSTM and time-series hybrid CNN-LSTM

Electrical equipment temperature, vibration, and load are continuous time-series data. LSTM exploits a three-gate mechanism to solve RNN gradient vanishing and capture long-term degradation rules. Core formulas for the LSTM unit are:

$$f_t=\sigma(W_f[h_{t-1},x_t]+b_f) \tag{6}$$

$$i_t=\sigma(W_i[h_{t-1},x_t]),\ \tilde{c}_t=\tanh(W_c[h_{t-1},x_t]) \tag{7}$$

DOI: 10.54254/2755-2721/2027.MELB39062

$$c_t=f_t\odot c_{t-1}+i_t\odot\tilde{c}_t,\ h_t=o_t\odot\tanh(c_t) \tag{8}$$

where f_t, i_t, o_t represent forget gate, input gate and output gate, c_t is cell state storing long-term fault-degradation information [4, 12].

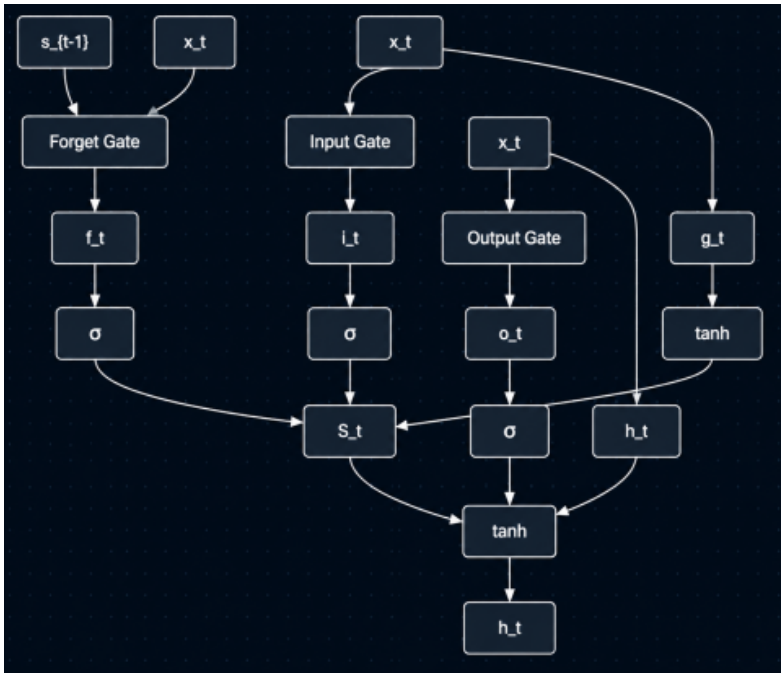


Figure 2. LSTM cell structure [4]

Lu proposed CNN-LSTM hybrid model: CNN extracts spatial multi-source features, while LSTM mines time-series rules. The model achieves 98.51% short-term load-prediction accuracy and can be migrated to motor vibration time-series fault diagnosis [4].

3.2.2. DGCNN-MobileNet lightweight graph-convolution model

For small-sample multi-modal diagnosis tasks, Wang proposed DGCNN combined with lightweight MobileNet to overcome static-GCN's limitation for time-varying faults [8]. Dynamic adjacency matrix updating formula:

$$\overline{A}_t=A_t\cdot\exp(-\gamma\cdot|t-t_0|)+I \tag{9}$$

where $\overline{A}_t$ is self-looped adjacency matrix at time step t, γ is the time-decay factor, t and t_0 denote current and historical timestamps, I is identity matrix [8]. MobileNet applies depth-separable convolution for parameter reduction:

$$\text{Params}=(k\times k\times d)+(d\times m) \tag{10}$$

DOI: 10.54254/2755-2721/2027.MELB39062

where k is kernel size, d input channel number and m output channel number [8].

