RESEARCH ARTICLE

Robust Imbalanced Learning for Aero-Engine Bearing Anomaly Detection via a Hybrid SMOTE-BLS Framework

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Abstract

The operational reliability of aeroengines is vital to civil aviation safety; however, bearings and other key components are prone to failure under harsh operating conditions. In real-world monitoring data, severe class imbalance often leads conventional fault diagnosis methods to be biased toward majority classes, limiting their ability to identify critical faults. To address this issue, this paper proposes a robust anomaly detection framework that integrates the Synthetic Minority Oversampling Technique (SMOTE) with a Broad Learning System (BLS). SMOTE is first applied to generate synthetic fault samples in the feature space, thereby balancing the data distribution and reducing bias. The balanced data are then fed into a BLS classifier, which exploits its flat architecture to achieve high-dimensional feature representation and fast non-iterative training. Experimental results on multiple aeroengine bearing datasets demonstrate that the proposed method outperforms comparative approaches in terms of fault detection accuracy and robustness.

Keywords: aircraft engine, fault diagnosis, imbalance learning, broad learning system.

1 Introduction

As the core power unit of aircraft, the operational reliability of aeroengines is directly linked to the safety threshold of civil aviation operations. However, aeroengine systems are highly complex and operate continuously under extremely harsh conditions such as high temperature, high speed, variable loads and intense vibration. These factors easily induce various mechanical failures and accelerate the aging process of components [1, 2]. Among numerous failure modes, wear of key friction pairs such as bearings is particularly prevalent. Subsequent replacement and maintenance of these components often incur substantial human and financial costs. Therefore, there is an urgent need to develop effective methods for monitoring and predicting the operational status and potential failures of aeroengines.

In the aeroengine health management system, wear particles carry abundant information about the surface conditions of mechanical friction pairs and serve as a crucial basis for analyzing fatigue failures [3]. Based on oil analysis technology, which detects particle and element contents in lubricating oil has become

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one of the mainstream diagnostic methods [4, 5]. Currently, oil analysis techniques mainly include spectral analysis, magnetic plug monitoring, and ferrography analysis. In particular, ferrography analysis utilizes a high-gradient magnetic field to separate wear iron particles from oil samples [6]. By observing their visual characteristics through microscopy, it enables qualitative and quantitative evaluation of wear conditions. However, despite its unique advantages in revealing wear mechanisms, ferrography analysis still faces significant challenges in practical engineering applications. Traditional analysis processes are highly dependent on experts' prior knowledge and manual experience, which not only leads to low diagnostic efficiency but also renders the analysis results highly subjective and uncertain. Consequently, it is difficult to meet the standardization and real-time requirements of modern aviation maintenance.

Machine learning and deep learning technologies have been introduced into aeroengine fault diagnosis to address the limitations of traditional methods, greatly promoting the development of intelligent diagnosis. As reviewed in recent progress surveys [7], early studies attempted to construct expert knowledge bases through fuzzy logic and clustering, but such methods are often constrained by the difficulty of knowledge acquisition and poor adaptive capacity [8]. With the iteration of algorithms, deep learning has demonstrated significant advantages in feature extraction. For instance, Lyu et al. [9] proposed a state-guided multi-task network (MTS-Net), which leverages auxiliary information to enhance the flexibility of few-shot diagnosis. Reference [10] developed a hybrid model integrating physical information and Beta-VAE, improving robustness under high-noise and missing data conditions. Reference [11] combined digital twins with graph neural networks (GNNs) to optimize feature extraction and domain adaptation capabilities under complex operating conditions. Despite the considerable reference value of these methods, such models typically rely on massive high-quality data for training, are time-consuming to train, and tend to get trapped in local optima. Furthermore, most existing methods are based on the assumption of balanced data, whereas real-world aeroengine monitoring data exhibits severe class imbalance, a huge number of normal samples alongside extremely scarce fault samples [12, 39, 42]. This data distribution bias causes models to overfocus on normal classes during training, thereby sacrificing the recognition accuracy of critical faults.

