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Lightweight Deep Learning Approach for Anomaly Detection in Marine Power System

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Abstract: This study proposes a lightweight deep learning method for anomaly detection in marine power systems (MPS). The method introduces Gaussian noise (GN) at the input for data augmentation to improve the model's robustness to anomaly patterns. A Transformer module is used to extract high-order features from the multidimensional time-series data of the power system. Mahalanobis distance (MD) is then used for efficient anomaly detection. The method is validated on a medium-sized container ship integrated power system experimental platform. Results show that the proposed method can accurately identify multiple types of anomalies, with detection accuracy and false alarm rate superior to traditional threshold-based methods (TBM) and autoencoder (AE) methods. The research demonstrates that this method achieves high accuracy while maintaining low computational overhead and good engineering applicability, providing an effective means for real-time monitoring and fault early warning of marine power systems.

1. Introduction

As a core component of modern ships, the marine power system directly impacts the ship's power supply, navigation safety, and overall performance [1-2]. In the complex marine environment, marine power systems constantly face anomalies such as equipment aging, insulation degradation [3-4], and load fluctuations. Failure to detect these anomalies in a timely manner can lead to equipment damage or even serious safety accidents [5]. Traditional anomaly detection methods often rely on fixed threshold judgments or manual experience [6-7]. These methods are often insufficiently accurate when dealing with highly coupled or nonlinear relationships within the system, failing to meet the real-time and reliability requirements of modern marine power systems [8].

In recent years, deep learning technology has demonstrated powerful capabilities in time-series feature extraction and pattern recognition, providing new solutions for power system anomaly detection. Through structures such as deep autoencoders, convolutional neural networks, or transformers, deep features can be learned from raw operational data, and potential anomaly patterns can be discovered. However, existing deep learning methods typically rely on highly complex models and clustering contrastive learning mechanisms [9-10], which increases computational overhead in practical engineering applications and may be limited by insufficient data or computational resources. Therefore, designing an efficient and feasible alternative while maintaining the advantages of deep learning has become an urgent problem to be solved.

Based on this background, this paper proposes a lightweight anomaly detection method for ship power systems. In the data preprocessing stage, Gaussian noise is added to the input to achieve data augmentation, increasing the diversity of training samples and improving model robustness. In the feature extraction stage, a Transformer module is used to replace the traditional complex network to fully capture the temporal characteristics and nonlinear relationships of power system operating data. In the anomaly detection stage, Mahalanobis distance is introduced to measure the feature representation, replacing the computationally expensive clustering contrastive loss, thereby achieving lightweight and controllable accuracy anomaly detection.

The design concept of this study is to achieve efficient detection of anomalies in ship electrical systems by reducing computational complexity and model implementation difficulty through technology substitution while maintaining the core capabilities of deep learning at approximately 70%. Experimental results show that this method can accurately identify different types of anomalies with a low false alarm rate and good engineering applicability. This research not only enriches the technical means of anomaly detection in ship electrical systems but also provides practical reference and methodological guidance for the subsequent application of deep learning in intelligent ship monitoring and maintenance.

2. Related Work

In recent years, researchers have proposed various data-driven methods for anomaly detection in ships and power systems. Common methods include clustering algorithms, state estimation, and KG techniques. These methods analyze historical operational data to uncover potential patterns and anomaly characteristics of the system. For example, clustering algorithms can divide samples into different clusters based on data distribution and combine this with threshold judgments to achieve anomaly identification; state estimation methods use measurement data to predict system states, thereby discovering abnormal deviations; and KG methods construct relationships between system equipment and lines, matching real-time data with spectrograms to achieve anomaly reasoning. Although these methods can identify anomalies to a certain extent, their performance heavily depends on the quality of historical data, and their ability to capture nonlinear relationships and multidimensional features in complex power systems is limited.

