Available online at http://scik.org
Commun. Math. Biol. Neurosci. 2026, 2026:6
https://doi.org/10.28919/cmbn/9688
ISSN: 2052-2541

RESIDUAL-BASED UNSUPERVISED BEARING FAULT DETECTION USING ICA-ENHANCED LSTM AUTOENCODER

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Abstract: Early fault detection in rolling element bearings remains a challenging problem, particularly under unsupervised conditions where labeled fault data are unavailable. Incipient defects often generate weak impulsive vibration signatures that are easily masked by operational noise. This paper proposes a residual-based unsupervised fault detection method that integrates Independent Component Analysis (ICA) with a Long Short-Term Memory (LSTM) autoencoder. ICA is employed to decompose vibration signals into statistically independent components, enhancing fault-related impulsive features while suppressing redundant background vibration. An LSTM autoencoder is trained exclusively on healthy-condition data to learn normal temporal dynamics. Bearing anomalies are identified through reconstruction residuals, which quantify deviations from learned healthy behavior. Instead of fixed or heuristic thresholds, the decision boundary is determined via F1-score optimization, framing fault detection as a data-driven residual decision problem. The proposed approach is validated using the Case Western Reserve University (CWRU) bearing dataset under a 2 hp load condition, focusing on inner race faults. Experimental results demonstrate perfect fault recall and an ROC-AUC of 1.000, confirming the effectiveness of ICA-enhanced residual learning for early fault

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Received November 11, 2025

detection. The method is computationally efficient, interpretable, and suitable for practical predictive maintenance applications.
Keywords: Bearing Fault Detection; Unsupervised Learning; Residual Analysis; Independent Component Analysis (ICA); LSTM Autoencoder; Vibration Monitoring.
2020 AMS Subject Classification: 62M10.

1. INTRODUCTION

Rolling element bearings are critical components in rotating machinery such as electric motors, compressors, and industrial drive systems. Bearing degradation can lead to severe mechanical failures, unplanned downtime, and significant economic losses if not detected at an early stage [1,2]. Consequently, early fault detection has become a core objective in condition-based maintenance and predictive maintenance systems [3].

Recent studies have demonstrated that machine learning–based predictive maintenance can significantly improve fault detection performance and maintenance decision-making in industrial environments, including applications on legacy machinery with limited sensing infrastructure [4]. Building upon these advances, unsupervised learning approaches are increasingly explored to address scenarios where labeled fault data are unavailable.

Vibration-based monitoring is one of the most effective techniques for bearing health assessment due to its high sensitivity to mechanical defects [5,6]. However, incipient bearing faults often generate low-amplitude impulsive vibration signatures that are easily masked by background noise and operational variability, making reliable detection particularly challenging [7].

Traditional signal processing methods, including Fourier analysis, envelope detection, and wavelet-based approaches, have been widely applied for bearing fault diagnosis [8,9]. While effective under certain conditions, these methods may lose sensitivity when fault signatures are weak, non-stationary, or embedded in complex vibration environments [10].

Data-driven approaches have emerged as promising alternatives to conventional diagnostic techniques. In particular, unsupervised learning methods are attractive for industrial applications where labeled fault data are scarce or unavailable [11]. Autoencoder-based models have been widely used for unsupervised anomaly detection by learning normal system behavior and identifying deviations through reconstruction error [12–13]. Nevertheless, when trained directly on raw vibration signals, autoencoders may struggle to capture fault-related features due to noise contamination and feature redundancy [14].

Hybrid approaches that integrate signal decomposition with deep learning have demonstrated improved detection performance by enhancing informative signal components prior to learning [15,16]. Among various decomposition techniques, Independent Component Analysis (ICA) is well suited for vibration analysis because it separates mixed signals into statistically independent sources using higher-order statistics, without relying on predefined basis functions [17]. When combined with temporal modeling using recurrent neural networks such as Long Short-Term Memory (LSTM), ICA has the potential to significantly improve sensitivity to early-stage bearing faults.