To address the performance degradation of classifiers caused by the severe imbalance between abnormal and normal samples in vibration data of aero-engine bearings, this study proposes an anomaly detection model that combines the synthetic minority oversampling technique with the broad learning system. The core idea consists of two stages. First, the SMOTE algorithm is employed to intelligently oversample the minority class (abnormal) samples in the feature space, thereby constructing a training dataset with a relatively balanced class distribution and mitigating the model's bias toward the majority class. Second, the balanced data are input into the broad learning system for rapid training and classification. Owing to its flat network structure that does not require deep iterative training, the broad learning system can efficiently extract patterns from high-dimensional vibration features and achieve accurate identification of abnormal states.

2 Related Work

2.1 Imbalanced Learning

The degradation process of an aircraft engine may last for several years, and most monitoring data correspond to the healthy operating state of the engine [41, 43, 45]. This leads to a data imbalance problem, in which samples representing the healthy state far outnumber those corresponding to fault states [19]. Under such data imbalance conditions, anomaly detection for aircraft engines can be adversely affected. Predictive models tend to be biased toward the majority class representing healthy conditions while neglecting the minority class representing fault conditions, which in turn degrades prediction accuracy [23, 44]. To address this issue, two main categories of strategies can be considered, namely data level strategies and algorithm level strategies.

From the data perspective, the primary approach involves data resampling [24–26]. By applying oversampling or undersampling techniques to rebalance the dataset, the class distribution can be made more uniform [20]. Vairetti et al. [21] proposed a hybrid resampling method based on the MapReduce framework, in which oversampling and undersampling are performed simultaneously to improve imbalanced classification performance while enhancing computational efficiency. Wang et al. [22] designed a three stage sampling algorithm