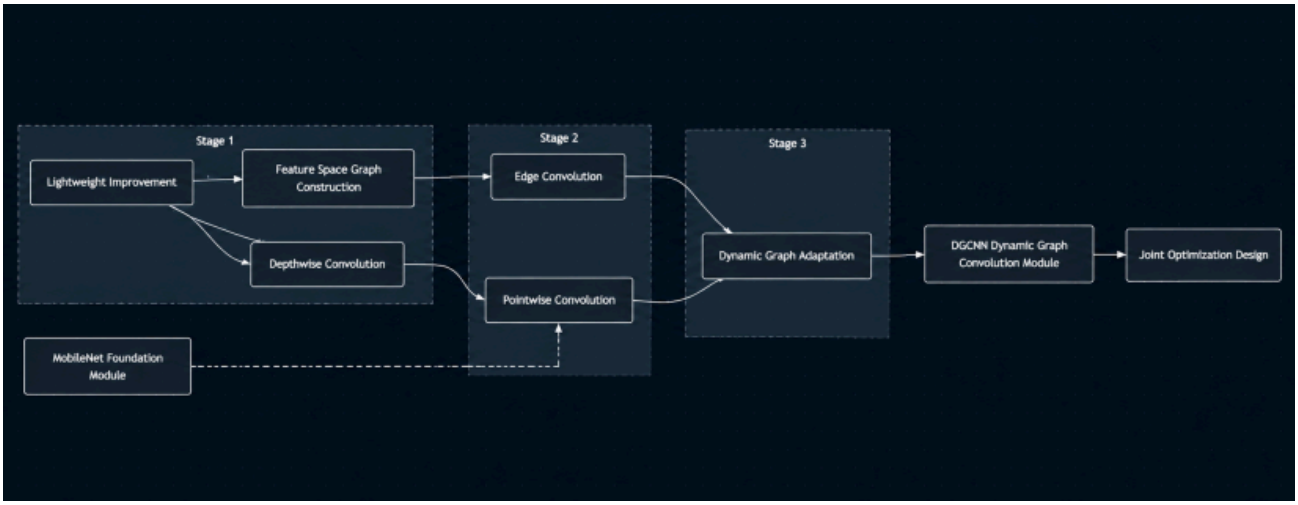


Figure 3. Process of DGCNN improved by MobileNet [8]

As reported in experiments, this hybrid model converges fast under small-sample conditions and gains high test-set accuracy for switchgear, transformer and insulator fault diagnosis [8].

3.3. Intelligent-optimization ensemble hybrid models

RF and SVM performance heavily depends on hyper-parameters. Meta-heuristic optimization algorithms realize automatic parameter search. Zhao proposed Improved Crested Porcupine Optimizer (ICPO), introducing logistic chaotic initialization, random disturbance, cross-mutation and adaptive step-size strategies. ICPO outperforms GA, PSO and original CPO in convergence accuracy. Built upon ICPO-optimized RF, ISMOTE-ICPO-RF transformer fault-diagnosis model reaches 96.89% accuracy, surpassing ordinary RF, SVM and XGBoost in ACC, AUC, recall, and F1-score [9].

4. Auxiliary dynamic threshold and engineering-test system

Machine-learning models can cooperate with adaptive dynamic thresholds and automatic test platforms to reduce false-alarm and missing-detection rates [3, 5]. Guo proposed a four-layer closed-loop adaptive-threshold architecture coupling temperature/current thresholds with real-time load, humidity, and equipment aging. After optimization, false-alarm rate drops from 20% to 6.8%, and the missing-detection rate reduces from 8.2% to 2.3% [5]. Ling constructed three-layer distribution-automation test system, including a source-meter closed-loop test bench and a digital-physical hybrid simulation platform. It provides a real-condition verification environment for machine-learning models and bridges gaps between laboratory datasets and field data. Figure 4 demonstrates the closed-loop test principle for distribution terminals [3].