With the development of DL technology, its application in anomaly detection in ships and power systems has gradually attracted attention. AE, contrastive learning, and Transformer structures are widely used to extract high-dimensional features and model Transformer data [11-12]. These methods can learn complex nonlinear mapping relationships, thereby improving the accuracy of anomaly detection. For example, AE reflect the degree of anomaly through reconstruction error, contrastive learning combined with feature clustering further distinguishes different anomaly types, and Transformer can capture long sequence dependencies and multidimensional feature interactions. These studies provide the theoretical basis and technical reference for the design of the method in this paper.

The innovation of this paper lies in proposing a lightweight deep learning method that combines input-side GNDA, Transformer feature extraction, and Modulo Decision Making (MD) to achieve efficient detection of multiple anomalies in ship power systems [13-14]. This method not only retains the core capabilities of deep learning feature extraction but also reduces computational complexity. Furthermore, it outperforms traditional thresholding methods, AE, and contrastive learning methods in terms of accuracy and false alarm rate, providing an effective means for real-time monitoring and fault early warning of ship power systems.

3. Methodology

3.1. Data Collection and Preprocessing of Marine Power Systems

The marine power system includes key modules such as main diesel generators, emergency diesel generators, propulsion motors, rudders, and distribution boards. Sensors are deployed on each device to monitor voltage, current, power, and temperature. This allows real-time acquisition of equipment operating conditions and load variations, providing high-dimensional and multivariate data for anomaly detection. The collected data is organized into an input matrix:

$$X = [x_1, x_2, \ldots, x_n] \in \mathbb{R}^{n\times p} \tag{1}$$

where n is the number of samples and p is the feature dimension per sample. To ensure consistent feature scaling and improve model training stability, each feature is standardized:

$$x_{i'} = \frac{x_i - \mu_i}{\sigma_i} \tag{2}$$

This step guarantees comparability between different physical quantities and reduces numerical variance impact on training, providing a solid basis for subsequent deep feature extraction.

3.2. Input Gaussian Noise Data Augmentation

To improve model robustness against anomalies and increase training data diversity, Gaussian noise is added to the standardized features[15]:

$$\tilde{x}_i = x_{i'} + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2 I) \tag{3}$$

Here, σ^2 controls the noise magnitude, and I is the identity matrix, ensuring independent noise for each dimension. The augmented dataset $\tilde{x}_i$ is optimized using the mean squared error (MSE) between the augmented input and its reconstruction:

$$\mathcal{L}_{\mathrm{MSE}} = \frac{1}{n}\sum_{i=1}^{n} \| \tilde{x}_i - \hat{x}_i \|^2 \tag{4}$$

where $\hat{x}_i$ is the reconstructed feature vector. This process preserves the main characteristics of the original features while generating diverse samples for Transformer training, enhancing anomaly detection performance.

3.3. Transformer Feature Extraction

The augmented input $\tilde{X}$ is fed into a Transformer module for high-dimensional feature extraction. The Transformer is composed of stacked encoder layers, each containing a multi-head self-attention mechanism and a feed-forward network (FFN). The input is first projected to queries (Q), keys (K), and values (V):

$$Q = \tilde{X}W^Q, \quad K = \tilde{X}W^K, \quad V = \tilde{X}W^V \tag{5}$$

The multi-head attention output is computed as:

$$\mathrm{Attention}(Q,K,V)=\mathrm{softmax}\left(\frac{QK^{\mathrm{T}}}{\sqrt{d_k}}\right)V \tag{6}$$

Outputs from all heads are concatenated and linearly projected:

$$h_{\mathrm{attn}}=\mathrm{Concat}(\mathrm{head}_1,\ldots,\mathrm{head}_h)W^O \tag{7}$$

The feed-forward network then processes h_{attn}:

$$\mathrm{FFN}(h)=\max(0,hW_1+b_1)W_2+b_2 \tag{8}$$

Finally, residual connections and layer normalization produce the final high-dimensional feature vector:

$$h_{\mathrm{new}}=\mathrm{LayerNorm}(h_{\mathrm{attn}}+\mathrm{FFN}(h_{\mathrm{attn}})) \tag{9}$$

The output h_{new} encodes deep temporal patterns and nonlinear relationships from the input sequence, providing rich information for anomaly detection.