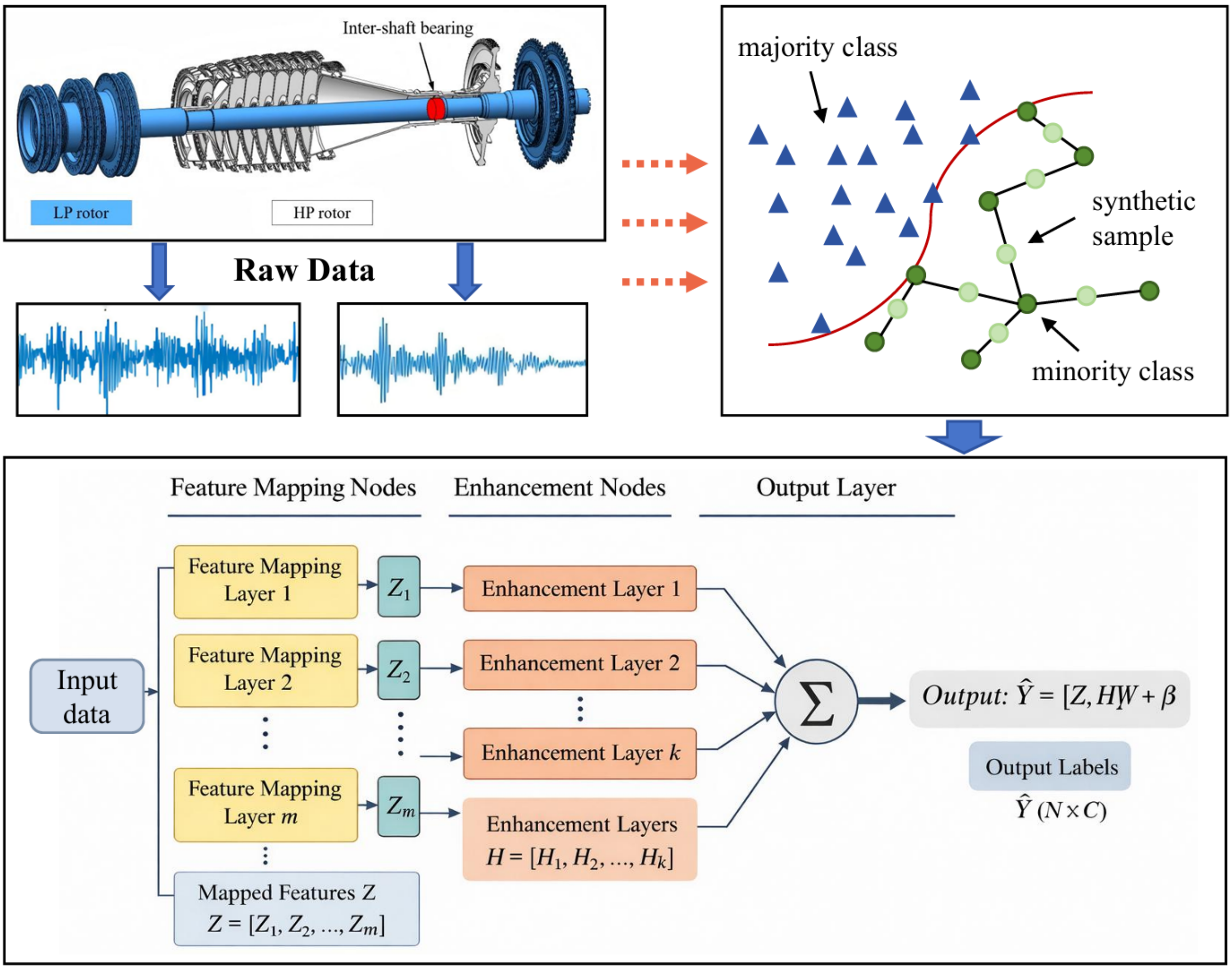


Figure 1. The framework of our method.

that first expands minority class samples through perturbed random oversampling, then applies the Synthetic Minority Over sampling Technique, and finally removes noisy samples near class boundaries using distance based methods.

From the algorithmic perspective, methods [27–29] specifically designed for imbalanced data can be employed. For example, cost sensitive learning [30, 31] adjusts class specific weights to encourage the model to focus more on minority classes, while ensemble learning [32, 33] improves overall predictive performance by combining the outputs of multiple base classifiers. These algorithms are generally more effective at identifying minority class samples and thus enhance model performance under imbalanced data conditions.

2.2 Broad Learning System

Inspired by the Random Vector Functional Link (RVFL) [13] neural network, Chen and Liu proposed the Broad Learning System (BLS) [40]. The BLS features a simple architecture and high classification accuracy, employing a single-layer, horizontally scalable network framework capable of extracting sparse features from input data. Compared with RVFL, BLS [46]can map input samples into a more suitable feature space, thereby efficiently handling large volumes of time-varying data. More crucially, BLS retains the core mechanism of randomly generating hidden layer node weights, which can be constructed based on any continuous probability distribution.

Compared to deep network models [49] that have gained significant attention in recent years, BLS exhibits notable efficiency during the training phase. This advantage stems from the absence of inter-layer coupling effects and the fact that its weight updating process does not rely on multi-layer connectivity mechanisms or gradient descent algorithms. Instead, the pseudo-inverse method is adopted to compute the weight parameters corresponding to each feature node [14]. The core computational step of BLS involves solving the pseudo-inverse of the combined matrix of feature nodes and enhancement nodes with respect to the target output values [15]. These feature nodes and enhancement nodes are concatenated to form the hidden layer of the model. By computing the pseudo-inverse matrix, BLS can rapidly determine the final output weights. This approach also effectively avoids common issues in deep learning models such as gradient vanishing or gradient explosion. Furthermore, the model possesses dynamic expansion capabilities, enabling the seamless integration of new data into the existing network structure for training. This effectively mitigates challenges associated with undersampling and oversampling, thereby further enhancing computational efficiency and model generalization performance.