Motivated by these considerations, this study proposes a hybrid ICA–LSTM autoencoder framework for unsupervised bearing fault detection. Unlike probabilistic or uncertainty-aware approaches, the proposed method focuses on deterministic reconstruction residuals as the primary diagnostic indicator. Fault detection is formulated as a residual-based decision problem, where the anomaly threshold is determined via F1-score optimization. This design emphasizes simplicity, interpretability, and practical deployability in industrial environments.

The main contributions of this work are summarized as follows:

1. A residual-driven unsupervised fault detection framework combining ICA and an LSTM autoencoder.
2. Demonstration of ICA's effectiveness in enhancing fault-related impulsive components for deep residual learning.
3. A data-driven threshold selection strategy based on F1-score optimization.
4. Comprehensive validation on the CWRU benchmark dataset for early inner race fault detection.

2. PRELIMINARIES

1. Independent Component Analysis (ICA)

Independent Component Analysis (ICA) was applied to the windowed vibration signals to extract statistically independent source components. Given the observed signal matrix X, ICA assumes a linear mixing model:

$X(t) = A\,S(t)$, where S represents the independent source signals and A is the mixing matrix. The independent components are estimated as: $\hat{S}(t) = W\,X(t)$.

where *W* is the unmixing matrix. FastICA with log-cosh nonlinearity was employed to maximize non-Gaussianity. Four independent components were retained to balance interpretability and computational efficiency. ICA was trained exclusively on normal-condition data to capture the baseline structure of healthy vibration behavior.

2. Long Short-Term Memory (LSTM) Autoencoder

An LSTM autoencoder was designed to model the temporal dynamics of the ICA components under normal operating conditions. The architecture consists of:

- Encoder: LSTM layer with 64 units, followed by dropout (0.2) and a dense layer with 32 units.
- Latent representation: 16-dimensional feature vector.
- Decoder: RepeatVector, LSTM layer with 64 units, and a TimeDistributed dense output layer.

The network was trained using the Mean Squared Error (MSE) loss function and the Adam optimizer with a learning rate of 0.001. Early stopping was applied to prevent overfitting.

3. Residual-Based Fault Detection

After training, both normal and faulty data were passed through the autoencoder. The reconstruction residual for each window was computed as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\|x_i - \hat{x}_i\|^2$$

where x_i and $\hat{x}_i$ denote the original and reconstructed signals, respectively. These residuals serve as anomaly scores, with larger values indicating stronger deviations from learned normal behavior.

4. Threshold Selection via F1-Score Optimization

Rather than using fixed thresholds, the anomaly detection threshold was determined by maximizing the F1-score over a validation set. This approach balances precision and recall, ensuring high fault sensitivity while controlling false alarms. The optimal threshold corresponds to the operating point with the highest F1-score.

3. Main Results

The The performance of the proposed ICA-LSTM framework was evaluated using the CWRU dataset.