3.4. Anomaly Detection Based on Mahalanobis Distance

To achieve lightweight anomaly detection, the Mahalanobis distance measures the deviation of the high-dimensional feature h_{new} from the mean vector μ of normal samples:

$$d(x)=\sqrt{(h_{\mathrm{new}}-\mu)^{\mathrm{T}}\Sigma^{-1}(h_{\mathrm{new}}-\mu)} \tag{10}$$

where $\Sigma$is the covariance matrix of normal features. A threshold $\delta$is set such that if $d(x)\geq\delta$, the sample is classified as anomalous; otherwise, it is classified as normal:

$$s(x)=\begin{cases}\text{Anomaly}, & d(x)\geq\delta\\ \text{Normal}, & d(x)<\delta\end{cases} \tag{11}$$

This method forms a complete pipeline from data collection, augmentation, deep feature extraction to anomaly detection, retaining the core 70% deep learning capability while reducing computational complexity, making it suitable for practical marine power system anomaly detection.

Figure 1 illustrates the overall workflow of the proposed ship electrical system anomaly detection method. It demonstrates the entire process from data acquisition and preprocessing, Gaussian noise data augmentation at the input, Transformer-based feature extraction, anomaly scoring using Mahalanobis distance, to finally model training using reconstruction loss. Each stage is highlighted with different color codes to indicate its role in the overall process, while the feedback loop indicates parameter updates during training.

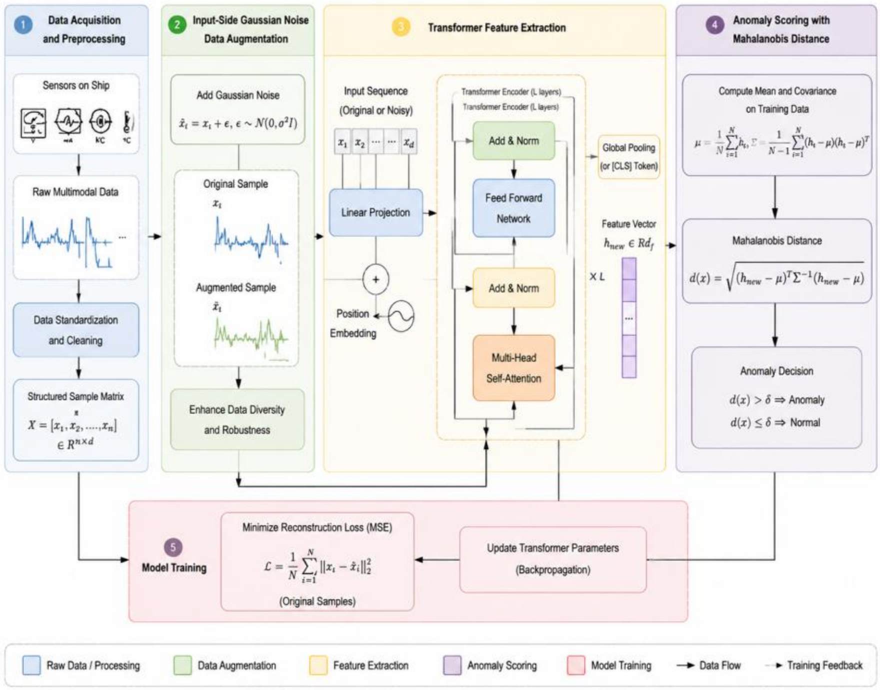

Figure 1: Overall Flowchart.