In recent years, multiple improved versions of BLS have been proposed [34, 47, 48]. For instance, the Adaptive Imbalanced Robust Graph Embedding BLS (AI-RGEBLS) [18] employs graph-based embedding to address class imbalance and enhance fault tolerance. Chen et al. [16] developed an adaptive broad learning system that integrates graph embedding and intuitionistic fuzzy theory to improve the robustness and accuracy of classification under imbalanced data conditions. Yin et al. [17] proposed an Adaptive Weighting Enhanced Broad Learning System (AW-EBLS), which significantly enhances the performance of fault diagnosis for aviation fuel pumps under imbalanced data scenarios by optimizing weight allocation [35] through density-based methods and employing a multi-enhancement window structure.

2.3 Aero-Engine Fault Diagnosis

Aero-engines operate under complex and harsh working conditions, and their long service life leads to gradual performance degradation and occasional sudden failures. As critical rotating components, bearings are particularly prone to localized defects such as inner race, outer race, and rolling element faults, which can significantly affect engine reliability and flight safety. Consequently, fault diagnosis and health monitoring of aero-engine bearings have become important research topics in the field of condition-based maintenance [36–38].

Existing studies [50] on aero-engine fault diagnosis primarily focus on vibration signal analysis, in which time-domain, frequency-domain, and time–frequency features are extracted to characterize different fault modes. Traditional machine learning methods, including support vector machines [51], random forests [52], and ensemble learning [53] techniques, have been widely applied to bearing fault classification. However, in real aero-engine monitoring scenarios, fault samples are extremely scarce compared with normal operating data, resulting in severe class imbalance. This imbalance often causes conventional classifiers to be biased toward healthy conditions, leading to high false-negative rates for early or incipient faults [54].

To address these challenges, recent research [55, 56] has explored deep learning-based methods, such as convolutional neural networks and recurrent neural networks, to automatically learn discriminative features from raw vibration signals. Although these approaches have shown promising performance, they usually require large-scale labeled datasets and extensive training time, which limits their applicability in practical aero-engine monitoring systems. Moreover, their performance may degrade significantly when trained on highly imbalanced datasets [19].

In summary, there remains a need for efficient and robust fault diagnosis methods that can effectively handle imbalanced aero-engine bearing data while maintaining high diagnostic accuracy and computational efficiency.

3 Methodology

3.1 SMOTE-Based Data Balancing for Rare Fault Samples

The overall procedure of the method is illustrated in Figure 1. In the monitoring data of aero-engine bearings, samples corresponding to the normal operating condition usually dominate, whereas fault samples, such as inner race faults, outer race faults, and rolling element faults, are extremely scarce. If a classifier is trained directly on the original dataset, the model tends to be biased toward the majority class, namely normal samples, which leads to an increased miss detection rate for fault samples. To overcome this issue, the SMOTE algorithm is employed in this study to oversample the minority class samples. Unlike simple random over sampling, which generates new data by directly duplicating existing samples, SMOTE creates synthetic samples based on interpolation in the feature space, thereby effectively avoiding the problem of model overfitting.

Let the minority class sample set in the training dataset be denoted as $X_{min} = \{x_1, x_2, \ldots, x_T\}$, where $x_i \in \mathbb{R}^d$ represents a d-dimensional feature vector. For each minority class sample x_i, the Euclidean distances between x_i and all other samples in X_{min}

are computed. The samples are then ranked according to these distances, and the k nearest neighbors of x_i are identified.

According to a predefined oversampling rate, one sample $\hat{x}_i$ is randomly selected from the k nearest neighbors as an auxiliary sample. A new synthetic sample x_{new} is generated along the line segment connecting x_i and the selected neighbor $\hat{x}_i$. The generation formula is given by

$$x_{new} = x_i + \delta \cdot (\hat{x}_i - x_i) \tag{1}$$

where δ is a random variable uniformly distributed in the interval $[0, 1]$.

