

Article

Anomaly Detection for Smart Grid Information Data Considering Sample Imbalance Using Improved AlexNet

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Abstract

In smart grid operation, the scarcity of abnormal samples causes data imbalance, which is a key factor limiting the accuracy of anomaly detection. To address this issue and simultaneously solve the problem of easily losing weak abnormal signals in one-dimensional time-series data, an abnormal data detection method for grid information using an improved AlexNet considering sample imbalance is proposed. Firstly, features like voltage, current, and power are extracted from historical data. Missing values are filled via Lagrange interpolation, and abnormal boundaries are determined using box plots to construct high-quality samples. Secondly, to address the problem of few abnormal samples and imbalanced distribution, an enhanced learning strategy combining time-series translation and Gaussian noise injection is adopted to expand the abnormal samples and obtain sufficient training data. Then, to preserve the integrity of weak signals in one-dimensional time-series data and amplify the differences in abnormal features, the Gram angle field is used to convert multi-dimensional time-series data into a two-dimensional image, achieving the visual representation of time-series features. Finally, combined with the powerful image detection capability of AlexNet, it is improved by lightweighting the network structure, introducing the multi-head self-attention mechanism, and optimizing the training strategy to adapt to abnormal detection in the small sample and imbalanced environment of the grid. The simulation experiments show that the proposed method achieves an accuracy rate of 91.32% on extremely imbalanced datasets, which is at least 3.1% higher than those of other models.

Keywords: intelligent distribution network; anomaly data; sample imbalance; AlexNet; data augmentation

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1. Introduction

As the construction of the new power system continues, the operation mode of the smart grid becomes increasingly complex, and a large amount of status sensing data accumulates. Due to factors such as equipment aging, operational disturbances, and external attacks, abnormal information data such as voltage abnormalities, current abnormalities, and power abnormalities will be generated during the operation of the power grid [1]. If these abnormal information data cannot be identified in time, it may further lead to operational deviations and status misjudgments and affect the safe and stable operation

of the power grid [2]. At the same time, in the current data collection process, normal operation samples are usually far more highly represented than abnormal samples, and the sample categories show a significant imbalance in distribution, making it difficult to identify abnormal information, especially weak abnormalities and rare sample abnormalities [3]. Therefore, achieving accurate detection of abnormal information data of the power grid under the condition of sample imbalance has become a key issue in the current intelligent operation and maintenance of the power grid [4].

For the imbalance classification problem, existing studies mainly focus on improvements at the data level and algorithm level. Huang Haisong et al. proposed the K-information quantity neighborhood over-sampling method to solve the imbalance problem of bearing fault samples [5], while Liu Didi et al. used ADASYN to over-sample the imbalanced data of transformers so the number of samples of each category in the training set reached equilibrium [6]. However, both over-sampling and under-sampling methods will easily change the original distribution or introduce noise; Chen Renxiang et al. proposed a rolling bearing life stage recognition method based on multi-classifier integration and weighted balanced distribution adaptation, which effectively identified the minority class samples [7]. He et al. designed a grid boundary domain sampling strategy to eliminate majority-class bias under severe sample skewness [8]. For grid-connected photovoltaic inverter open-circuit fault diagnosis with imbalanced measurements, Wang et al. constructed a global feature perception network to capture subtle fault features of minority abnormal samples [9]. However, the methods in the aforementioned literature do not take into account the abnormal features under imbalanced samples. With the rapid development of deep learning, a series of intelligent diagnosis and monitoring frameworks have been proposed for power systems. Li et al. adopted deep reinforcement learning to realize parallel power system restoration [10]; Liang et al. constructed a transfer learning-based concurrent fault diagnosis framework applicable to nuclear power time-series data [11]; Moayyed et al. developed a multi-source fusion deep learning model to defend against false data injection attacks in smart grids [12]. Therefore, developing the means to enable the model to autonomously and evenly learn various abnormal features without destroying the true distribution of the data, and improving the model's detection ability for minority abnormal samples and weak abnormal patterns, has become an urgent problem to be solved in the improvement of the accuracy of abnormal information data detection in the power grid [13].

In the process of detecting abnormal information data in the power grid, it is necessary to simultaneously address the challenges of scarce abnormal samples, imbalanced data distribution, and the easy loss of weak abnormal signals in one-dimensional time-series data. Most existing studies have failed to effectively address the coupled influence of these problems and are thus unable to meet the accurate detection requirements for concealed and subtle abnormal data under the imbalance of power grid samples. Therefore, this paper conducts research on the detection of abnormal information data in the power grid based on the improved AlexNet under the condition of imbalanced samples. Firstly, based on historical data, Lagrange interpolation and the box plot method are used to extract the characteristics of abnormal data, and through time-series translation and Gaussian noise injection, enhanced learning is used to expand the abnormal samples. Combined with dynamic weighted fusion and the Gram angle field (GAF), the time-series data is converted into a two-dimensional image to retain the weak abnormal signals and the correlation with the data time sequence. The AlexNet is improved by replacing the fully connected layer with a feature expansion layer, multi-head self-attention layer (MHSA), and Softmax layer. The transfer deep learning and dropout mechanism are introduced to optimize the model. The accuracy and effectiveness of the proposed method on different imbalanced proportion datasets are verified through simulation experiments.

Compared with the existing anomaly detection methods, the improved AlexNet framework proposed in this paper can effectively alleviate the overfitting problem under the condition of a highly imbalanced sample distribution, and enhance the recognition ability of minority class abnormal samples. By combining Gram angle field transformation with an attention mechanism, it completely retains the weak abnormal features in time-series data, making up for the deficiency of traditional methods in easily losing subtle abnormal information. At the same time, the lightweight structure combined with a transfer learning design achieves a better balance between detection accuracy and training efficiency, making it more suitable for the actual small sample anomaly detection scenarios in power grids.

2. Construct Sample Data Based on Historical Data and GAF

In response to the problems of missing values in power grid data, scarcity of abnormal samples and imbalanced distribution, the original data were first filled with the Lagrange interpolation method [14], and high-quality sample data and the boundary characteristics of abnormal data were obtained through box plots [15]. To solve the problem of sample imbalance, data augmentation was carried out by time shift and Gaussian noise injection [16], to obtain sufficient sample data. Meanwhile, to detect weak abnormal information, the Gram angle field was introduced to convert one-dimensional time-series data into a two-dimensional image, and a sample matrix was constructed.

2.1. Determine the Boundary of Abnormal Data Based on Lagrange Interpolation and Box Plots

To effectively extract abnormal features from historical data, a combination method of Lagrange interpolation and box plots is adopted. The specific process is as follows:

Step 1: Missing value filling based on Lagrange interpolation. Suppose the time-series data sequence of a certain node is $(t_1, y_1), (t_2, y_2), \dots, (t_n, y_n)$. If there are missing values within the interval $[t_k, t_{k+m}]$, then Lagrange interpolation using the known k neighboring points is employed. The Lagrange interpolation basis functions and the interpolation polynomial are defined as

$$L_j(t) = \prod_{i=0, i \neq j}^{k-1} \frac{t - t_i}{t_j - t_i}, \quad P(t) = \sum_{j=0}^{k-1} y_j L_j(t) \quad (1)$$

where $L_j(t)$ is the Lagrange basis function, and $P(t)$ is the interpolation polynomial that passes through the known data points, used to estimate the value at the missing time point t .

