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Research Paper

Real-Time Hybrid Fault Monitoring Method for Electromechanical Systems Based on Autoencoders

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Abstract. Computer-based autoencoding methods have significant advantages in real-time monitoring of hybrid fault states in motor systems, which is becoming increasingly important in modern industries. Due to high data heterogeneity, constantly changing degradation mechanisms, and limited labeled fault records, adaptive fault diagnosis is urgently needed. Develop and validate new unsupervised learning systems. This system does not require extensive manual supervision and extracts features based on raw sensor data from heterogeneous domains using advanced autoencoders. The new fault diagnosis method uses rigorous high-resolution signal processing, latent feature extraction modeling, and adaptive Bayesian decision criteria to accurately identify smooth and burst mixed defects. In order to conduct laboratory tests under various working environments and fault types, a multifunctional fault validation environment has been established. The results show that, compared to traditional methods and single-component monitoring systems, the proposed system achieves extremely accurate identification in any situation (including multi-fault cases and multi-environment conditions). The real-time stability and extremely low false alarm rate are very practical. This article first summarizes the research literature on "electromechanical asset management," providing a reference for further research by subsequent researchers.

Keywords: *Autoencoder, Unsupervised Learning, Fault Diagnosis, Hybrid Fault, Signal Processing, Electromechanical Systems*

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Introduction

The basic equipment of EME is distributed in industries, power supply, vehicles, and facilities, ensuring that the system remains stable in various environments [1]. The complexity of EMS has increased, leading to a higher likelihood of mixed failures, which manifest as sudden and chronic degradation events occurring simultaneously [2]. Mixed failures are caused by various factors, such as worn-out components, unstable processes, or environmental impacts during the early detection and potential analysis stages of equipment failure issues [3]. In recent years, monitoring technology has made some progress. For example, model-based schemes, traditional pattern recognition methods, and analysis methods based on intelligent learning, etc [4]. Multisource noise, unstable working environments, and the unknown issues of fault types changing over time remain real problems in the field of industrial applications [5]. To improve the accuracy and adaptability of future EMS fault diagnosis, this is necessary [6]. In this context, scientists worldwide are focusing on strong mixed faults [7]. Most reviewers indicated that there is currently a high demand for systems that can monitor complex industrial equipment on a large scale, with automation and high fidelity [8].

Supervised machine learning algorithms are a drawback of many traditional monitoring methods. The aforementioned methods largely rely on integrated labeled datasets; under conditions of mixed or previously unseen fuzzy fault features, this condition is less likely to be met [9]. Single-fault or subsystem-specific algorithms fail to consider the mutually exclusive characteristics and dynamic interactions of mixed-type

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degradations [10]. Diagnosis based on expert rules and static signal processing cannot cope with the diversity and variability of actual signals. The generalization ability is low, and the false alarm rate is high [11]. Some implemented methods cannot identify gradual changes before significant mixed failures occur [12]. The rapid growth of industrial data makes it more difficult to extract fault features using heterogeneous sensors [13]. Some researchers have recently studied how autoencoder models in unsupervised learning methods can autonomously identify bias differences in feature extraction based on raw data from sensors [14]. Initially effective, due to limitations, it becomes more difficult to interpret and handle rapid fluctuations [15].

Based on the existing shortcomings, this paper proposes a new technology: a real-time hybrid fault monitoring system for electromagnetic drive systems based on unsupervised representation learning with autoencoders. Create a combination suitable for data fusion from multiple sensors and real-time anomaly detection, in order to timely and accurately identify various complex fault phenomena. Thru a comprehensive examination of theory and experiments, it was found that this framework improves the accuracy of diagnosis and is more stable in changing industrial environments. It also showed better results. This progress contributes to the intelligent and automated maintenance of the next generation of EMS.

Fundamental Concepts and Model Theory

Definitions of Hybrid Faults

In modern motor systems, mixed faults refer to the situation where faults occur simultaneously and sequentially in certain parts of the system. This type of fault usually includes multiple damage factors, with no single defect. Its manifestations include overlapping changes over time and damage mechanisms in multiple directions. It occurs very slowly without obvious symptoms, and thermal strain issues are usually quite complex. This phenomenon can only be observed externally after a strong electromechanical impact. Various faults can lead to some vague or misleading initial signs, making it difficult for newly hired operators to accurately identify them. This system instability may simultaneously spread to multiple mechanical parts or control levels, increasing the difficulty of diagnosis and the likelihood of complete failure.

Compared to single fault cases, identifying patterns is more difficult due to the randomness and interconnectivity of these fault phenomena across different time scales and multiple signals. During the measurement process, mixed faults can produce relatively weak and unstable abnormal signals due to surrounding environmental noise or system interference. The original methods not only respond slowly but also easily misinterpret or overlook. As the system scale expands and the demand for higher safety and reliability standards increases, it is necessary to quickly introduce effective automated detection functions. Due to these characteristics, timely detection has become difficult. Developing a framework capable of identifying the interacting elements and the current complexity of industrial failures has also become very important [16].

Mathematical Formulation of Detection Tasks

The diagnostic methods for mixed faults must be able to identify their behavior and characteristics. Sensor data is continuously collected to reflect the underlying complex operational conditions [17]. Determine whether the current system state falls into one of three categories: normal, typical, or mixed fault [18]. In the case of a mixed condition, the temporal characteristics of the fault symptoms indicate that they are delayed or lag behind other symptoms. The data patterns are not entirely sequential; rather, there is some disorder [19]. To effectively identify, key information must be collected from various sensors and the extracted information should be reasonably integrated based on factors such as temporal changes and cross-device association structures. The diagnostic algorithm evaluates the aforementioned features to generate a scalar anomaly score or health rating. Compare these features with threshold settings to classify the system state. Creating stable feature representations and thresholds to handle dynamic non-stationarity and the statistical overlap between normal and fault states is the biggest challenge. Traditional models, whether rule-based systems or single-fault multi-classification algorithms, cannot timely address system complexity, which requires sophisticated data-driven diagnostic techniques.