Through this procedure, SMOTE fills the sparse regions between minority class samples in the feature space, thereby making the decision boundary of the fault class more distinct. The processed dataset not only achieves a balanced class distribution but also, to a certain extent, simulates feature variations of the same fault mode under different operating conditions or noise disturbances. This enhances the robustness of subsequent classification models in identifying bearing fault characteristics.

3.2 BLS–Driven Fault Diagnosis Model

After data balancing is completed, BLS is adopted as the classifier in this study. The framework of the BLS is shown in Figure 1. Unlike traditional deep neural networks, which extract features by increasing network depth, BLS enhances its approximation capability by horizontally expanding feature nodes and enhancement nodes. Its main advantage lies in the flat network architecture, in which weight determination is transformed into a pseudoinverse solution of a linear system. This significantly reduces training time and makes the method well suited for real time monitoring of aero-engines.

The balanced dataset after SMOTE processing is denoted as X.The input data are first transformed into n groups of feature nodes through feature mapping. The i-th group of mapped features Z_i is computed as:

$$Z_i = \phi_i(XW_{e_i} + \beta_{e_i}), \quad i = 1, \ldots, n \tag{2}$$

where W_{e_i} and β_{e_i} are randomly generated weight matrices and bias terms, respectively, and ϕ_i denotes a linear or nonlinear activation function. All feature nodes are concatenated as $Z^n = [Z_1, \ldots, Z_n]$.

To further enhance the nonlinear approximation capability of the model, the mapped features Z^n are taken as input to generate m groups of enhancement nodes. The j-th group of enhancement nodes H_j is computed as:

$$H_j = \xi_j(Z^n W_{h_j} + \beta_{h_j}), \quad j = 1, \ldots, m \tag{3}$$

where ξ_j is the Sigmoid activation function, and W_{h_j} and β_{h_j} are also randomly generated parameters. All enhancement nodes are denoted as $H^m = [H_1, \ldots, H_m]$.

The final state matrix of the broad learning system, denoted as A, is obtained by concatenating the feature nodes and enhancement nodes, that is:

$$A = [Z^n | H^m] \tag{4}$$

If the target output matrix of the system is Y, the training process can be formulated as solving the linear equation:

$$Y = A \cdot W \tag{5}$$

where W is the weight matrix connecting the feature layer and enhancement layer to the output layer. To obtain the optimal weights, ridge regression theory is applied to compute the pseudoinverse $A^\dagger$:

$$W = (\lambda I + A^T A)^{-1} A^T Y \tag{6}$$

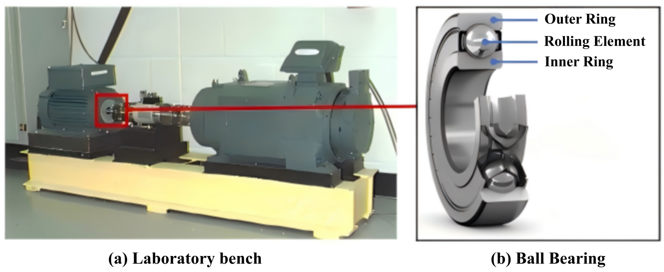


Figure 2. Physical pictures of the experimental platform and structural diagrams of the rolling bearings.

where λ is the regularization coefficient used to improve the numerical stability of the system.

4 Experiments

4.1 Datasets

Rolling bearings are critical components in aero engines and various types of rotating machinery, and their operating condition is directly related to the safety and reliability of the entire system. As shown in Figure 2, within the bearing structure and experimental test setup, localized damage occurring on key components such as the inner ring, outer ring,

Table 1. Performance comparison under different imbalance ratios.