Step 2: Abnormal feature extraction based on box plots. The box plot with interval quintiles is used to determine the boundary values of abnormal data, as shown in Figure 1.

$$x_i = \begin{cases} \text{Normal} & x_i \in [q1 - 1.5r, q3 + 1.5r] \\ \text{Abnormal} & \text{others} \end{cases} \quad (2)$$

where $q1$ and $q3$ represent the ordered first quartile and third quartile; r is the difference between $q1$ and $q3$; and abnormal data are located outside the boundaries $q3 + 1.5r$ and $q1 - 1.5r$.

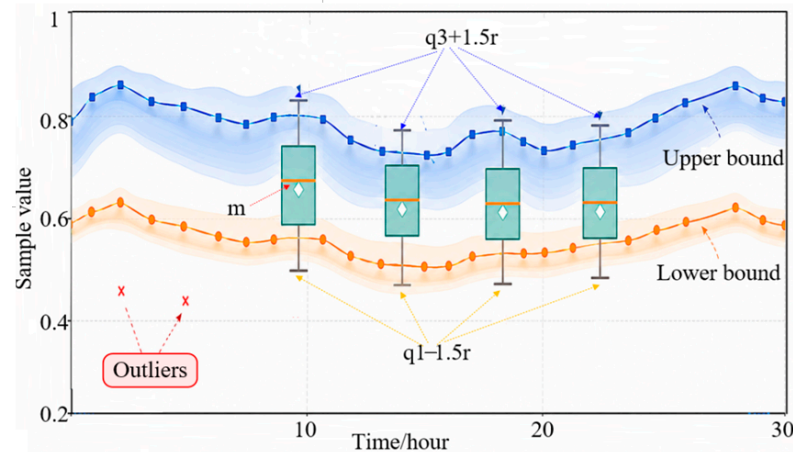


Figure 1. The schematic of the interquartile range based on the box plot.

2.2. Generation of Abnormal Data

Abnormal data exhibit distinct temporal evolution characteristics, and Gaussian noise injection can simulate the weak disturbances during the operation of the power grid, bringing the enhanced samples closer to the actual operating state. Therefore, this paper adopts the data augmentation strategy of time sequence shifting and Gaussian noise injection to expand the abnormal data samples [17]. Set the time-series data with outliers as $X = \{x_1, x_2, \dots, x_t, \dots, x_n\}$ and the time-series data after the shift step length Δt as $X' = \{x_{1+\Delta t}, x_{2+\Delta t}, \dots, x_{t+\Delta t}, \dots, x_{n+\Delta t}\}$, and the enhanced abnormal data after Gaussian noise injection as X'' .

$$X'' = X' + \varepsilon, \varepsilon \sim N(0, \sigma^2) \quad (3)$$

where ε represents the injected Gaussian noise, which follows a normal distribution with a mean of 0 and a standard deviation of σ .

Grid search is a hyperparameter tuning method that involves traversing candidate parameter combinations. Therefore, by using it to determine the data augmentation strategy parameters as $\Delta t = 5$ and $\sigma = 0.02$, diverse abnormal samples can be generated without disrupting the inherent time-series feature distribution of the real power grid measurement data.

2.3. Construction of Image Sample Matrix Based on Gram Angle Field

One-dimensional time-series data such as voltage, current, and power are prone to losing minute signals, which affects the efficiency of anomaly detection. Therefore, by adopting GAF [18], through data scaling, polar coordinate mapping and GASF encoding, one-dimensional time-series data are transformed into a two-dimensional image. While preserving the temporal correlation of the data, the abstract dynamic features are converted into visual textures, amplifying weak signals and facilitating the subsequent extraction of deep features by convolutional neural networks.

Step 1: Multi-feature weighted fusion. The importance of each feature varies in different categories. The weight coefficients are determined through the feature relative fluctuation discrimination method. The coefficient of variation (CV) is used as a quantitative indicator to evaluate the stability of each electrical feature. The larger the CV value, the more intense the fluctuation of the feature, and it deviates further from the normal operating state. It is regarded as the main factor causing anomalies, and thus is assigned a higher weight; conversely, features with a smaller CV value operate stably and have a

lower weight. To highlight the contribution of the features that dominate the abnormal type, the voltage, current, and power features are weighted and fused to obtain $F(i)$:

$$F_i = \alpha f_u + \beta f_i + \lambda f_p \quad (4)$$

where f_u , f_i , and f_p represent voltage, current, and power respectively. The corresponding adaptive weights are α, β, λ .

Step 2: GAF Conversion. Taking the feature vector 1 of the i node as an example, the specific process is as follows:

(1) Data scaling. To prevent the inner product from being biased towards the maximum observation value, F_i is scaled to the range of $[-1, 1]$, and the formula is

$$F'_{i,t} = \frac{2F_{i,t} - \max(F_i) - \min(F_i)}{\max(F_i) - \min(F_i)} \quad (5)$$

(2) Polar coordinate transformation. Convert the scaled data into polar coordinate form. The scaled values are converted to angle φ , and the timestamp is encoded as radius r . The formula is:

$$\begin{cases} \varphi = \arccos(F'_{i,t}) \\ r_{i,t} = \frac{t}{N} \end{cases} \quad (6)$$

(3) Generate GASF encoding graph. Use the Gramian Angular Summation Field (GASF) to generate a $224 \times 224 \times 3$ color image as the input for the subsequent AlexNet.

Step 3: Sample matrix construction. Improve AlexNet to a supervised learning model, and construct the sample matrix D , which contains the attribute value matrix X and the label matrix Y .

3. Anomaly Information Data Detection Based on the Improved AlexNet

AlexNet, as a classic convolutional neural network, excels in image feature extraction and classification tasks. Its original structure consists of five convolutional layers, three max pooling layers, three fully connected layers, and one Softmax classification layer, which can effectively capture basic features such as edges and textures in images. The two-dimensional images of abnormal grid data after GAF transformation mainly exhibit local texture differences and global correlations. The multi-layer convolution structure of AlexNet can extract features from edges and textures to advanced semantics layer by layer. Compared with one-dimensional time-series models such as 1D-CNN and TCN, it can better fully explore the temporal correlation features encoded in the GAF images of abnormal grid data, and it has a stronger ability to detect minor abnormalities.

However, the original AlexNet model has a parameter quantity of 60 million or more, which is prone to overfitting in the case of grid sample imbalance, affecting the detection effect. Considering that the parameter quantity of the fully connected layer accounts for more than 90% of the total parameter quantity, it is likely to cause model overfitting and unable to fully extract the key abnormal features in the transformed images of time-series data. Therefore, this paper improves AlexNet from two aspects—network structure light-weight adjustment and training strategy optimization—in order to enhance the abnormal detection ability in the scenario of sample imbalance. The algorithm framework is shown in Figure 2.