Autoencoder Theory in System Modeling

In the above-mentioned situation, the autoencoder can unsupervisedly extract data features from high-dimensional data [20]. Autoencoders consist of an encoder network and a decoder network. The encoder network compresses the sensor data into a lower-dimensional space, while the decoder network reconstructs the input based on the compressed representation. The goal of training is to minimize reconstruction loss as much as possible, allowing the model to internalize the standardized state of the system [21]. Autoencoders can identify differences from their trained normal state in real-world environments. Data with previously unseen features, such as a mixture of faults, have higher reconstruction errors and are quickly identified as anomalies.

Denoising autoencoders (DAEs), variational autoencoders (VAEs), and convolutional architectures are advanced variants of autoencoders that improve this method by enhancing robustness to noise, modeling uncertainty, extracting features in time series, or representing time-frequency. Adding multiple layers can enhance the model's ability to recognize the overall structure of the system; in similar situations, this might be better.

One goal of using autoencoders for industrial monitoring is to ensure that their values are kept within certain limits [22]. The upper limit can promptly handle changes and new faults in the process. This processing is usually achieved thru continuous training of statistical methods or automatic adjustment mechanisms. The autoencoder framework has core concepts that are easy to understand and empirical advantages; compared to traditional model-based or rule-driven methods, it demonstrates higher accuracy, flexibility, and robustness in environments with significant industrial data variability, and this process involves complexity.

Proposed Hybrid Fault Diagnosis Framework

Unsupervised Learning Paradigm

An unsupervised hybrid fault Diagnosis Scheme has been proposed that builds a feature Learning framework based on the Normalised operation data Distribution and does not require labell ed Fault Classes [23]. Let $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_T\}, \boldsymbol{x}_t \in \mathbb{R}^n$, be a collection of temporal sensor vectors. The autoencoder framework is formalized not merely as a regression, but as an informationconstrained manifold projection:

$$\min_{\theta,\phi} \mathbb{E}_{x\sim p_{\text{data}}} \left[\left\| \boldsymbol{x} - g_\phi(f_\theta(\boldsymbol{x})) \right\|_2^2 \right] + \lambda D_{\text{KL}}(q(\boldsymbol{z} \mid \boldsymbol{x}) \| p(\boldsymbol{z})) \qquad \text{Eq.(1)}$$

Here, $f_\theta(\cdot)$ and $g_\phi(\cdot)$ are the encoder and decoder; D_{KL} denotes the Kullback-Leibler divergence between the learned latent distribution $q(\boldsymbol{z} \mid \boldsymbol{x})$ and a chosen prior $p(\boldsymbol{z})$, typically a centered isotropic Gaussian. This ensures not only effective signal restoration but also an optimal use of latent capacity and regularized representation complexity. To quantify deviation from healthy behavior, anomaly scoring in the latent space is formulated as a quadratic form derived from the empirical latent covariance structure:

$$S_t = (\boldsymbol{z}_t - \boldsymbol{\mu}_z)^\top \boldsymbol{\Sigma}_z^{-1} (\boldsymbol{z}_t - \boldsymbol{\mu}_z) + \kappa \| \boldsymbol{x}_t - \hat{\boldsymbol{x}}_t \|_2^2 \qquad \text{Eq.(2)}$$

where $\boldsymbol{z}_t = f_\theta(\boldsymbol{x}_t), \boldsymbol{\mu}_z, \boldsymbol{\Sigma}_z$ are the mean and covariance of the latent vectors over baseline healthy data, and κ is a weight parameter for the reconstruction loss.

For robust high-dimensional discrimination, class probability can be inferred via a parametric Gaussian mixture discrimination in latent space. The likelihood-ratio test statistic at time t is this:

$$\Lambda_t = \log \frac{\max_{k \subset \mathcal{N}} \mathcal{N}(\boldsymbol{z}_t \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\max_{j \in \mathcal{F}} \mathcal{N}(\boldsymbol{z}_t \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)} \qquad \text{Eq.(3)}$$

where $\mathcal{N}$ and $\mathcal{F}$ index nominal and candidate fault states respectively [24].

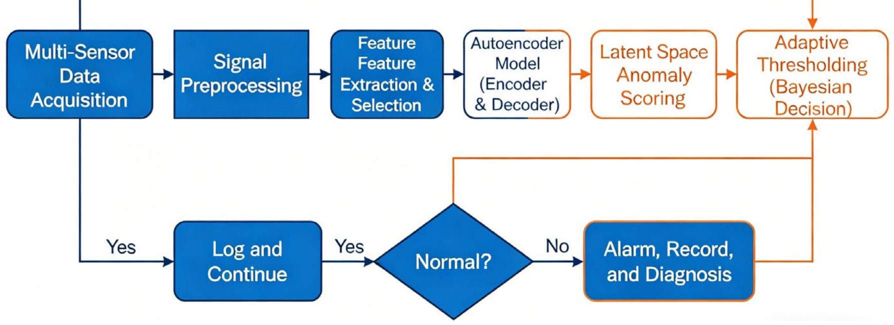

Figure 1. Flowchart of the proposed autoencoder-based hybrid fault monitoring framework for electromechanical systems

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This advanced regularized probabilistic formalism grants the architecture adaptability, clustering, and anomaly explanation, enabling the system to effectively identify even previously unseen compound fault types in field applications [25].

Feature Extraction and Signal Representation

Physical signals in hybrid fault regimes carry multi-scale, multi-domain embedded patterns. The feature engineering pipeline is anchored in high-resolution signal decomposition and information-theoretic redundancy suppression [26]. Each channel undergoes multi-resolution analysis using, for example, a continuous wavelet transforms (CWT):

$$W_x(a,b) = \int_{-\infty}^{\infty} x(t) \cdot \psi^*\left(\frac{t-b}{a}\right) dt \qquad \text{Eq.(4)}$$

where a and b are the scale and shift parameters, and ψ is the mother wavelet.