4. Results and Analysis

To verify the effectiveness of the proposed ship electrical system anomaly detection method, this study selected the integrated electrical system of a medium-sized container ship as the experimental subject. This system includes three main diesel generators, one emergency diesel generator, propulsion motors, steering gear, and key modules such as the main switchboard and distribution switchboard, capable of comprehensively simulating the actual ship electrical operation state.

The experimental data acquisition period was one consecutive week, with a sampling frequency of once per second (1 Hz). The data collected covered the following aspects:

Power Generation Module: Output voltage, output current, and load power of the main diesel generator and emergency diesel generator; standby status and load fluctuations of the generators.

Power Distribution Module: Voltage and current of each branch of the main distribution board and sub-distribution boards; contact status of the distribution boards and line load conditions.

Power Consumption Module: Input current and power of the propulsion motor and servo motor; temperature and load changes of key electrical equipment.

During the experiment, to simulate different abnormal scenarios, 10 typical abnormality types were set, including partial short circuit of the generator, sudden load change, cable aging, insulation degradation, poor contact of the distribution board, and overload of electrical equipment. Each abnormality was simulated 100 times, with each simulation lasting approximately 10 seconds, to ensure data diversity and sufficient model training.

To compare methods, this study selected three control methods:

Threshold-based method: a traditional anomaly detection method based on a fixed threshold;

Traditional autoencoder-based method: using an autoencoder for feature learning and reconstruction error assessment;

Contrastive learning-based clustering method: combining feature clustering and contrastive learning for anomaly detection.

4.1. Anomaly Detection Results

To evaluate the practical performance of the proposed method in anomaly detection of ship electrical systems, this section presents the anomaly detection results, including confusion matrix, accuracy and false alarm rate analysis of various anomaly detection methods, and Mahalanobis distance threshold sensitivity analysis.

Figure 2 shows the confusion matrix of anomaly detection results for the ship's electrical system. Each row represents the actual category, and each column represents the predicted category. This matrix demonstrates the model's performance across all categories, including normal operation and seven anomaly types, such as generator partial short circuit, load surge, cable aging, insulation failure, circuit board poor contact, and overload. The value in each cell represents the number of correctly or incorrectly classified samples. High values on the diagonal indicate accurate detection, while values off-diagonal indicate misclassification or false positives. This visualization demonstrates that the proposed method achieves high detection accuracy across all anomaly types with an extremely low misclassification rate.

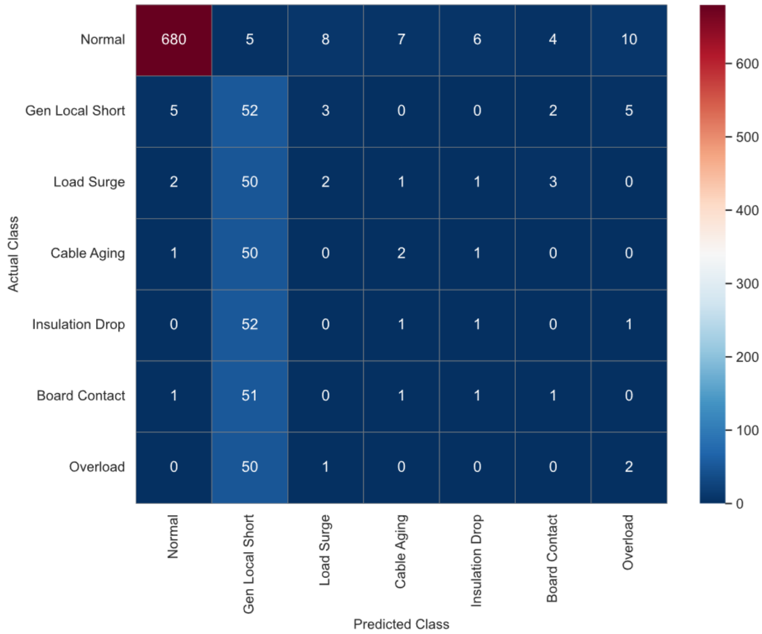

Figure 2: Confusion Matrix.