DOI: 10.54254/2755-2721/2027.MELB39062

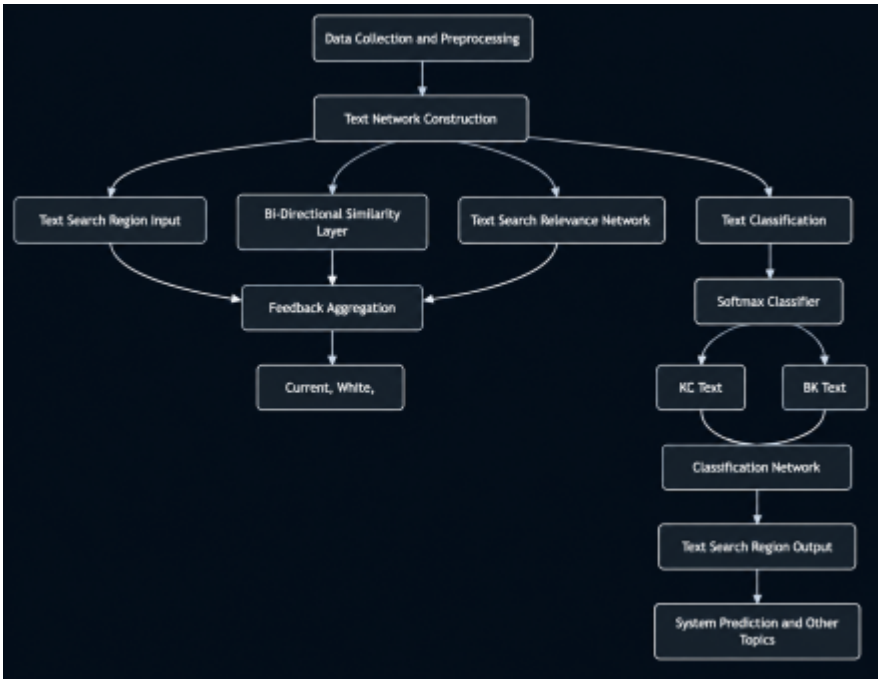


Figure 4. Principle of closedloop test for distribution terminals [5]

5. Core problems in current researches

Small-sample and sample-imbalance bottlenecks: Most deep-learning models rely on massive labeled fault samples. Improved sample-enhancement methods relieve sample skew, yet identification performance for extremely rare faults remains unsatisfactory [7-9]. Insufficient multi-source heterogeneous data fusion: Most research adopts single-source data. Effective multi-modal fusion for electrical, thermal, image, and partial-discharge data is insufficient, increasing the risk of missing internal-defect detection [3, 8]. Edge-side lightweight-deployment contradiction: Deep networks own huge parameter volume. Edge terminals are constrained by computation and storage resources. Existing multi-collaborative lightweight compression schemes are not fully adapted for power-equipment scenarios [10]. Model interpretability and engineering-adaptability defects: Deep networks are black-box models that cannot satisfy power-grid fault-tracing requirements. Model performance degrades significantly under field noise, load fluctuation, and equipment aging [2, 5, 6]. Incomplete early-warning closed-loop mechanism: Many models only output classification results without trend prediction and life evaluation functions. The "monitoring-early-warning-simulation-O&M feedback" closed-loop is rarely realized [3, 5].

6. Future research and development trends

Small-sample multi-modal fusion learning: Combine transfer learning, meta-learning and GAN for sample expansion. Adopt DGCNN-based multi-modal graph network to fuse oil-chromatography, vibration, infrared, and partial-discharge data for early-weak-fault identification [7, 8]. Cloud-edge collaborative lightweight intelligent diagnosis: Apply pruning-quantization-knowledge-distillation joint compression for graph-convolution and CNN-LSTM models. Build cloud-edge collaborative architecture: the edge undertakes local real-time early-warning, cloud implements incremental model training, adapting to embedded IoT deployment [5, 10]. Hybrid optimization of optimization algorithms and deep networks: Improve meta-heuristic optimizers to automatically tune network