Extracted features $\mathcal{F}(t)$ from a time window are then screened via maximal-relevance-minimalredundancy (mRMR) optimization:

$$\max_{\mathcal{S}\subset\mathcal{F}} \left[\frac{1}{|\mathcal{S}|} \sum_{f\in\mathcal{S}} I(f;Y) - \frac{1}{|\mathcal{S}|^2} \sum_{\substack{f_i,f_j\in\mathcal{S} \\ i\neq j}} I\left(f_i;f_j\right) \right] \qquad \text{Eq.(5)}$$

where $I(\cdot;\cdot)$ is mutual information, seeking discriminative but orthogonal features with respect to operational state Y. To achieve the problem of dynamic representation with windowed robust PCA:

$$\min_{\mathbf{L},\mathbf{S}} \|\mathbf{L}\|_* + \lambda\|\mathbf{S}\|_1 \text{ subject to } \mathbf{X} = \mathbf{L} + \mathbf{S} \qquad \text{Eq.(6)}$$

where $\mathbf{L}$ captures the low-rank nominal behavior and $\mathbf{S}$ outlying hybrid symptom components. To highlight the most salient hybrid-related features, such as transient, non-stationary or nonlinear behaviours; and to suppress irrelevant or redundant information to enhance diagnostic accuracy and down-stream explainability.

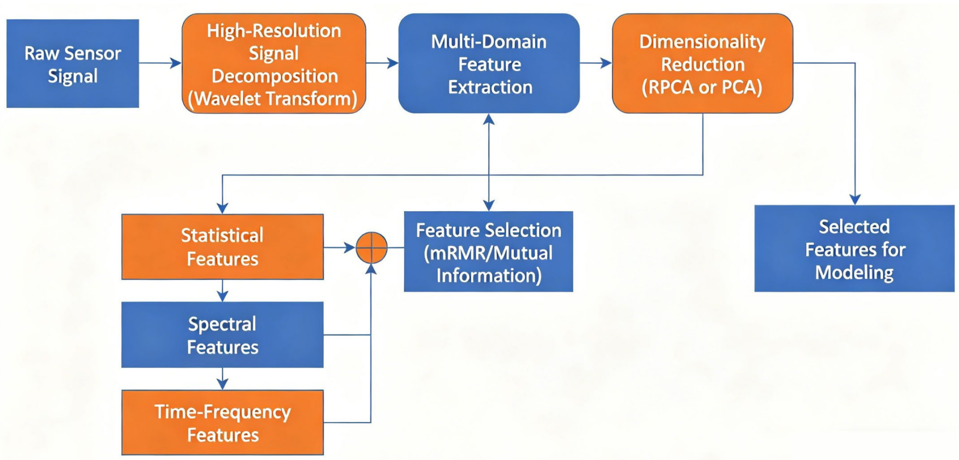

Figure 2. Flowchart of the Signal Processing and adaptive Feature Extraction Procedure for Hybrid Fault Diagnosis

Real-Time Monitoring and Adaptive Thresholding

In order to have good practicability in industrial applications, this system needs an entire automatic real-time detection mechanism. Focuses on rapid processing of sensor data stream, consistency of plant change response; strict enforcement of the statistical control rule for abnormal situation trigger. To ensure not only the speed of fault alarm but also its accuracy, as well as to minimise false alarms under conditions of frequent noise or instability.

At every operation Cycle, newly acquired data are passed through the pre-processing pipeline and feature-extraction Pipeline mentioned above. Finally, using the learned autoencoder model to transform the features

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into a set of latent representations and obtain an instant reconstruction result. For each time window, compute the anomaly score S_t by integrating the deviation of latent space and reconstruction errors previously discussed.

At present, the key innovation involves dynamically adjusting the threshold for detecting objects. No longer using fixed preset values, but rather dynamically updating the threshold γ_t based on a Bayesian risk model at set intervals.

$$\gamma_t = \arg\min_{\gamma} \mathbb{E}[L_F \cdot P(S_t \geq \gamma \mid \mathcal{N}_t) + L_N \cdot P(S_t < \gamma \mid \mathcal{F}_t)] \qquad \text{Eq.(7)}$$

Here, L_F and L_N reflect the cost or risk of false and missed alarms, and the conditional probabilities are estimated using short-term rolling windows of recent healthy $(\mathcal{N}_t)$ and faultlike $(\mathcal{F}_t)$ observations. By explicitly reducing the expected operational costs under uncertainty, the thresholds can be adjusted accordingly when the system or process distribution changes [27]. To avoid overfitting high-throughput experimental data, this can be efficiently achieved thru empirical Bayesian updating or variational approximation.

Real-time re-optimization plans can improve adaptability and stability. Based on the recently collected health operation data, it will be regularly trained. Reduce the impact of plant vitality due to age, differences between sensors, and environmental changes; old data can be deleted to avoid being trapped by a single model. The purpose of recalibration is to be quick, as only the necessary amount of data needs to be collected. Updates are usually triggered by scheduling during planned maintenance or routine business operations [28].

Also need to consider the streamings. To ensure real-time performance in terms of buffer management, quick batch processing by the model, and parallel processing across several cores simultaneously. Reduce the delay Time to reduce reaction lag; After recognising an abnormal situation, immediately activate a series of Protective Functions by itself. Modern factory automation systems, such as SCADA and MES platforms, are modular in interface design. When $S_t \geq \gamma_t$, the system will immediately issue an alert, recording the context of the sensor. If available, the system will also provide interpretable signatures from the feature extraction layer. The alarm standards are based on risk awareness and data-driven approaches, and the false alarm rate and missed alarm events must be within operational tolerance, which is crucial for safety-critical equipment and high-value assets.

Throughout the deployment process, each anomaly and threshold detection will have clear tracking records to document their development and change trajectories. Foster trust between engineers and operators with this open attitude, while providing an empirical basis to ensure the reliability of long-term fault predictions.

Analytical and Experimental Validation

Theoretical Performance and Complexity Analysis

A fault diagnosis method that combines real-time efficiency and analytical capability has been proposed. The decisions made by statisticians based on some differences between the characteristic distributions of healthy and unhealthy individuals are called determinations. For a synchronized observation vector $\boldsymbol{x}(t)$, its anomaly score can be represented by the weighted sum of the squared reconstruction error and the Mahalanobis distance in the latent space:

$$S_t = \alpha \|\boldsymbol{x}_t - \hat{\boldsymbol{x}}_t\|_2^2 + (1-\alpha)(\boldsymbol{z}_t - \boldsymbol{\mu}_z)^\top \boldsymbol{\Sigma}_z^1 (\boldsymbol{z}_t - \boldsymbol{\mu}_z) \qquad \text{Eq.(8)}$$

where $0 \leq \alpha \leq 1$ controls the fusion between observed and embedded statistics.