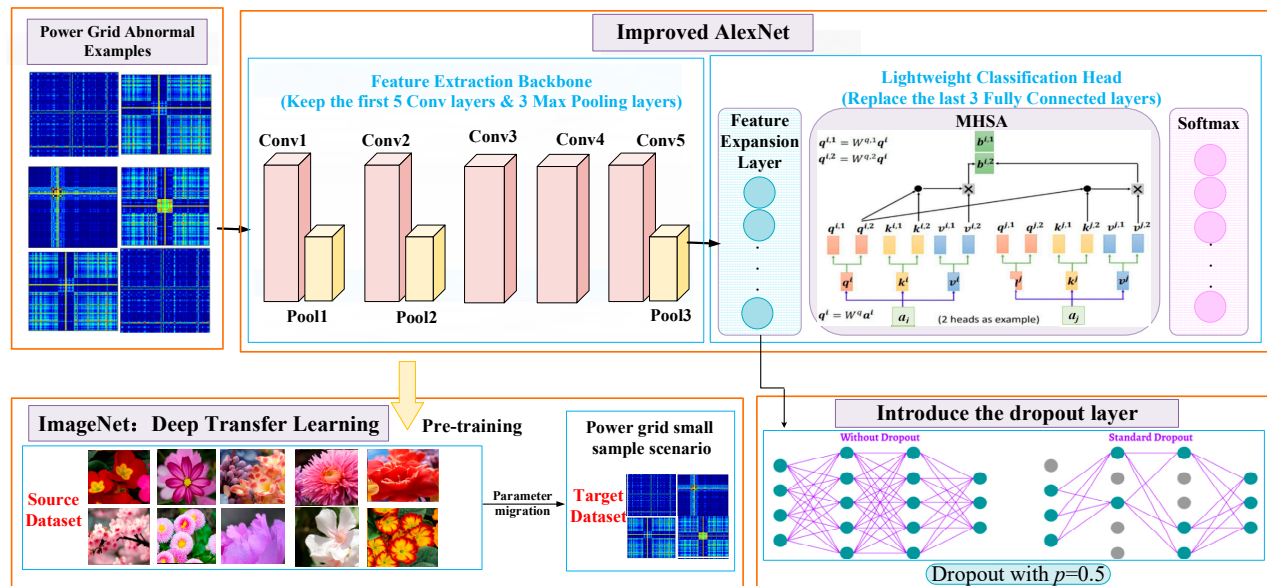


Figure 2. Anomaly data detection based on improved AlexNet.

3.1. Lightweight Improvement of Network Structure

The last three fully connected layers of the original AlexNet model account for over 90% of the total model parameters. In the case of an imbalanced sample distribution, it is prone to overfitting. Therefore, the fully connected structure of the last three layers was modified to include feature expansion, dropout regularization, multi-head self-attention (MHSA), and a Softmax layer. This reduced the number of parameters while enhancing the model's ability to capture weak abnormal features, making it suitable for detection scenarios with imbalanced samples.

Step 1: Feature Expansion Layer. Here, 1×1 lightweight convolution is used to build the feature expansion layer. The $256 \times 6 \times 6$ feature map output by the pooling operation is dimensionally transformed and mapped to a 2048-dimensional one-dimensional feature vector, reducing redundant parameters in the model. Additionally, a dropout layer is embedded after this layer, with a dropout probability of 0.5. During training, some neurons are randomly masked to effectively prevent overfitting of the model in scenarios with small sample sizes. Let the feature map output by the max pooling layer be $F \in R^{C \times H \times W}$, with $C = 256$ being the number of channels, and $H = 6$ and $W = 6$ being the height and width of the feature map, respectively. The 2048-dimensional feature vector output by this layer is x .

$$x = \text{Flatten}(F * K + b) \quad (7)$$

where $*$ represents convolution operation, and $\text{Flatten}(\cdot)$ is the flattening operation, which can convert the two-dimensional feature map after convolution into a one-dimensional vector [19].

Step 2: To enhance the capture of weak abnormal features, MHSA establishes global correlations between features through parallel computations of multiple attention heads [20,21]. Consider the subsequent detection of the four types of operating states of the power grid. With four parallel attention heads, focus on capturing the characteristic patterns of the corresponding operating state, thus achieving multi-dimensional and fine-grained anomaly feature mining. The input feature dimension of MHSA is 2048, which is evenly distributed across the four attention heads. The query, key, and value vectors of each head are all set to have a dimension of $d_k = 512$. The 2048-dimensional input feature vector is first projected into three groups of vectors Q , K , and V with a dimension of 2048

each through three independent learnable linear matrices. Then, each attention head independently performs scaled dot-product attention calculation. For the i -th attention head, its output a_i is normalized by the *Softmax* function to process the attention weights, enabling the model to automatically focus on the key abnormal feature regions. The calculation formula is

$$a_i = \text{Softmax}\left(\frac{Q_i K_i^T}{\sqrt{d_k}}\right) V_i \quad (8)$$

where Q_i , K_i , V_i represent the query, key and value vectors of the i -th attention head; d_k is the dimension of a single-head attention; each head adopts a feature dimension of 512; *Softmax*($\cdot$) normalizes the weights to the range [0, 1]; and a_i is the output of the i -th attention head [22].

$$y = \text{Concat}(a_1, a_2, a_3, a_4) W_o \quad (9)$$

where *Concat*($\cdot$) represents the concatenation operation; W_o is the linear transformation matrix; and y is the 2048-dimensional vector output by MHSA.

Step 3: Softmax layer. The global feature vector output by MHSA is input into the Softmax layer to complete the detection of abnormal data in the power grid and obtain the corresponding probabilities for the four states of normal, voltage abnormality, current abnormality, and power abnormality. The maximum probability is taken as the final detection result.

$$P = \text{softmax}(W_s y + b_s) \quad (10)$$

where y represent the output feature vector of MHSA, W_s and b_s are the weight parameters and bias parameters of the classification layer, respectively, and P is the probability output vector for the four types of power grid operation states.

3.2. Training Strategy Optimization Based on Deep Transfer Learning

Considering the imbalance of power grid samples, where the number of abnormal samples is significantly less than that of normal samples, the model is prone to problems such as slow convergence speed, poor feature learning, and weak generalization ability. To further adapt to the scenario of sample imbalance detection, deep transfer learning is introduced to further improve the model performance [23]. The parameters of AlexNet pre-trained on the ImageNet dataset are used to initialize the first five convolutional layers of the network, reusing its learned general image feature extraction ability to reduce the training cost of the model on small sample data of the power grid and accelerate model convergence.

4. Simulation Experiment

The proposed model and method were verified through simulation using the MATLAB R2024a platform. The working system environment was an NVIDIA GeForce MX250 graphics processor with a 256-bit memory interface, 8 GB RAM, and an Intel core i5-8265U processor.