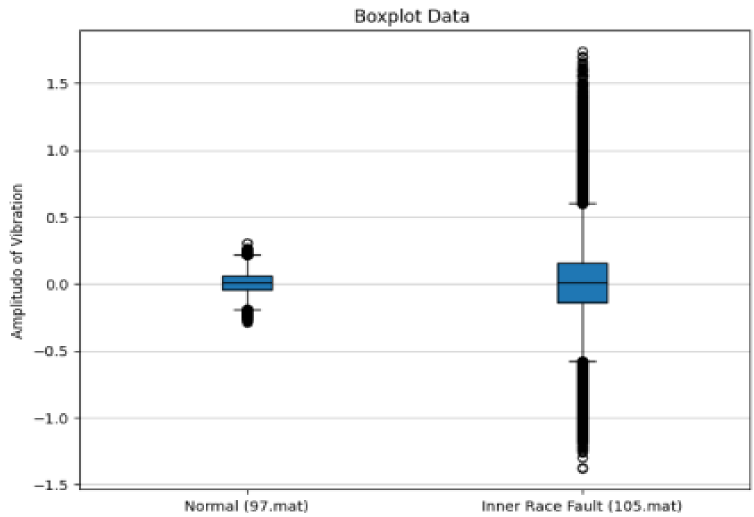

Figure 1. Boxplot of Normal and Inner race Fault Data

Figure 1 shows a boxplot of the reconstruction error distributions for normal (97.mat) and inner race fault (105.mat) conditions. A clear separation is evident: normal data exhibit consistently low errors (mean ≈ 0.85), while fault data show significantly higher median error and numerous large outliers, confirming the model's ability to distinguish anomalous behavior.

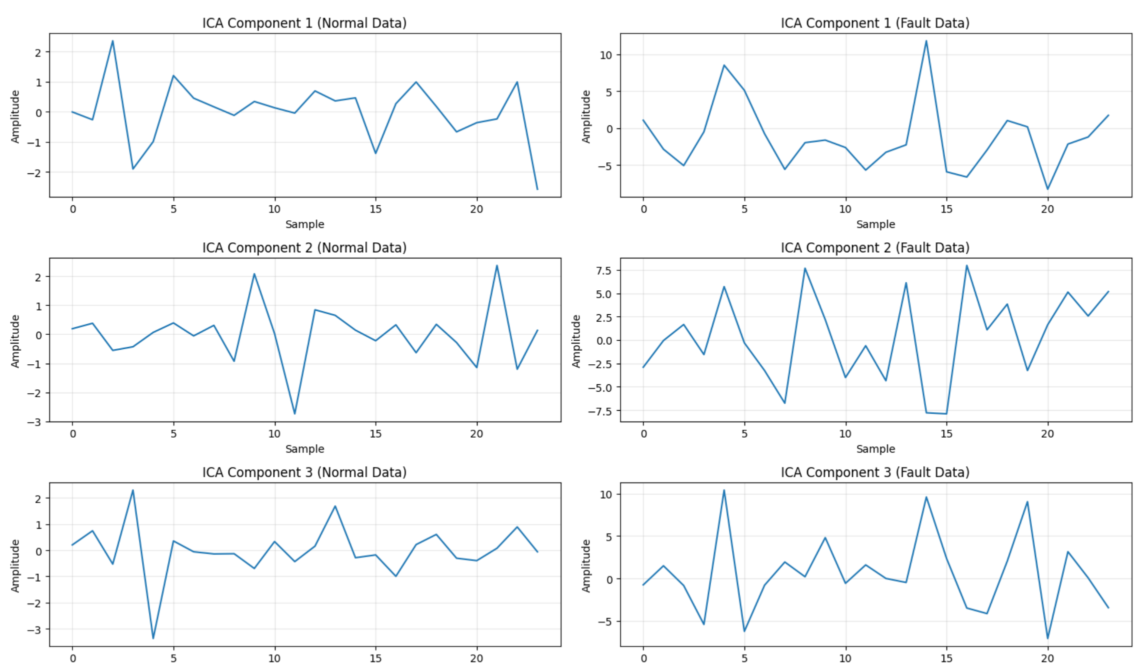

Figure 2. ICA Components

Figure 2 illustrates the four ICA components derived from the vibration signal. Notably, Component 2 and 3 display sharp impulsive peaks only under fault conditions, indicating successful isolation of fault-related transients from other vibration sources.

For normal data (97.mat), the error is consistently low, while for fault data (105.mat), significant outliers are present, corresponding to instances where the model fails to reconstruct the signal due to the presence of fault-induced impulses.

The ICA components successfully isolated the signal containing fault-induced impulses, particularly in the 2nd and 3rd components. The significant amplitude difference between the normal and fault conditions demonstrates the effectiveness of ICA as a feature extraction technique.