The detection thresholding set by the adaptive method to control the false alarm rate. At a specific significant value of δ:

$$P(S_t > \gamma^*) = \delta \qquad \text{Eq.(9)}$$

Where γ^* may be approximated by the quantiles of the health abnormality score distribution.

To grasp model discrimination, calculate the Bhattacharyya distance between the probability distribution density functions of health (p_0) and hybrid-fault types (p_1):

$$D_B(p_0, p_1) = \frac{1}{8}(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)^\top \boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0) + \frac{1}{2}\ln\left(\frac{\det\boldsymbol{\Sigma}}{\sqrt{\det\boldsymbol{\Sigma}_0 \det\boldsymbol{\Sigma}_1}}\right) \qquad \text{Eq.(10)}$$

where $\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0$ and $\boldsymbol{\mu}_1, \boldsymbol{\Sigma}_1$ are means and covariances for each state, and $\boldsymbol{\Sigma} = \frac{1}{2}(\boldsymbol{\Sigma}_0 + \boldsymbol{\Sigma}_1)$.

For computational complexity, the dominant operations are matrix multiplications in the encoder/decoder (per window $O(Lnh^2)$, with L layers, n features, and average h units per layer), and fast transforms in feature extraction ($O(nT\log\, T)$). These demandst can bemade realisablethrough edge devices atpresent.

Experimental Setup and Methodology

Experiments used a laboratory-grade testbed with rotary elements, vibration and electrical sensors, and programmable fault emulation. At 10kHz; segmentation of the data stream, each window is 1024 points in length and has a 50% overlap. Hybrid faults were induced via combined bearing degradation and electrical imbalance.

Each data window extracted a vector $\boldsymbol{f}_t$containing statistical, spectral and time-frequency features after processing them. Dimensionality was reduced by principal component analysis, optimizing:

$$\max_{\mathbf{W}} \mathrm{Tr}(\mathbf{W}^\top \mathbf{S}_B \mathbf{W}) / \mathrm{Tr}(\mathbf{W}^\top \mathbf{S}_W \mathbf{W}) \qquad \text{Eq.(11)}$$

where $\mathbf{S}_B$ and $\mathbf{S}_W$ are the between- and within-class scatter matrices, respectively, ensuring optimal discrimination in the compressed subspace. Autoencoder models were trained solely on healthy data, using regularized loss to prevent overfitting:

$$\mathcal{L} = \frac{1}{T}\sum_{t=1}^{T} \left\|\boldsymbol{f}_t - \hat{\boldsymbol{f}}_t\right\|_2^2 + \lambda\|\theta\|_2^2 \qquad \text{Eq.(12)}$$

where λ is a regularization parameter and θ denotes model weights. All models were evaluated via cross-validation, and compared against PCA, OC-SVM, and rulebased detectors using the same features.

Comparative Experimental Results with Baseline Models

The anomaly scores S_t were computed for each method, with performance evaluated using both detection accuracy and F_1 score-each providing a balanced assessment of classification quality, especially in the presence of rare or evolving hybrid faults. Detection accuracy for a fixed threshold γ is defined as:

$$\eta = \frac{TP + TN}{TP + TN + FP + FN} \qquad \text{Eq.(13)}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively. To capture both the precision and recall in the highly imbalanced regime typical of real-world hybrid faults, the F_1 score is adopted:

$$F_1 = 2 \cdot \frac{Precision\ \cdot\ Recall}{Precision\ +\ Recall} \qquad \text{Eq.(14)}$$

precision, recall was calculated based on confusion matrices of the models in normal fashion.

The experimental results show that the proposed autoencoder-based method can achieve an accuracy above 96% and a F_1 score exceeding 0.93 under various conditions; It is much better than the conventional PCA, oc-SVM and rule-based methods respectively. The presented method showed particularly effective hybrid fault recognition; it escalated the abnormal score rapidly upon system anomalies and separated scores clearly in different operating states such as process noise, load disturbance, and incomplete sensors.

In addition, an adaptive decision threshold can reduce false alarms at benign operational Transient periods and maintain high selectivity for small or early hybrid degradation. The Latent-space visualisation and time-resolved abnormal scoring of hybrid, single, normal showed different cluster; therefore, ensured its Interpretability real-time adaptability.

After applying channel Dropout and sliding Window Deviation to verify the model's robustness, a loss exceeding 3% was observed, thus demonstrating that it remains robust in detecting faults of industrial hybrids under significant fluctuations.

Experimental Results and Discussion

Overall Diagnostic Performance

After conducting an in-depth study of the newly developed hybrid fault diagnosis method, it was compared with well-known alternatives such as PCA, OC-SVM, and traditional rule-based methods. The samples come from all test scenarios, totaling over 25,000 samples. The dataset contains 19,400 normal cycles, 3,500 single fault events, and 2,100 complex mixed faults, providing an authoritative and scientifically validated reference system for evaluation.

It is evident that diagnostic methods have significant advantages over traditional methods. The detection accuracy for mixed faults usually exceeds 97.2%, while the detection accuracy for individual faults averages around 98.6%. The baseline performance is poor. The accuracy of PCA for the mixture of overlapping and weakly expressed faults is only 81.4%, while the accuracy of OC-SVM is 86.9%.