DOI: 10.54254/2755-2721/2027.MELB39062

hyper-parameters, constructing hybrid models balancing accuracy and computation overhead [9]. Digital-twin-driven closed-loop early-warning system: Embed machine-learning models into digital-twin simulation platforms to reproduce compound-fault scenarios for iterative model optimization. Combine adaptive dynamic threshold to lower false-alarm and missing-detection rates [3, 5]. Explainable AI and field-engineering adaptability: Introduce attention-mechanism and feature-attribution methods to interpret deep-network decision logic. Validate algorithms on automatic test platforms using real-world measured datasets [2, 11].

7. Conclusion

This paper systematically reviews machine-learning-driven electrical-equipment monitoring workflow covering data preprocessing, feature engineering, fault diagnosis, lightweight deployment, and engineering tests. Mainstream models including RF, SVM, LSTM, DGCNN-MobileNet, and ISMOTE-ICPO-RF are compared in principle and performance. Current research faces challenges of poor small-sample generalization, insufficient multi-modal fusion, edge-deployment constraints and limited model interpretability. Future work will focus on meta-learning sample augmentation, cloud-edge lightweight architecture, digital-twin closed-loop O&M and explainable artificial intelligence. It promotes machine-learning applications for full-scenario equipment monitoring and fault early-warning, supporting intelligent O&M of new-type power systems.

References

[1] Chen, F. Y., Huang, X., & Li, H. H. (2017). Measures to prevent user-side electrical-equipment faults from affecting power-grid safety. *Shandong Industrial Technology*, (14), 182. https://doi.org/10.16640/j.cnki.37-1222/t.2017.14.159

[2] Li, Z. F., Qin, J. J., & Yang, X. B. (2025). Cause analysis and preventive measures for common mechanical faults of motors. *Today's Manufacture and Upgrading*, (4), 186-189. https://kns.cnki.net/kcms2/article/abstract?v=Tadyhzi4uofdIqgnCqOb6WbG4QGyxyvtHrBqqWPijaNyhnIjbIRf9zUlRpTu5NQ2ejL3nWYuNcRxA4IUZrhJfwkPYt9S2aYPBCHGaotVjsUjnsDA2zKVa8ZAF7CjeHfe7pCgQb95--egpr1mkkiu7OZqvLQcVH5SKZ5cvBrZGKP6QvpBDULwJw==&uniplatform=NZKPT&language=CHS

[3] Guo, G. T., & Qiao, X. (2026). Threshold adaptive optimization and dynamic adjustment strategy for power-equipment fault diagnosis. *Electric Power Equipment Management*, (5), 25-27. https://doi.org/10.26977/j.cnki.dlsbgl.2026.05.006

[4] Lu, J. X., Zhang, Q. P., Yang, Z. H., et al. (2019). Short-term load forecasting method based on CNN-LSTM hybrid neural network model. *Automation of Electric Power Systems, 43*(8), 131-137. https://link.cnki.net/urlid/32.1180.TP.20190226.1603.012

[5] Ling, W. S., Wang, K. L., & Gao, J. (2026). Thirty-years exploration and practice of distribution-automation test technology. *Distribution & Utilization, 43*(8), 50-62. https://doi.org/10.19421/j.cnki.1006-6357.2026.08.006

[6] Chen, G., Bi, J. C., & Yang, L. M. (2026). Application of intelligent algorithms in condition monitoring and fault diagnosis of power equipment. *Light Source & Illumination*, (4), 107-109. https://kns.cnki.net/kcms2/article/abstract?v=Tadyhzi4uofDm52c4jXLwLtTrT2wocujlHXQ7wLhefh5KSm0MJvIx7y_E3DJJIGAb3-RGLdY5bs8PC09Ti9yAhUeAaBiwixuo-L29LtgGMx4eLVckmr6cZKMiRIEq7YX4xqb2e7tsUhxy9qhdtvJ6lkGkDWv4izBQ08A0JQZDTmF9bt-0n1VVA==&uniplatform=NZKPT&language=CHS