4.1. Sample Data

In order to accurately extract data features, based on MATLAB simulation, historical time-series data such as voltage, current and power were generated. Data was collected every 15 min, with a total of 96 sampling points collected per day. Four sample sets, including normal state, voltage anomaly, current anomaly, and power anomaly, are constructed. To simulate the imbalance situation of samples in the actual power grid, the enhanced learning method mentioned earlier is used to construct three datasets with different imbalance ratios, as shown in Table 1. The $224 \times 224 \times 3$ image sample sets obtained

after GAF transformation are shown in Figure 3. The data was divided into a training set and a test set in a ratio of 7:3.

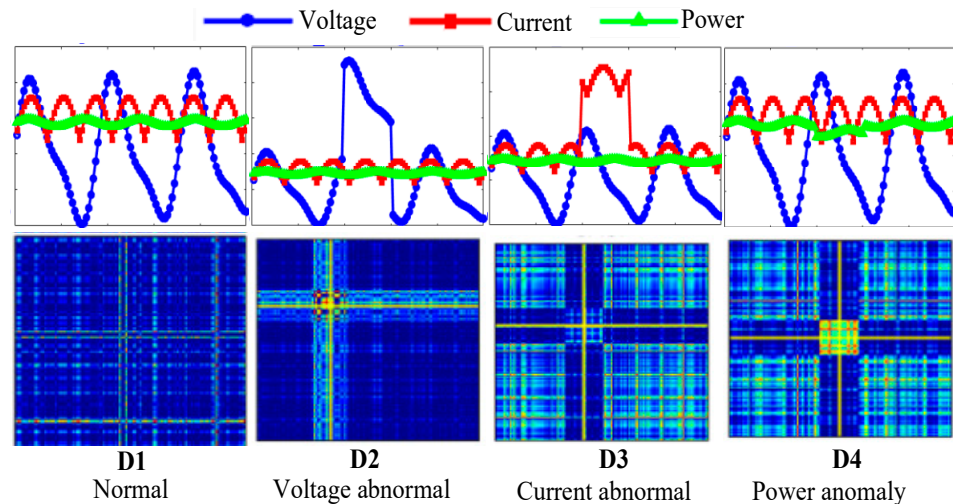


Figure 3. Eight-state GASF schematic diagram.

Table 1. Construction of imbalanced datasets.

Dataset	Normal	Abnormal			Imbalance Ratio
		D2	D3	D4	
A	6000	2000	2000	2000	1:1
B	9000	1500	1500	1500	2:1
C	12,000	800	800	800	5:1

Considering the simultaneous detection of normal samples and abnormal samples, mutual verification is adopted to avoid false alarms. Based on the statistical indicators of true positive (TP), true negative (TN), false positive (FP), and false negative (FN), this paper uses three indicators: accuracy (Acc), precision ($Prec$), and recall rate (Rec). True positive represents the samples that are correctly classified as abnormal in the classification results, true negative represents the samples that are correctly classified as normal, false positive represents the samples that are misclassified as abnormal, and false negative represents the samples that are misclassified as normal. The $F1$ -Score evaluation algorithm is introduced to assess the stability of abnormal data detection. The $F1$ -Score is a comprehensive evaluation of precision and recall, and its value is closer to 1, indicating better performance of the model.

$$Acc = \frac{N_{TP} + N_{TN}}{N_{TP} + N_{FP} + N_{TN} + N_{FN}} \quad (11)$$

$$Prec = \frac{N_{TP}}{N_{TP} + N_{FP}} \quad (12)$$

$$Rec = \frac{N_{TP}}{N_{TP} + N_{FN}} \quad (13)$$

$$F1 = \frac{2 \times Prec \times Rec}{Prec + Rec} \quad (14)$$

4.2. Model Training Parameter Optimization

To investigate the impact of different training parameters on the model training performance, the control variable method was adopted for testing. The optimizer was set as sgdm, and the loss function was the cross-entropy loss [24]. The model was trained and tested. The final experimental results are shown in Figure 4.

In Figure 4, when the learning rate $L = 0.01$, the training effect is better than when $L = 0.005$. Too small a learning rate will prevent the loss function of the network from converging to the global minimum. When $L = 0.1$ or $L = 0.05$, the detection accuracy of the model is very low, because the loss function cannot converge. With the increase in the number of training rounds, when $E = 40$, the accuracy of the model for fault detection reaches its best point. When E exceeds 40, its accuracy slightly decreases, because too many training rounds will cause the model to overfit during training. Therefore, the learning rate $L = 0.01$ and the number of training rounds $E = 40$ were selected.

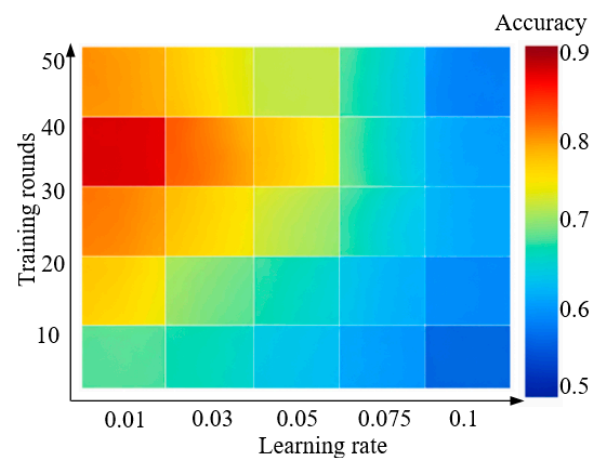


Figure 4. Schematic model parameters.

4.3. Model Convergence Performance Analysis

To verify the convergence performance and generalization ability of the model, this study statistically calculated the accuracy and loss values of the training set and test set for different training rounds. The results are shown in Figure 5.

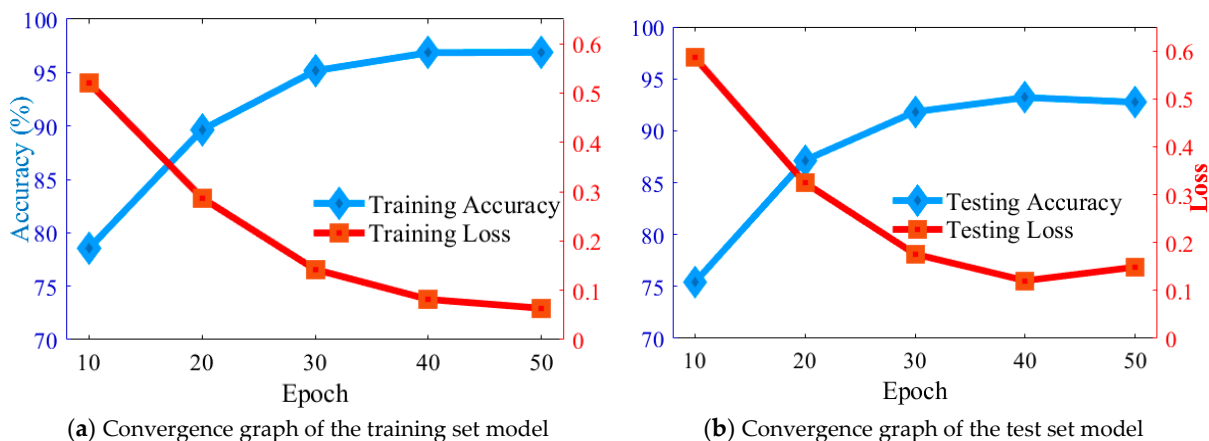


Figure 5. Model convergence performance graph.