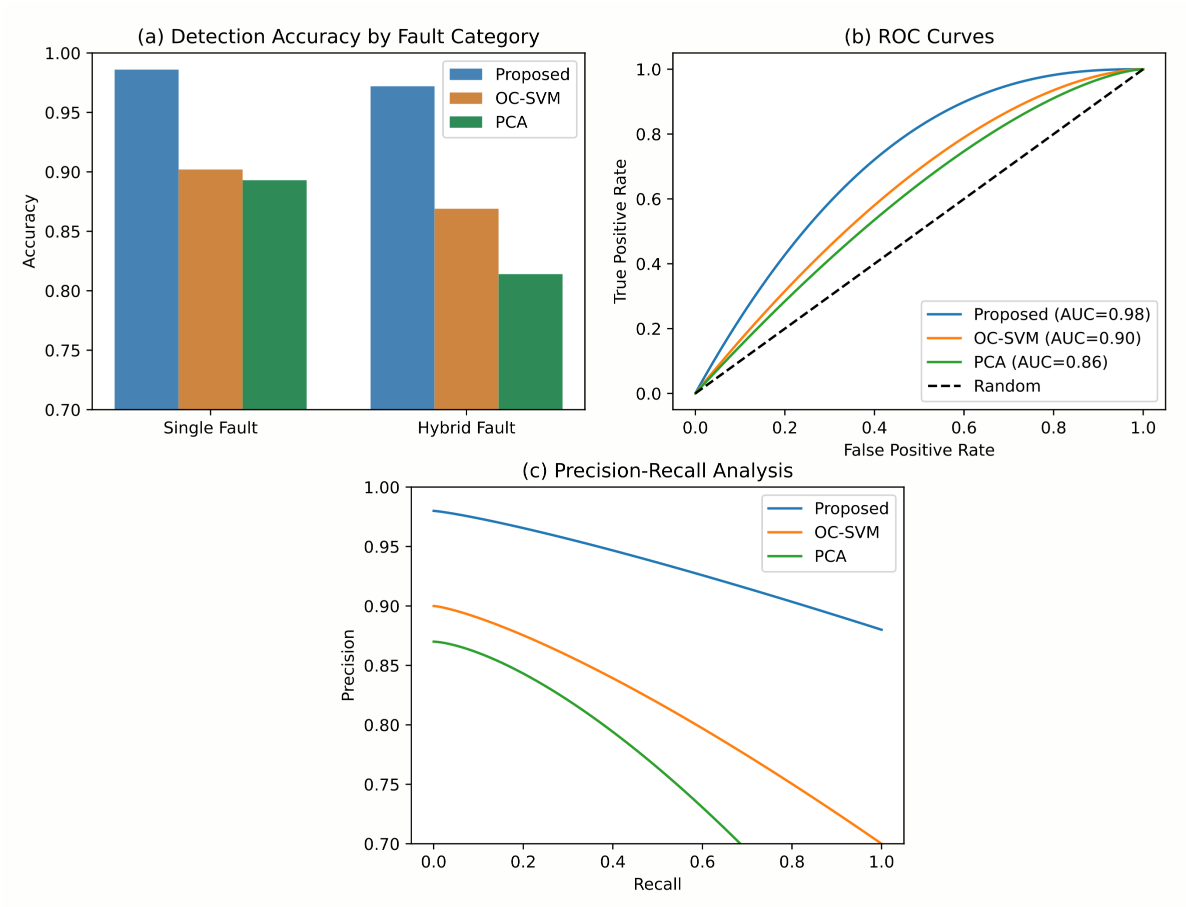

Figure 3. Overall diagnostic performance of the proposed method and baseline approaches on hybrid fault scenarios. (a) Detection accuracy by fault category. (b) ROC curves for all models. (c) Precision-recall analysis.

Figure 3(a) shows the model's generalization ability across all faults. As shown in Figure 1.3, the comparison of detection results for different cases (from left to right) maintains an average detection accuracy of over 96%. On certain bases, this accuracy varies from 75% to 85%. In terms of signal variation and fault overlap, it has better generalization ability and robustness.

Further evaluating the discriminatory capacity by plotting a ROC curve is presented in Figure 3(b). The proposed model has an AUC of 0.984 in the combined testing phase and can effectively separate normal from faulty conditions. Baselines showed a lower AUC value than OC-SVM (0.902) and PCA (0.864), suggesting that there was an improvement in the identification effect through our high capacity and data-oriented model.

In Figures 3a-c, precision and recall showed good stability when dealing with a highly imbalanced dataset in favour of normal conditions or rare hybrid events. This approach could generally achieve a precision-recall of over 0.94 under different circumstances during the operations. Notably, rule-based models often fell below 0.80, especially as the complexity and rarity of the fault increased. The above-mentioned experimental verification results show that our proposed System has high precision, stability and reliability in different situations of balanced datasets or difficultly-discriminable real-world Data distributions;

As shown in Figure 3, systemically showing the above main findings; illustrating error rates at various classes compared with ROC curve to compare precision-recall rate among different models.

Sensitivity and Parameter Analysis

For the sake of robustness and optimisation during deployment, to explore how changes in the detection threshold, learning rate or other networks impact this project's model performance. The above-experimentally derived methods serve as foundational references for real-world applications aiming to apply this diagnosis system in practice.