[7] Li, Y. J. (2026). Condition monitoring and fault-diagnosis method of electrical equipment based on artificial intelligence. *Proceedings of the 4th Academic Exchange Conference on Digital Technology Empowering Digital Transformation in Engineering Construction*, 433-434. https://doi.org/10.26914/c.cnkihy.2026.021330

[8] Wang, Y. X., & Su, Z. Q. (2026). Research on small-sample fault diagnosis of power equipment based on improved graph convolution network. *Automation & Instrumentation*, (3), 32-36. https://doi.org/10.14016/j.cnki.1001-9227.2026.03.032

DOI: 10.54254/2755-2721/2027.MELB39062

[9] Zhao, Q., & Hao, S. (2026). Research on transformer fault diagnosis method based on improved SMOTE and ICPO-RF. *Communications and Information Technology*, (4), 38-45. https://kns.cnki.net/kcms2/article/abstract?v=Tadyhzi4uof0DIBrlRRRBeMBOEMdsWW09UV_aphPwNw4tSPhDpFo-Cd1_Q1BdH5OS78V1qaLHUNIDIap0d9TAmZqCGnJkYu2uAeoYzqwcgCwxKCo4v2BbxXnpXYBqDyE17KRoshI68EJbW-5SDZWd0xca4kMd6Uqsm_dKi1ftYayzs5pzroOXA==&uniplatform=NZKPT&language=CHS

[10] Jiang, L. (2026). Research on lightweight compression strategy for edge-computing model driven by artificial intelligence. *Information & Computer, 38*(14), 81-83. https://kns.cnki.net/kcms2/article/abstract?v=Tadyhzi4uoevzcF850Pgif1uiJ5RDlxmtkdubVfrm0_s1772yGAU0bVrPi4LjOOyYMiJ8jCdNesWisrs2KDdmeAqrwO6ceMfJnlJV8TZUfl2rpOg3GPBhM-8FGo9yZ2kXjMhu4PtMLz2ijYK7inWG_ky7G3GfoMAstU7u-fXMbQfMwBO4ffXbw==&uniplatform=NZKPT&language=CHS

[11] Wang, R. X., & Qiao, Y. T. (2024). Operation-data analysis and fault-diagnosis research of substation equipment based on machine learning. *Electric Power Equipment Management*, (17), 105-107. https://kns.cnki.net/kcms2/article/abstract?v=Tadyhzi4uof1fwparF3cFb8tDeF9U7QEQ2kbPD2h7phzdHa7z1atW37-YBHWV1Gc6sAjrvA95L7bTI5SCHoYsFnXToX_4ze0EGhMqZCQA5V479073CK2GNlj4TDPxxTZZ3ZXLhZtbAwRT1UJjUbyMixmY709y2oWBj5RUe4_evG7S4_7r60N1g==&uniplatform=NZKPT&language=CHS

[12] He, S. Y., Han, Z. Z., Qian, Z. W., et al. (2026). Fault-diagnosis technology of high-speed rapier loom based on random forest and long-short-term memory network. *Mechanical & Electrical Engineering Technology, 55*(11), 40-45. https://kns.cnki.net/kcms2/article/abstract?v=Tadyhzi4uoeMzyJH9i9DFJFgQ0_8IhY-XS2JoXs0ix5YTWVteXVcBPDpSIXrxEcWUt4vFeYO3jVW2rKyxu1gu6cfP5b9OQ2nvbu5jgOZkzvaapLEd3YkOIHk9lgWgHVD3ewWkcFgSZ1VhVCKZ0wOa76gnOSSHEm7EZmTErHqPBejU3lRVQ7MFg==&uniplatform=NZKPT&language=CHS