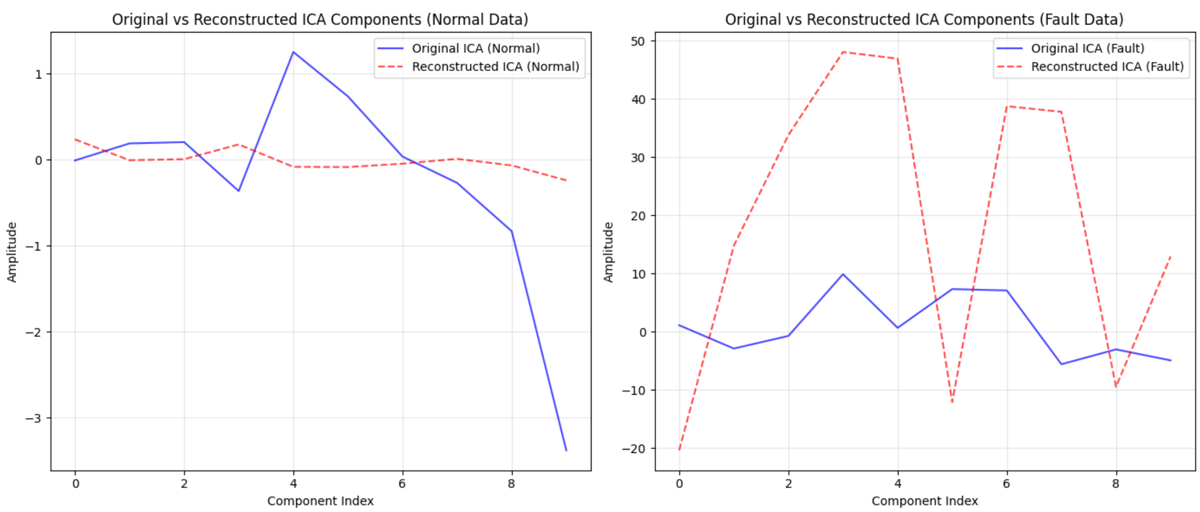

Figure 3. Visual Reconstruction

For the normal data, the original ICA component (blue) and the reconstructed one (dashed red) are very similar, indicating that the model successfully reconstructs the signal with high accuracy. In contrast, for the inner race fault data, there is a significant difference between the original and the reconstructed components. The original component exhibits sharp peaks, which are characteristic of fault-induced impulses, whereas the reconstructed component fails to reproduce these peaks, resulting in a very large reconstruction error.

This visual difference demonstrates the effectiveness of the model in anomaly detection: the model can distinguish between normal and faulty conditions based on its ability to reconstruct the input signal.