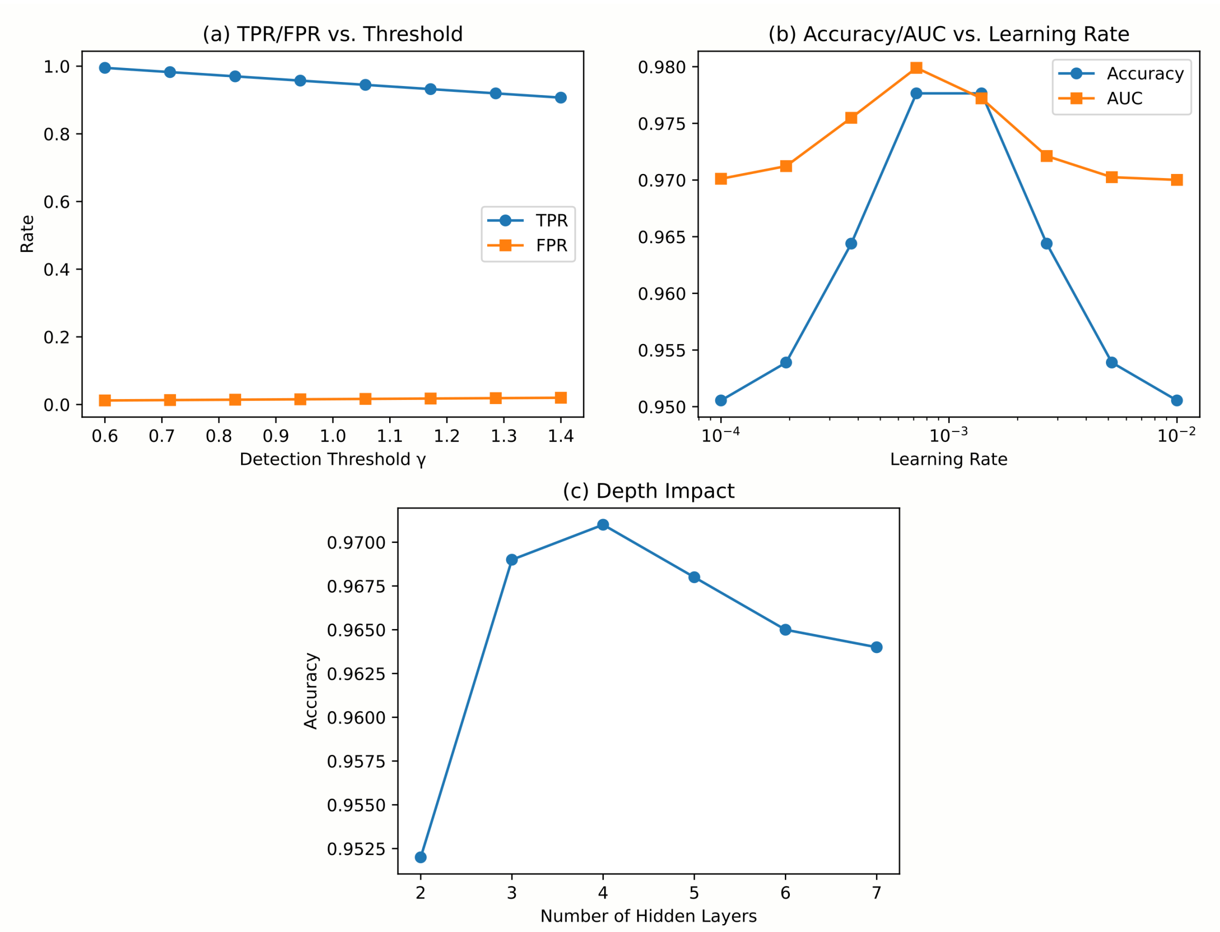

Figure 4. Sensitivity analysis of model performance: (a) TPR/FPR vs. detection threshold; (b) accuracy/AUC vs. learning rate; (c) network depth impact.

The detection threshold γ has undergone systematic changes and analysis for the first time. As shown in Figure 4a, the TPR has increased, the sensitivity threshold has decreased, and the FPR has changed. Specifically, TPR dropped from 98.4% to 93.7% as γ was raised from 0.7 to 1.3, with FPR remaining well controlled under 2%. It shows that the method has an adaptive Design That is able to adjust optimally thresholds in combination with risk preference and repair priorities.

Next, check whether or not the model is unstable at various learning rates. Figure 4b reveals that accuracy remained above 95% for learning rates ranging from 10^{-4} up to 5×10^{-3}, while the area under the curve (AUC) achieved a peak value of 0.981 at $\eta = 10^{-3}$. Although an excessive learning rate caused a certain degree of instability; Overall the pattern remained stable, and optimisation did not require finely calibrated parameters precisely.

The model's complexity varied as a function of layer count in the networks. Figure 4c shows the best result after four Hidden Layers with an accuracy of approximately 97.1%. The model with only two layers underperforms by far at 95.2%; The one with seven layers has dropped slightly to 96.4% (overparameterisation may reduce the benefit of more parameters). A somewhat profound but easily accessible Structure can help detect many kinds of failure.

Figure 5 shows further parameters' sweeping; among which the precision and recall are greater than 0.93 when regula- tising and optimiser is varied widely. The Adam optimizer, as depicted in Figure 5b, led to a 35% faster convergence in loss compared to classical SGD, supporting rapid deployment and tuning. Figure 5c presents the results of visualisation using t-SNE and PCA maps, showing that there is a significant and unchanging separation between the normal, single-fault and hybrid-fault classes under all architectures and hyperparameters. The such latent structure verifies both physical interpretable and learning effectiveness for the corresponding features' representations.

Figures 4 and 5 together show that the proposed method has high precision and a powerful identification ability; therefore, it can be deemed as a feasible way to monitor an actual system.