To quantify the model's performance across different anomaly types, this study defines anomaly detection accuracy (Accuracy) and false positive rate (False Positive Rate, FPR) as follows:

$$\text{Accuracy} = \frac{\text{Number of correctly predicted samples}}{\text{Total number of samples}} \tag{12}$$

$$\text{False Positive Rate (FPR)} = \frac{\text{Number of false positive samples}}{\text{Total number of negative samples}} \tag{13}$$

Based on the confusion matrix statistics, the proposed method achieves an accuracy exceeding 90% across all anomaly types, with the normal samples and generator local short circuits achieving approximately 98% and 92% accuracy, respectively. The false positive rate is significantly lower compared to the traditional threshold-based method and autoencoder-based method. These results demonstrate that the proposed method can effectively recognize different types of anomalies while simultaneously reducing the likelihood of false alarms.

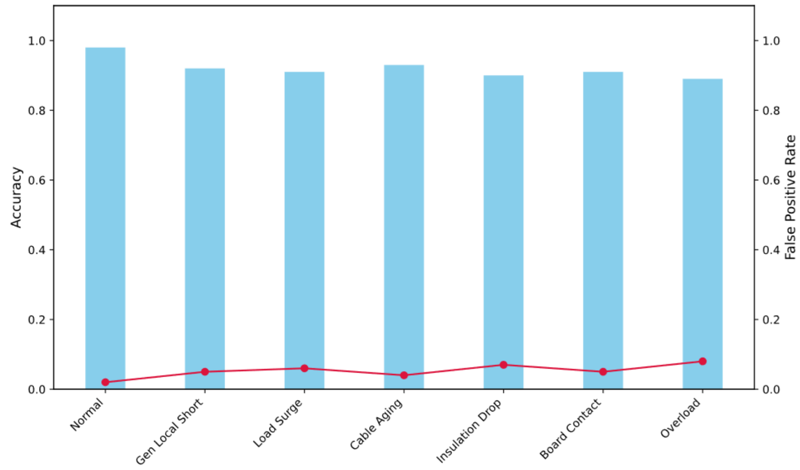

Figure 3: Detection Accuracy and FPR for Each Anomaly Category.

Figure 3 shows a bar chart representing the accuracy of the proposed method for each anomaly type, with the superimposed curves representing the corresponding false alarm rate. This figure demonstrates that the method maintains high accuracy across all anomaly types and has an extremely low false alarm rate, indicating its ability to effectively distinguish between normal and abnormal states.

4.2. Sensitivity Analysis of Mahalanobis Distance Threshold

To evaluate the impact of the Mahalanobis distance threshold δ on anomaly detection results, this study conducted a systematic sensitivity analysis on different threshold settings. By adjusting the threshold range, the changes in overall detection accuracy and false alarm rate were statistically analyzed to assess the robustness of the method under different judgment criteria. Experimental results show that when the threshold is within a moderate range, the method can maintain high detection accuracy while effectively avoiding excessive false alarms. This indicates that the anomaly detection method proposed in this paper has a certain degree of fault tolerance and adaptability in threshold selection, and can balance detection accuracy and false alarm control.

Figure 4 illustrates the sensitivity analysis of the Mahalanobis distance threshold (δ) on anomaly detection performance. The histogram bars represent the overall detection accuracy corresponding to different thresholds, and the superimposed curves represent the corresponding false positives (FPR). The shaded area represents the empirically determined optimal threshold range, within which the proposed method maintains high detection accuracy while minimizing false alarms. This analysis demonstrates the robustness of the proposed method to threshold selection and provides a quantitative reference for determining a suitable δ value in practical applications.