Metric	Dataset	HIT			CWRU			PU		
	Imbalance ratio	5	10	20	5	10	20	5	10	20
AUC	Logistic Regression	0.5904	0.5794	0.5732	0.6356	0.6345	0.6306	0.6518	0.6439	0.6292
	Random Forest	0.8488	0.7956	0.7425	0.8223	0.7995	0.7777	0.6755	0.6658	0.6544
	Adaboost	0.6712	0.6468	0.6325	0.7528	0.7414	0.7197	0.6478	0.6195	0.6146
	Ours	**0.8706**	**0.8280**	**0.7880**	**0.8459**	**0.8304**	**0.7987**	**0.7019**	**0.6900**	**0.6645**
ACC	Logistic Regression	0.4258	0.4262	0.4237	0.5285	0.5200	0.5196	0.1394	0.1282	0.1200
	Random Forest	0.6779	0.6128	0.5684	0.6271	0.6083	0.5680	0.2013	0.1757	0.1614
	Adaboost	0.4946	0.4635	0.4312	0.4900	0.4863	0.4778	0.1867	0.1599	0.1568
	Ours	**0.7351**	**0.6986**	**0.6654**	**0.7166**	**0.6851**	**0.6559**	**0.2177**	**0.2087**	**0.2067**
F1 score	Logistic Regression	0.2158	0.2120	0.2075	0.4209	0.4060	0.4096	0.1253	0.1068	0.0907
	Random Forest	0.5867	0.4715	0.4068	0.5297	0.4873	0.4170	0.1724	0.1548	0.1435
	Adaboost	0.4116	0.2897	0.2387	0.3650	0.3563	0.3306	0.1309	0.1031	0.0857
	Ours	**0.7123**	**0.6629**	**0.5932**	**0.6592**	**0.6108**	**0.5627**	**0.1994**	**0.1748**	**0.1499**

or rolling elements will induce pronounced abnormal vibration characteristics during operation. Therefore, bearing anomaly detection and fault identification based on vibration signals have become important research topics in the field of condition monitoring and fault diagnosis. In this study, three representative bearing fault datasets are employed for experimental validation, namely partial data from HIT dataset [36], PU dataset [38] and CWRU dataset [37].

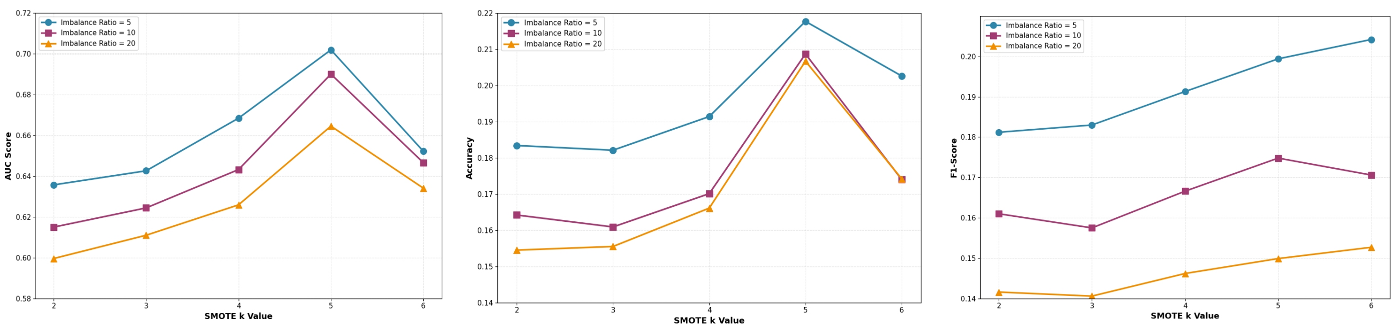
The key hyperparameters of the BLS architecture were configured as follows: number of feature mapping nodes = 40, number of enhancement nodes = 20, with each node group containing 50 neurons. The SMOTE algorithm was configured with $k = 5$ nearest neighbors, and the oversampling ratio was dynamically adjusted to balance the minority and majority classes.