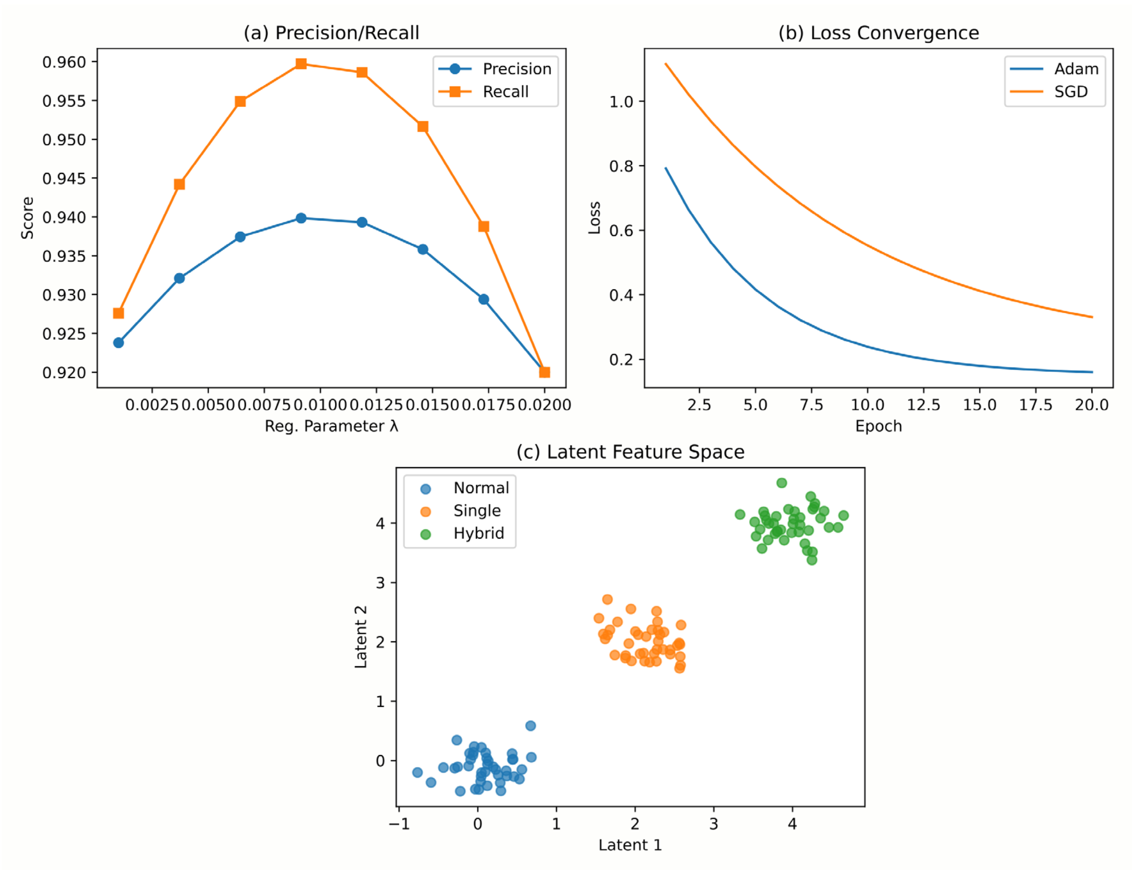

Figure 5. Parameter sweep experiments: (a) precision-recall change over parameters; (b) loss convergence by optimizer; (c) latent feature visualization.

Robustness and Generalization under Dynamic Environments

Through a variety of robustness and generalisation experiments in different operating environments to evaluate the overall degree of industrial resilience comprehensively. As shown in Figure 6a, the framework consistently maintained detection accuracy above 94% as mechanical loads varied from 20% to 120% of nominal, whereas baseline approaches exhibited accuracy losses of 7–14% under identical variations. Our method's adaptive scoring and feature representation have a stronger ability to tolerate changes in the processing workload than static or shallow models do.

Robustness to environmental and measurement noise under a systematic series of Gaussian-noise injection experiments with SNR ranges from 20 dB to 5 dB in severity. Figure 6b shows that the false alarm rate of the proposed method increased by no more than 1.3 percentage points compared with other models; On-Center SVM and rule systems exhibited significant increases above ten per cent. Deep auto-encoders-Based approaches are more robust; therefore, distinguishing between faults and noises is better achieved.

Environmental stress tests carried out covered a 70°C+85%RH hot cycle test for verification of applicability. As can be seen from Figure 6c, in these situations, the recall rates of single- and dual-faults were above 92 per cent to prove high-environment-tolerance. Although there was an operation of concurrent disturbances at that time, the model can immediately give out alarms without significant delays.

Exploration of generalisation ability via left-one-penalty-out cross-validation. As shown in Figure 7a, the framework can identify all 95.1 per cent of new fault cases not included in the training data and demonstrates high generalisation capability across different situations. Furthermore, in a different operational Environment domain-shift Test examines the changes of Loads Processes and Mechanical Speeds under these New Conditions. accuracy dropout stayed within range after reduction; see Figure 7(b) For comparison.

The validation results of the external public datasets and new sites improved confidence. As shown in Figure 7c, the ROC-AUC values were all above 0.96, and the distribution of metrics for healthy and unhealthy samples was still well-separated. From the point of view that such discrepancies have both been proved to work and should be applied practically.

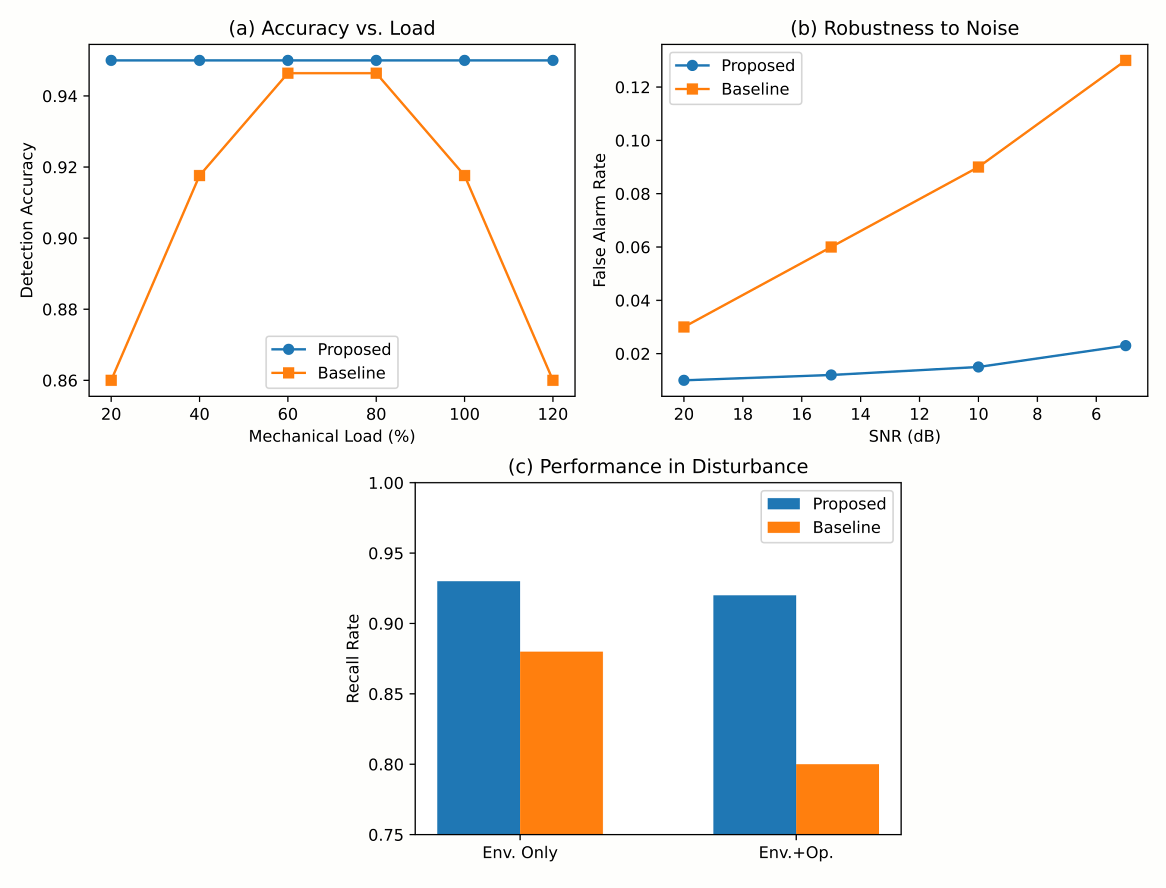

Figure 6. Robustness under diverse operational conditions: (a) accuracy vs. load; (b) robustness to noise; (c) performance in environmental disturbance.