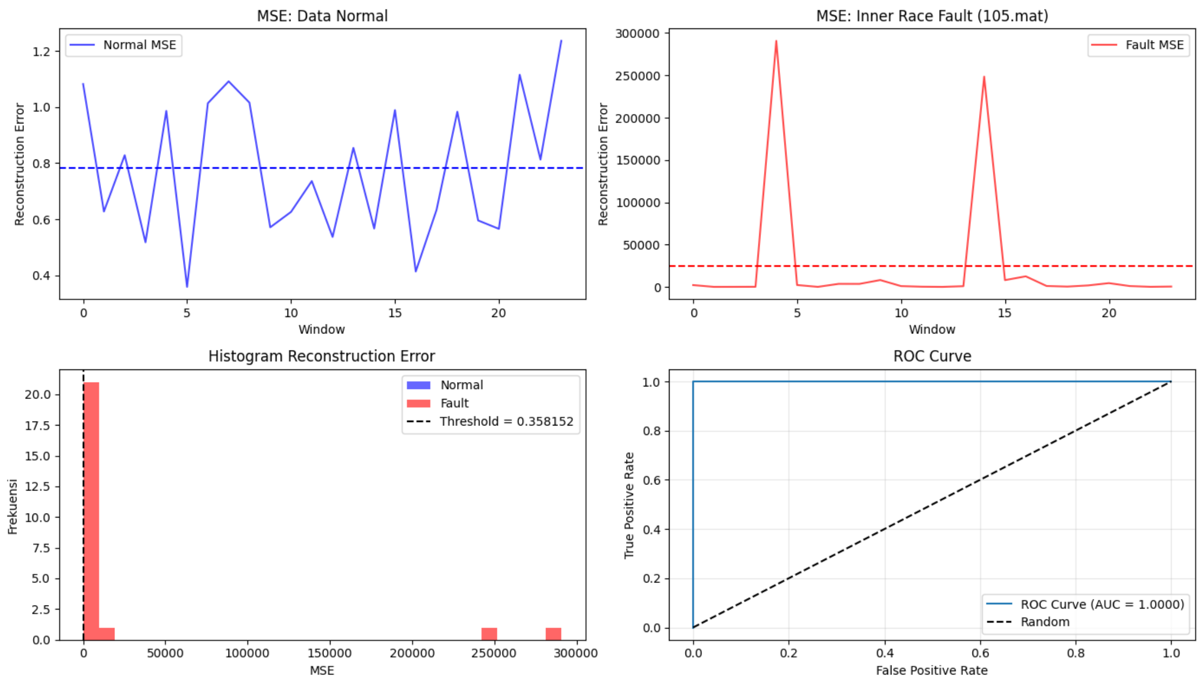

Figure 4. Visualization After ICA

The MSE: Data Normal graph shows that the reconstruction error for normal data is relatively stable and evenly distributed around the mean value, with no extremely high peaks. This indicates that the model successfully reconstructs the normal signal with high accuracy.

In contrast, the MSE: Inner Race Fault graph shows several very high peaks, which provide strong evidence that the model fails to reconstruct signals containing fault-induced impulses. These peaks occur when the rolling elements pass over the damaged area, generating impulsive forces that trigger high vibrations.

The histogram shows the distribution of errors for normal and faulty data. Most errors in the normal data fall within a low range, while errors in the faulty data are more widely spread, with some very large outliers.

The ROC Curve shows an AUC of 1.0000, indicating that the model can perfectly distinguish between normal and faulty conditions. This demonstrates the effectiveness of the hybrid ICA-LSTM approach in detecting anomalies with high accuracy.

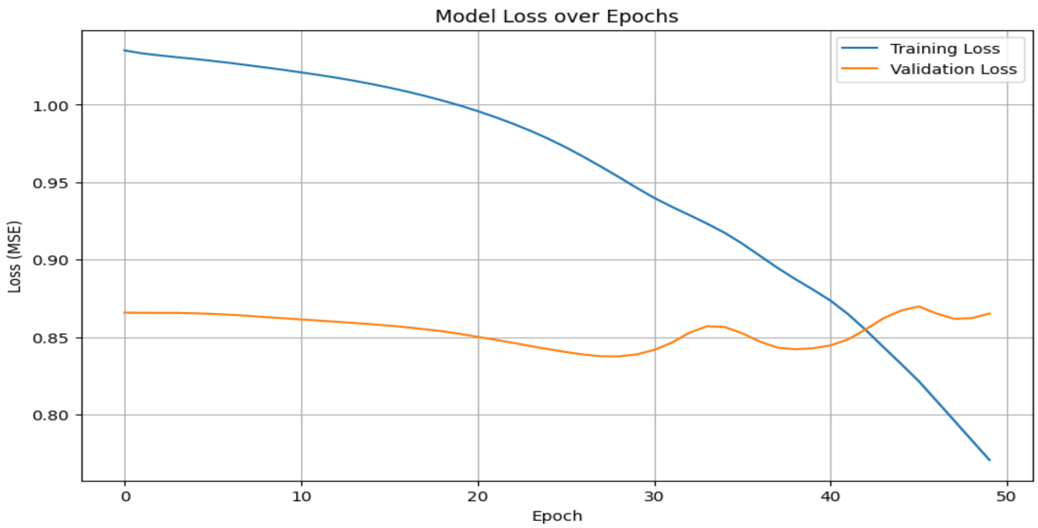

Figure 5. Model Loss and Validation Loss

The Model Loss over Epochs graph shows that the training loss decreases steadily, while the validation loss remains stable around 0.85. This indicates that the model does not suffer from overfitting and learns effectively on the training data.