From Figure 5, it can be seen that as the number of training rounds increases, the accuracy of the training set and the test set continues to rise, while the loss value keeps

decreasing. When the number of training rounds reaches 40, the model converges to the optimal state. At this point, the accuracy of the training set is 96.86%, the loss value is 0.0816, and the accuracy of the test set is 93.20%, with a loss value of 0.1204. When the number of training rounds increases to 50, although the accuracy of the training set slightly increases to 96.89% and the loss value drops to 0.0635, the accuracy of the test set slightly decreases to 92.75% and the loss value rises to 0.1487. Only a slight overfitting phenomenon occurs. When the number of training rounds is only 20, the model's test set accuracy reaches 87.15%, which verifies the effectiveness of the lightweight model and the transfer learning strategy. The reuse of pre-trained weights accelerates model convergence and reduces the training cost in small sample scenarios. Overall, the model convergence trend is good, with no serious overfitting phenomenon, effectively solving the problem of overfitting of the original AlexNet in small sample scenarios.

4.4. Results of Abnormal Data Detection

To visually evaluate the detection performance of this model for various types of abnormal data, statistical analysis was conducted on the accuracy, precision, recall rate, and F1-Score of the abnormal data detection in the test sets of different proportions of the imbalanced sample sets. The results are shown in Table 2.

Table 2. Abnormal data identification results.

Dataset	Abnormal Type	Acc(%)	Prec(%)	Rec(%)	F1-Score
A	D1	96.25	96.01	96.42	96.21
	D2	94.36	94.12	94.58	94.35
	D3	93.98	93.75	94.21	93.98
	D4	93.52	93.41	93.67	93.54
B	D1	95.12	94.89	95.36	95.12
	D2	93.15	92.87	93.42	93.14
	D3	92.46	92.13	92.75	92.44
	D4	91.89	91.58	92.16	91.87
C	D1	93.86	93.62	94.10	93.86
	D2	91.75	91.23	92.26	91.74
	D3	90.62	90.15	91.08	90.61
	D4	90.05	89.63	90.47	90.04

In Table 2, as the imbalance ratio of the dataset increases from 1:1 to 5:1, the detection performance of the model for each abnormal type shows a gradually decreasing trend. On balanced dataset A, D1 has the best detection effect, with an F1-Score of 96.21%. The F1-Scores of D2, D3, and D4 decrease slightly, respectively, to 94.35%, 93.98%, and 93.54%, indicating that the model has a good ability to identify various single abnormalities. On dataset B, all indicators show a slight decrease, with the F1-Score of power abnormalities dropping to 91.87%. On dataset C, the performance decline is more significant, but the F1-Score of the normal state still remains at 93.86%, and the F1-Score of power abnormalities is 90.04%. Overall, the model maintains a high detection accuracy under different levels of imbalance, and its robustness in identifying normal samples is the strongest, verifying the effectiveness and stability of the proposed method in scenarios with imbalanced samples.

4.5. Ablation Experiment

To verify the effectiveness of the improved model, 10 independent ablation experiments were conducted on three datasets. The specific parameter settings are shown in Table 3, and the results are presented in Table 4.

Table 3. Model parameter settings.

Scenario	Baseline Model	Data Augmentation	GAF Conversion	MHSA	Transfer Learning
1	AlexNet	×	×	×	×
2	AlexNet	√	×	×	×
3	AlexNet	√	√	×	×
4	AlexNet	√	√	√	×
5	Proposed	√	√	√	√

Table 4. Results of the ablation experiment.

Dataset	Abnormal Type	Acc (%)	Prec (%)	Rec (%)	F1-Score
A	1	73.52	72.91	74.03	73.47
	2	79.78	79.15	80.36	79.75
	3	87.59	87.02	88.11	87.56
	4	91.19	90.65	91.72	91.18
	5	94.10	93.87	94.32	94.09
B	1	70.19	69.55	70.78	70.16
	2	76.49	75.83	77.09	76.46
	3	84.27	83.62	84.88	84.25
	4	89.11	88.47	89.69	89.08
	5	92.75	92.15	93.28	92.71
C	1	67.83	67.12	68.39	67.75
	2	73.16	72.44	73.77	73.10
	3	80.01	79.32	80.58	79.95
	4	87.58	86.93	88.14	87.53
	5	91.32	90.56	92.05	91.30

According to Table 4, as each improvement module was gradually introduced, the detection performance of the model on the three datasets showed a continuous upward trend, verifying the effectiveness of each module.

On dataset A, the F1-Score for Scenario 1 was only 73.47%; in Scenario 2, the F1-Score increased to 79.75%, an increase of 6.28%, indicating that data augmentation effectively alleviated the problem of scarce abnormal samples; in Scenario 3, the F1-Score further increased to 87.56%, an increase of 7.81%, which was the most significant performance improvement section, indicating that the Gram angle field [25], after converting the time-series data into a two-dimensional image, can better retain weak abnormal features; in Scenario 4, the F1-Score reached 91.18%, an increase of 3.62%; after introducing transfer learning, the F1-Score of Scenario 5 reached 94.09%, an overall improvement of 20.62% compared to the baseline model, fully demonstrating the effectiveness of each improvement module.

On datasets B and C, the performance variation pattern is consistent with that of dataset A. The baseline model's F1-Score dropped to 67.75% on the more imbalanced dataset C, but the model in this paper still achieved 91.30%, an increase of 23.55%. On dataset C with the highest imbalance ratio, during the transfer learning phase from scenario 4 to scenario 5, the F1-Score still increased by 3.77%, indicating that transfer learning is particularly crucial for enhancing the model's generalization ability in extremely small sample scenarios.

4.6. Comparative Experiments and Method Validity Verification

To verify the superiority of the anomaly detection method proposed in this paper, comparative experiments with different network models and different feature inputs

were designed. The specific experimental settings are as follows, taking the extremely imbalanced dataset C as an example:

(1) Comparative experiments of different network models

To verify the superiority of the improved AlexNet in the intelligent grid scenario of small-sample and time-series data visualization detection, the mainstream network models in the fields of image classification and anomaly detection were selected as the comparison objects, including ResNet [26], MobileNetV1 [27], CNN + SE attention mechanism [28], and Swin-T Transformer [29]. Among them, ResNet is a classic model in the field of image classification with deep feature extraction capabilities, the CNN + SE attention mechanism represents a common image detection scheme with the introduction of an attention module, and MobileNetV1 represents a lightweight model with small parameters and high computational efficiency. The four models can comprehensively verify the effectiveness of this method in terms of network structure improvement and feature capture ability. The comparative experiment results on the test set are shown in Figure 6.