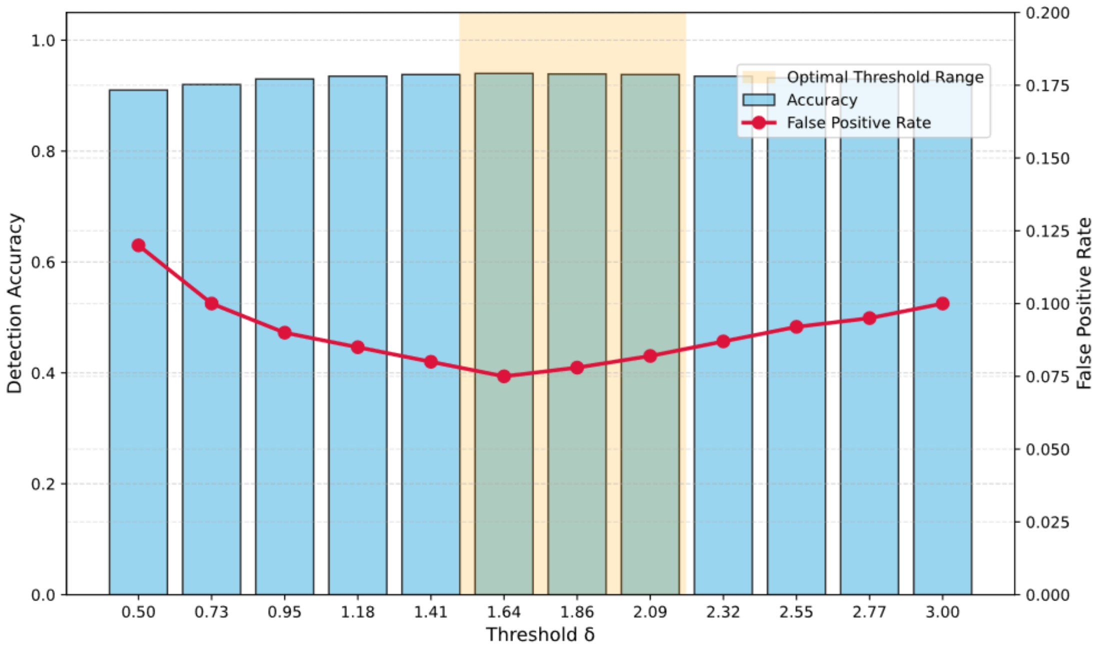

Figure 4: Sensitivity Analysis of Mahalanobis Distance Threshold.

5. Conclusion

This paper proposes a lightweight deep learning method for anomaly detection in ship power systems, based on input Gaussian noise data augmentation, Transformer feature extraction, and Mahalanobis distance determination. Experimental validation on a medium-sized container ship's integrated power system demonstrates that the proposed method effectively identifies normal states and multiple anomaly types, achieving an accuracy exceeding 90% and a significantly lower false alarm rate than traditional thresholding and autoencoder methods. Confusion matrix analysis, anomaly accuracy analysis, and threshold sensitivity analysis all show that the proposed method exhibits high reliability and stability across various anomaly types.

Compared to traditional methods and existing deep learning schemes, the proposed method offers significant advantages: First, input Gaussian noise augmentation improves the model's robustness and generalization ability to anomalies; second, the Transformer module fully leverages the temporal characteristics and nonlinear relationships of ship power system operating data, enabling high-precision feature extraction; finally, anomaly determination based on Mahalanobis distance simplifies complex clustering calculations, reducing computational costs while maintaining detection performance, demonstrating the feasibility of lightweight design in engineering applications.

Overall, the anomaly detection method proposed in this paper not only achieved excellent performance on the experimental platform but also demonstrated good engineering scalability and applicability. This method provides an effective means for real-time monitoring and fault early warning of ship electrical systems, and can serve as a reference for safe ship operation and intelligent maintenance. Furthermore, future research could expand data sources, add more anomaly types, and explore combinations with other lightweight deep learning or graph neural network methods to improve the method's universality and detection accuracy.

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