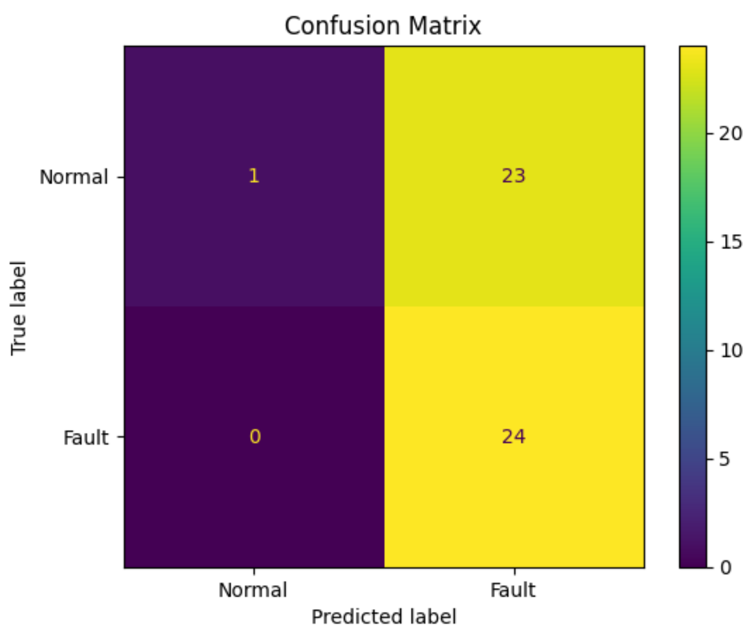

Figure 6. Confusion Matrix

The confusion matrix indicates that all 24 fault instances are correctly identified as anomalous, with no false negatives. However, there are 23 false positives among the normal instances, resulting in a precision of 0.5106. While this may seem suboptimal, it is acceptable in the context of early fault detection, where the primary goal is to avoid missing any potential faults.