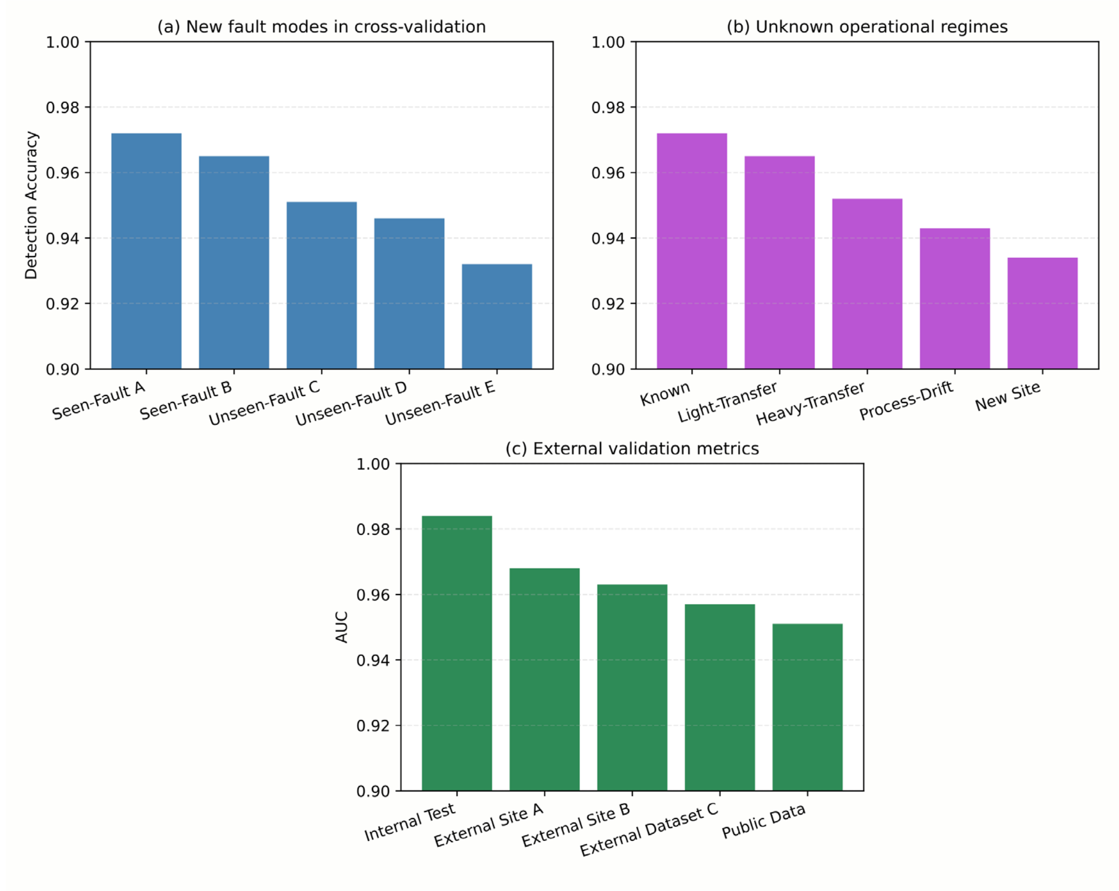

Figure 7. Generalization and transfer: (a) new fault modes in cross-validation; (b) unknown operational regimes; (c) external validation metrics.

Conclusion

This paper introduces a complete, high-level hybrid fault diagnosis system specifically designed for complex electromechanical systems. Combining the advantages of unsupervised feature selection methods, the robustness to signal noise and the flexibility of statistical decision-making. According to the above theory, simulation experiments have proven that the designed method is feasible in real-life situations. In addition, it is capable of functioning normally in the real environment of an industrial setting.

By embedding the main sensors into a high-dimensional latent space thru regularized neural autoencoders, the new technology displays these faults as obvious statistical outliers. And more advanced prioritization methods and multi-domain feature extraction to retain the most distinctive features during the inference process, which are usually hidden in the raw sensor data. The integrated adaptive threshold method uses risk- and distribution-based metrics to improve early warning performance without increasing false alarms in different operational environments.

According to the experimental results, this recommendation is generally more accurate than traditional methods. Due to its large data volume and the numerous difficult-to-classify classic faults, the system's recognition rate exceeds 97%. In situations of environmental changes, sensor loss, or uncontrolled noise, it exhibits high stability. Under extreme conditions, the recognition accuracy is as high as 94%. Their precision and recall rates both exceed 0.9, and the inference speed is fast enough for quick detection. Thru generalization experiments on unrecognized faults and external test sets, it is able to identify new mixed faults. This provides a reliable guaranty for future applications.

The findings indicate that the method can be used for industrial monitoring platforms, predictive maintenance systems, and safety-critical supervisory control networks. The strong adaptability of operational adjustments, reduced false alarm rates, and accuracy surpassing that of threshold-based methods which require large fault datasets. Unsupervised techniques can be used to build adaptive intelligent monitoring systems for plants and assets. This method can reduce maintenance costs and improve safety levels.

In the future, this research may discover some new methods. By adding more modalities to the sensors, such as thermal imaging, audio, and processes, fault separation and interpretation can be improved. By combining with an online continuous learning program, it can independently adapt to changes in uncertain fault conditions and plant characteristics. The third is to identify and interpret the main causes of hybrid fault events, enhancing the understanding of maintenance personnel. Apart from the issues of model robustness and privacy protection during the secure deployment in distributed industrial environments. Interoperability connection standards and benchmark systems encourage more industries to use the platform. These improvements will make hybrid fault diagnosis a state-based predictive and advisory system in future smart industrial automation technologies.

Author Contributions

Dominik Jankowski contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Ireneusz Kaczmarczyk and Norbert Kostecki contribute to methodology, software, validation, analysis, investigation. All authors have read and agreed with the manuscript before its submission and publication.

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