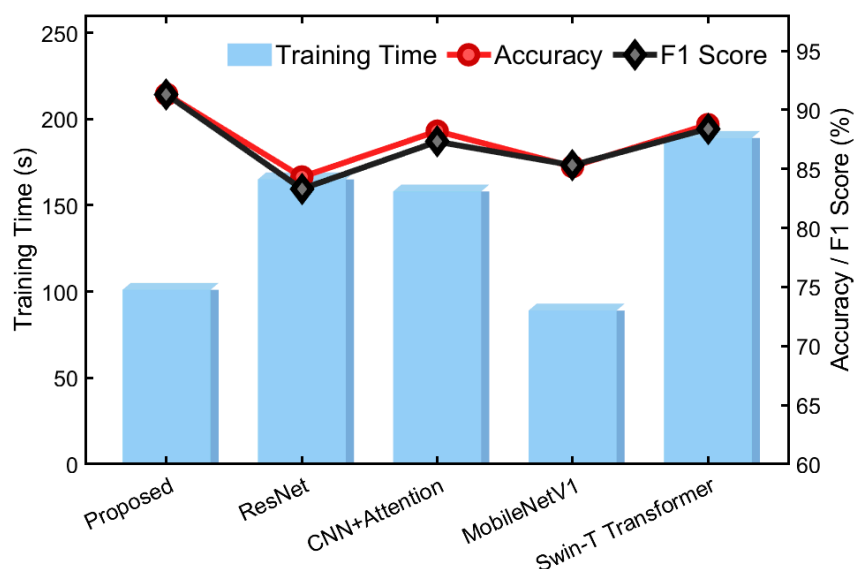


Figure 6. Comparison of different network models.

From Figure 6, it can be seen that the accuracy of the model in this paper on the test set reached 91.32%, which was 6% higher than that of the ResNet model, 3.1% higher than the CNN + SE attention mechanism model, 6.12% higher than MobileNetV1, and 3.02% higher than Swin-T Transformer, and the F1-Score was at least 0.043 higher than other models.

In terms of training time, it was only slightly higher than MobileNetV1. This is because the improved AlexNet model in this paper significantly reduced the number of parameters, while MobileNetV1 achieved a shorter training time by using depthwise separable convolution, but its feature extraction ability was insufficient to capture weak abnormal signals in the time-series data of the power distribution network. CNN + attention mechanism only enhanced features through channel weight distribution, and could not fully explore the texture information and abnormal patterns of transformed images in multi-dimensional time-series data. ResNet alleviated the gradient disappearance problem in deep networks through residual connections, but its targeted adaptation to abnormal features in power grid scenarios was still insufficient in small sample scenarios. Swin-T transformer, although achieving global image feature modeling through window self-

attention, had a large number of parameters, resulting in high training costs, and its detection performance was limited in the rare abnormal scenarios with insufficient balanced labeled samples. Therefore, the model proposed in this paper combines the advantages of GAF image time-series encoding with the global feature modeling ability of a multi-head self-attention mechanism, achieving dual improvements in detection accuracy and generalization ability in the detection of abnormal information data of the power grid under imbalanced conditions.

(2) Comparison of detection results with different feature inputs

To verify the advantage of GAF images for power grid time-series data, the mainstream time-series data processing methods were selected as comparison objects, including raw time-series data + 1D-CNN, wavelet energy spectrum + 2D-CNN, and raw time-series data + TCN. The model detection performance of different feature input methods was compared. The test set comparison results are shown in Figure 7.

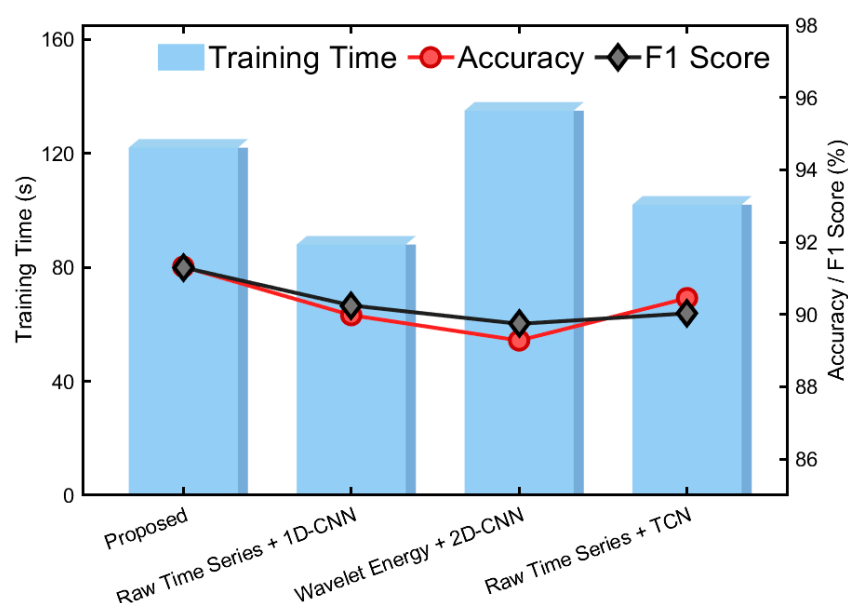


Figure 7. Comparison of different feature inputs.

From Figure 7, it can be seen that the accuracy rate of the method in this paper is 91.32%, and the F1-Score is 0.9130. Compared with the original time-series data + 1D-CNN, the accuracy rate has increased by 3.22%; compared with the wavelet energy spectrum + 2D-CNN, the accuracy rate has increased by 3.92%; and compared with the original time-series data + TCN, the accuracy rate has increased by 2.75%. The F1-Score is at least 0.0436 higher than those of other models. In terms of training time, although the method in this paper takes more time than the original time-series data + 1D-CNN and the original time-series data + TCN, both the accuracy rate and the F1-Score have significantly improved.

It can be seen that the GAF transformation, through polar coordinate mapping, not only completely retains the absolute positional relationship and global correlation of the time-series data but also amplifies the differences in weak abnormal signals into image texture differences, which is conducive to the capture by the convolutional neural network. Meanwhile, the original time-series data + 1D-CNN has difficulty in capturing long-distance time-series correlations and is prone to losing weak abnormal features, resulting in low detection accuracy; the wavelet energy spectrum + 2D-CNN loses some time-series

information during the feature transformation process, resulting in a decrease in abnormal discrimination; and the original time-series data + TCN can capture time-series correlations, but has insufficient sensitivity to weak abnormal signals and a low accuracy rate. Therefore, compared with the one-dimensional time-series-specific models, the method in this paper has a significantly better ability to capture hidden and small abnormalities and a higher accuracy rate.