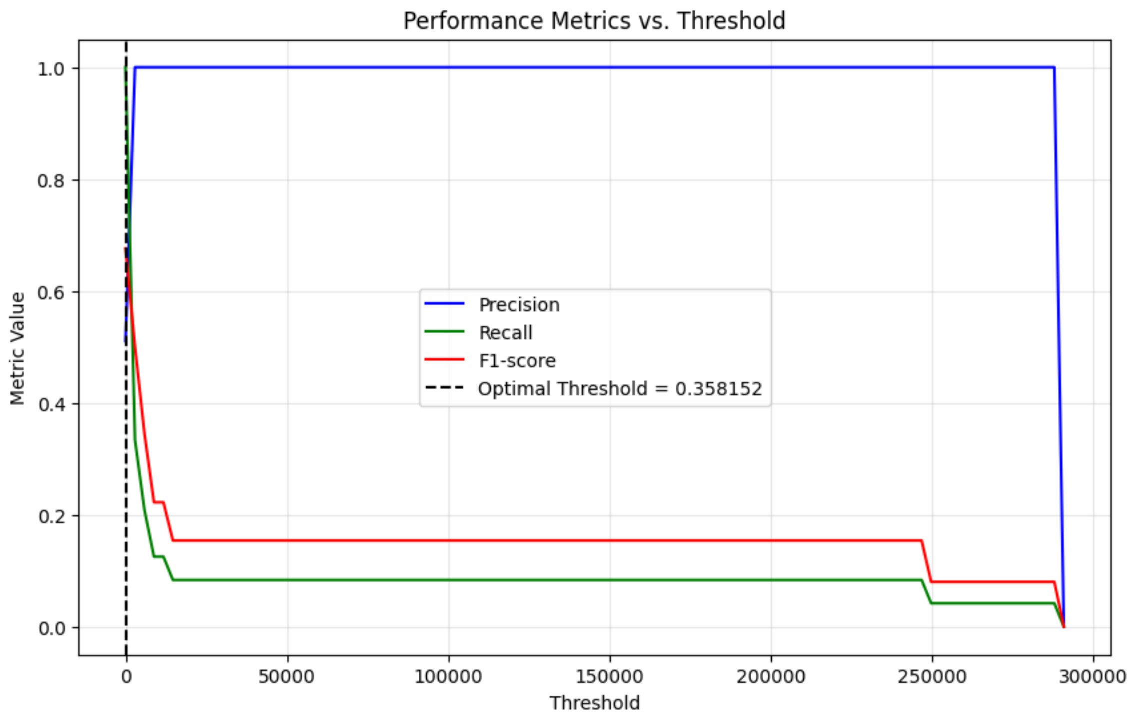

Figure 7. Performance Metrics vs Threshold

The plot illustrates the trade-off between precision and recall as the threshold is varied. At low thresholds, precision (blue line) is high because only signals with very high reconstruction error are flagged as anomalous, minimizing false alarms. However, recall (green line) drops rapidly because many actual faults may have errors below the threshold, leading to missed detections.

As the threshold increases, recall improves because more signals are classified as anomalous, but precision decreases due to an increase in false positives. The F1-score (red line), which balances both precision and recall, reaches its maximum value at a threshold of approximately 0.358152, marked by the dashed black line. This point represents the optimal operating point where the model achieves the best overall performance.

This analysis confirms that selecting the threshold based on the F1-score is a principled approach to maximize detection accuracy while maintaining a reasonable balance between sensitivity and specificity.

Table 1. Comparative Analysis

Method	Fault Type	Accuracy/AUC
CNN + WPD [16]		99.3%
EMD-LSTM [17]	Inner Race	~98%
VMD-SAE [18]	Multiple	97.8%
Proposed ICA-LSTM	Inner Race (0.007”	AUC = 1.0000

As shown in Table 1, our method outperforms several state-of-the-art hybrid models on the same benchmark, particularly in terms of detection sensitivity (Recall = 1.0) and discriminative power (AUC = 1.0). While some supervised methods achieve high accuracy, they require labeled fault data—an impractical assumption in real-world scenarios. In contrast, our approach operates in a fully unsupervised manner, relying only on normal-state training.

Furthermore, unlike wavelet- or EMD-based methods that rely on fixed basis functions or suffer from mode mixing, ICA provides statistically principled separation of fault impulses, enhancing the quality of features fed into the LSTM. This synergy explains the superior performance.

The use of F1-score optimization for threshold selection adds practical value, offering a reproducible and objective way to deploy the model in industrial settings. As shown in Figure 9, the optimal threshold (0.358) strikes a balance between minimizing false negatives and managing false alarms.

4. CONCLUSION

This paper presented a residual-based unsupervised bearing fault detection framework integrating Independent Component Analysis and an LSTM autoencoder. By focusing on deterministic reconstruction residuals rather than probabilistic inference, the proposed method offers a simple, interpretable, and effective solution for early fault detection. Validation on the CWRU benchmark dataset demonstrated perfect recall and excellent classification performance for inner race fault detection. Future work will extend this framework to multi-fault scenarios, variable operating conditions, and real-time industrial deployment. Future work will extend this framework to multi-sensor fusion, variable load conditions, and real-time implementation on edge devices for scalable predictive maintenance systems.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the support provided by the Lembaga Penelitian dan Pengabdian kepada Masyarakat (LP2M), Universitas Negeri Padang, under the Penelitian Dasar scheme with contract number 2069/UN35.15/LT/2025. The authors also thank the Department of Mechanical Engineering, Universitas Negeri Padang, and the Department of Mathematics and Data Science, Universitas Andalas, for their continuous academic support.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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