4.2 Main Result

The experimental results demonstrate that for the task of aero-engine bearing anomaly detection, the proposed model achieves significantly superior comprehensive performance on the HIT, CWRU and PU datasets compared with mainstream benchmark algorithms such as Logistic Regression, Random Forest and Adaboost, as shown in Table 1.

This performance advantage can be attributed to two main factors. First, the SMOTE preprocessing stage effectively balances the class distribution by generating synthetic minority samples, which reduces the classifier's inherent bias toward the majority class and enhances its sensitivity to fault features. Second, the BLS classifier leverages its broad, flat network structure to efficiently extract discriminative features from the high-dimensional vibration data. Its training via the pseudoinverse method provides a stable and optimal solution, avoiding convergence issues common in iterative methods.

It is noteworthy that all algorithms exhibit an overall performance decline on the PU dataset. This is primarily attributed to two inherent characteristics of the PU dataset: first, its acquisition environment contains stronger industrial background noise, which may mask some fault features; second, the fault signals are comparatively weaker than in other datasets, resulting in reduced feature discriminability. Despite these challenges, the performance degradation of



(a) AUC vs. K (b) Accuracy vs. K (c) F1 score vs. K

Figure 3. Performance metrics vs. SMOTE k value under different imbalance ratios in the PU dataset.

the proposed method is much smaller than that of traditional algorithms. This comparison further validates the robustness advantage of the SMOTE-BLS framework when dealing with challenging data. SMOTE enhances the model's adaptability to noise to some extent by generating synthetic samples through reasonable feature space interpolation, while the flat architecture and pseudo-inverse solution mechanism of BLS reduce the risk of overfitting to noisy data, maintaining better generalization capability.

It exhibits particularly strong robustness when handling scenarios with extremely imbalanced samples including an imbalance ratio of 20. The AUC, ACC, and F1 metrics have generally decreased, but they still outperform all comparison algorithms and maintain the best performance. These findings verify that the proposed algorithm can not only effectively capture the early fault features of aero-engine bearings but also maintain low false alarm and missing report rates under the interference of a high proportion of normal data. It thus holds remarkable application value in practical industrial health monitoring and condition-based maintenance scenarios.

4.3 Sensitivity

We conducted a sensitivity analysis on the selection of the k value in SMOTE for the PU dataset. Through systematic experiments, we verified the impact of different k values on model performance. As shown in Figure 3, the experimental results indicate that $k = 5$ yields the optimal performance across different imbalance ratios. The model performance continuously improves from $k = 2$ to $k = 5$, which suggests that when $k < 5$, insufficient sampling may occur, and the generated synthetic samples may be overly confined to the vicinity of the original samples, resulting in insufficient diversity and failure to fully utilize the neighborhood information of minority-class samples. When $k = 6$, excessive noise may be introduced or the distribution characteristics of the original data may be disrupted, leading to a decline in performance. Therefore, this study ultimately adopts $k = 5$ as the neighbor parameter of the SMOTE algorithm.

5 Conclusion

This study proposes a hybrid model integrating SMOTE and BLS to address the class imbalance issue in aero-engine bearing anomaly detection. SMOTE balances the dataset by generating synthetic fault samples via feature space interpolation, while BLS enables efficient and accurate classification through its flat architecture and pseudoinverse-based weight computation. Experimental results on HIT, CWRU, and PU datasets confirm the model's superiority over mainstream algorithms. It exhibits strong robustness under extreme imbalance scenarios, effectively captures early fault features, and maintains low rates of false positives and missed detections.

Models developed on laboratory standard datasets are confronted with the risk of performance degradation when transferred to the complex operational environments of actual aeroengines, especially under the scenarios of real and variable working conditions, extreme environmental noise, and multi-fault coupling. To address this issue, we plan to enhance the model's robustness to noise and data quality issues in future research, and further validate the model on real or semi-physical simulation platforms.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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