4.7. Model Robustness Testing

To evaluate the robustness of the proposed method under the presence of measurement errors, electromagnetic noise and other uncertainties in actual power grid operation, different standard deviation Gaussian noises were superimposed in the test sets A, B, and C to simulate the interference in sensor measurements. The comprehensive accuracy rate (Acc) was used as the evaluation index. The test results are shown in Table 5.

Table 5. Detection accuracy under different noise intensities.

Dataset	$\sigma = 0.00$	$\sigma = 0.02$	$\sigma = 0.06$	$\sigma = 0.10$
A	94.10	93.47	92.15	90.63
B	92.75	92.01	90.74	89.22
C	91.32	90.46	88.97	87.31

As the noise level keeps increasing, the detection accuracy rates of all three datasets continue to decline. Under the same noise conditions, dataset A has the smallest decrease in detection accuracy, at 3.47%, while dataset C has the largest decrease, at 4.01%. This indicates that the intensification of sample imbalance will amplify the impact of noise on detection performance. However, in the extremely imbalanced dataset C, with the highest noise level of $\sigma = 0.10$, the accuracy rate still remains at 87.31%, without experiencing a sharp decline in accuracy, proving that the proposed method exhibits good robustness under different noise conditions.

5. Discussion

The proposed anomaly detection method for power grid information data based on the improved AlexNet in this paper addresses the common problems in actual power grids, such as severe imbalance between normal and abnormal samples and the easy loss of weak abnormal signals in one-dimensional time-series data. This method effectively improves the anomaly detection accuracy in imbalanced scenarios.

However, this research still has the following limitations: First, the generalization ability of the data augmentation strategy is limited. The time-series translation and Gaussian noise injection methods used in this paper mainly generate new samples based on the transformation of existing abnormal patterns, resulting in insufficient generalization ability of the model for unknown abnormalities [30–32]. Second, the model does not fully integrate spatial prior information such as grid topology. The current model only uses electrical time-series information features for anomaly discrimination and does not introduce spatial physical information such as grid topology, line impedance parameters, etc. [33,34]. Third, it is highly dependent on labeled data. This paper adopts a supervised learning framework and requires a large number of high-quality labeled samples for training. However, the cost of labeling abnormal data in actual power grids is high, and the labeling quality is uneven. Deploying the model in remote areas of distribution grids with no or incomplete labeling is difficult.

6. Conclusions

This paper addresses the issues of sample imbalance and the easy loss of weak signals in one-dimensional time-series data during the detection of abnormal information in the smart grid. It proposes a detection method that combines data augmentation and improves AlexNet. By adopting a mixed enhancement strategy of time-series shifting and Gaussian noise injection, the problem of sample imbalance is solved. It maps multi-dimensional time-series data to two-dimensional images through dynamic weighted fusion and Gram angle field transformation, fully preserving the temporal correlation and weak abnormal features. By introducing the multi-head self-attention mechanism and transfer learning strategy, the lightweight structure of AlexNet is improved, enhancing the model's feature extraction ability and generalization performance in scenarios with small samples. The main conclusions are as follows:

- (1) A mixed data enhancement strategy combining time-series shifting and Gaussian noise injection is proposed. While preserving the essence of abnormal features, it generates enhanced samples close to the actual operating state, effectively alleviating the problem of scarce abnormal samples and data distribution imbalance. The ablation experiments show that in extreme imbalance situations, introducing the data enhancement module alone can increase the detection accuracy by 6.88%.
- (2) The Gram angle field was introduced to achieve the visual transformation of one-dimensional time-series data into two-dimensional images. Through dynamic weighted fusion and polar coordinate mapping, multiple-dimensional features such as voltage, current, and power were encoded into GASF images that retained the global temporal correlation, and the differences in weak abnormal signals were magnified into image texture differences. Ablation experiment results show that the accuracy can be improved by 7.81% after the introduction of the module, indicating that it significantly improves the ability of the model to extract small abnormal features.
- (3) Specific improvements were made to AlexNet in terms of network structure and training strategy. In terms of structure, the last three fully connected layers were replaced with a lightweight structure of the feature expansion layer—multi-head self-attention—Softmax; in terms of training strategy, transfer learning based on the ImageNet pre-trained model was introduced to accelerate convergence and prevent overfitting in small sample cases. The final model achieved a detection accuracy of 91.32% on an extremely imbalanced dataset, with the minimum improvement compared to other models being 3.1%.

In conclusion, the proposed method significantly improves the accuracy and generalization ability of anomaly detection in imbalanced grid sample scenarios. Future work will focus on integrating graph neural networks to incorporate grid topological spatial information and achieve joint modeling of temporal-spatial features [35]; exploring unsupervised or semi-supervised learning mechanisms to reduce the reliance on large-scale labeled data; and further optimizing the lightweight design of the model to meet the real-time detection requirements of edge computing nodes.

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References

- Hassine, L.; Quadar, N.; Ledmaoui, Y.; Chaibi, H.; Saadane, R.; Chehri, A.; Jakimi, A. Enhancing smart grid security in smart cities: A review of traditional approaches and emerging technologies. *Appl. Energy* **2025**, *398*, 126430.
- Tairo, D.C.; Silva, J.A.A.; López, J.C.; Rider, M.J. Implementation of a microgrid energy management system considering fair EV charging, uncertainties and contingencies: A multi-objective approach. *Appl. Energy* **2025**, *396*, 126242.
- Ding, W.; Xu, M.; Huang, Y.; Zhao, P.; Song, F. Cyber attacks on PMU placement in a smart grid: Characterization and optimization. *Reliab. Eng. Syst. Saf.* **2021**, *212*, 107586.
- Lin, W.-T.; Chen, G.; Huang, Y. Incentive edge-based federated learning for false data injection attack detection on power grid state estimation: A novel mechanism design approach. *Appl. Energy* **2022**, *314*, 118828.
- Huang, H.; Wei, J.; Ren, Z.; Wu, J. Rolling bearing fault diagnosis based on imbalanced sample characteristics oversampling algorithm and SVM. *J. Vib. Shock* **2020**, *39*, 65–74.
- Liu, D.; Wang, Y.; Liu, H.; Li, H.; Zhu, Q. POA-SVM Transformer Fault Diagnosis Based on ADASYN Balanced Dataset. *Power Grid Clean Energy* **2023**, *39*, 36–44.
- Chen, R.; Wu, H.; Yang, L.; Tang, L.; Xu, X. Multi-Classifer Ensemble Weighted Balanced Distribution Adaptation for Rolling Bearing Life Stage Recognition. *J. Instrum.* **2019**, *40*, 66–73.
- He, H.; He, J.; Zhang, L. Imbalanced data sampling design based on grid boundary domain for big data. *Comput. Stat.* **2025**, *40*, 27–64.
- Wang, H.; Hu, K.; Yang, H.; Lu, B.; Lu, Y.; Liu, Z. Global Feature Perception Network for Open-Switch Fault Diagnosis in Grid-Connected Photovoltaic Inverters Under Imbalanced Data Conditions. *IEEE Trans. Instrum. Meas.* **2025**, *74*, 3519114.
- Li, C.; Chang, W.; Zhang, D.; He, J. A Deep Reinforcement Learning-Based Partitioning Method for Power System Parallel Restoration. *Energy Eng.* **2026**, *123*, 243–264.
- Liang, W.; Liu, Z.; Wang, P. A concurrent fault diagnosis method for nuclear power plants based on deep transfer learning. *Ann. Nucl. Energy* **2026**, *225*, 111703.
- Moayyed, H.; Moradzadeh, A.; Abdeltawab, H.; Mohammadi-Ivatloo, B.; Faria, P.; Muyeen, S.M.; Vale, Z. Innovative defense strategies: Fusion deep learning approach to counter false data injection attacks in power systems. *Reliab. Eng. Syst. Saf.* **2026**, *268*, 112003.
- Sun, Y.T.; Zhang, F.M.; Chen, S.B.; et al. Power data anomaly detection method based on multi-domain feature extraction. *Power Syst. Autom. J.* **2022**, *34*, 105–113.
- Song, X. Application of Lagrange Interpolation Method in Predicting Building Discontinuous Settlement. *Surv. Spat. Inf. Technol.* **2022**, *45*, 2–3.
- Li, Q.; Zhang, L.; Zhang, G.; Ouyang, H.; Bai, M. Simultaneous detection for multiple anomaly data in internet of energy based on random forest. *Appl. Soft Comput.* **2023**, *134*, 4–5.
- Wang, X. Research on Imbalanced Data Classification Method Based on Generative Data Augmentation. Master's Thesis, Beijing Jiaotong University, Beijing, China, 2021; pp. 15–17.
- Yuan, X.; Wu, D.; Wang, K.; Ye, L.; Wang, Y.; Yang, C.; Gui, W.; Cheng, S. A Data Augmentation Method Based on Image Generation for Rock Structural Surface Trace Detection With Single-Sample Class Imbalance. *IEEE Sens. J.* **2025**, *25*, 3–4.
- Chen, J.; Li, K.; Tang, Z.; Bilal, K.; Yu, S.; Weng, C.; Li, K. A Parallel Random Forest Algorithm for Big Data in a Spark Cloud Computing Environment. *IEEE Trans. Parallel Distrib. Syst.* **2017**, *28*, 2–3.
- Gilanifar, M.; Wang, H.; Cordova, J.; Ozguven, E.E.; Strasser, T.I.; Arghandeh, R. Fault classification in power distribution systems based on limited labeled data using multi-task latent structure learning. *Sustain. Cities Soc.* **2021**, *73*, 103094.
- Abdulmohsin, H.A.; Wahab, H.B.A.; Hossen, A.M.J.A. A Novel Classification Method with Cubic Spline Interpolation. *Intell. Autom. Soft Comput.* **2022**, *31*, 339–355.
- Ganjkhani, M.; Gilanifar, M.; Giraldo, J.; Parvania, M. Integrated cyber and physical anomaly location and classification in power distribution systems. *IEEE Trans. Ind. Inform.* **2021**, *17*, 7040–7049.
- Wen, L.; Ye, Y.; Zuo, L. GAF-Net: A new automated segmentation method based on multiscale feature fusion and feedback module. *Pattern Recognit. Lett.* **2025**, *187*, 86–92.

23. Sridharan, N.V.; Vaithiyanathan, S.; Aghaei, M. Voting based ensemble for detecting visual faults in photovoltaic modules using AlexNet features. *Energy Rep.* **2024**, *11*, 3889–3901.
24. Shi, Y.; Suk, H.-I.; Gao, Y.; Lee, S.-W.; Shen, D. Leveraging Coupled Interaction for Multimodal Alzheimer’s Disease Diagnosis. *IEEE Trans. Neural Networks Learn. Syst.* **2020**, *31*, 186–200.
25. Guo, L.; Wang, H.; Fu, A.; Lu, Z.; Qian, G.; Wang, D. Fault Diagnosis Method for Large Transformer Windings Based on Gramian Angular Field Image Fusion and Deep Learning Algorithm. *High Volt. Eng.* **2026**, 1–13.
26. Zhao, Q.; Wang, J.; Lin, F.; Chen, J.; Nan, D.; Ouyang, J. Transmission Line Fault Identification Method Based on Gramian Angular Field and ResNet. *Power Syst. Prot. Control* **2024**, *52*, 95–104.
27. Pang, G.; Xiao, Z. Qualitative Analysis of Textile Fibers Based on Gramian Angular Field and Lightweight Convolutional Neural Network. *J. Text. Eng.* **2025**, *3*, 20–32.
28. Qian, G.; Yang, K.; Liu, H.; Li, D.; Wang, D. Transformer Winding Fault Diagnosis Based on Gramian Angular Field and Optimized CNN with Fusion Attention Mechanism. *Guangdong Electr. Power* **2026**, *39*, 106–117.
29. Diao, K.; Zhu, J.; Liu, G.; Li, M. MDTrans: Multi-scale and dual-branch feature fusion network based on Swin Transformer for building extraction in remote sensing images. *IET Image Process.* **2024**, *18*, 2930–2942.
30. Zhang, A.; Li, Z.; Xue, M. Intrusion Detection Based on Multi-Scale Graph Diffusion Contrastive Learning. *Comput. Eng.* **2026**, 1–12. <https://doi.org/10.19678/j.issn.1000-3428.0252938>.
31. Chen, H.; Luo, Y.; Wei, Y.; Guo, W.; Hang, F.; He, Y.; Yang, N. Federated Learning-Based Collaborative Detection Technology for SDN Anomaly Traffic. *Comput. Eng.* **2023**, *49*, 168–176. <https://doi.org/10.19678/j.issn.1000-3428.0064310>.
32. Huo, W.; Li, W.; Zhang, Z.; Sun, C.; Zhou, F.; Gong, G. Performance prediction of proton-exchange membrane fuel cell based on convolutional neural network and random forest feature selection. *Energy Convers. Manag.* **2021**, *243*, 114367.
33. Wang, R.; Ma, J.; Dong, J.; Liu, W.; Zhang, H.; Yin, K.; Zhao, B. Industrial Load Forecasting Method Based on MTS-BiGRU-DMHSA. *Comput. Eng.* **2024**, *50*, 169–178. <https://doi.org/10.19678/j.issn.1000-3428.0068641>.
34. Ashrafuzzaman, M.; Das, S.; Chakhchoukh, Y.; Shiva, S.; Sheldon, F.T. Detecting stealthy false data injection attacks in the smart grid using ensemble-based machine learning. *Comput. Secur.* **2020**, *97*, 101994.
35. Ren, J.; Chen, Y. Intelligent Grid Remote Inspection Anomaly Monitoring Method Based on Deep Learning. *Electr. Technol. Econ.* **2025**, *(12)*:332–334.

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