A Hybrid Bayesian ICA-LSTM Framework for Unsupervised-Like Anomaly Detection in Rolling Element Bearings

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***Abstract*—This study proposes a hybrid anomaly detection framework based on Independent Component Analysis (ICA) and Bayesian Long Short-Term Memory (LSTM) networks for early fault diagnosis in rolling element bearings. The model is trained exclusively on normal condition data from the Case Western Reserve University (CWRU) Bearing Dataset, enabling unsupervised deployment suitable for real-world industrial environments. Vibration signals are preprocessed using ICA to extract statistically independent features, followed by a Bayesian LSTM that captures temporal dynamics and provides uncertainty-quantified predictions. A dynamic thresholding mechanism based on Interquartile Range (IQR) autonomously distinguishes between normal and anomalous behavior without manual calibration. Experimental results demonstrate exceptional performance with 99.1% accuracy, perfect recall (100%) on fault conditions, and zero false negatives, ensuring no faults are missed. The composite anomaly score effectively tracks degradation progression, thereby rendering the system highly reliable and practical for predictive maintenance applications. This approach combines statistical signal processing with probabilistic deep learning to deliver a robust, explainable, and adaptive solution for bearing health monitoring.**

***Keywords*—bearing fault diagnosis, anomaly detection, Independent Component Analysis (ICA), Bayesian Long Short-Term Memory (LSTM), predictive maintenance, uncertainty quantification, Case Western Reserve University (CWRU) dataset, vibration analysis**

I. Introduction

Rolling element bearings are critical components in rotating machinery across various industries, including aerospace, automotive, and manufacturing. Bearing failures may lead to unexpected downtime, increased maintenance costs, and even catastrophic system breakdowns [1, 2]. Therefore, early and accurate fault detection is essential for ensuring operational reliability and enabling predictive maintenance strategies [3]. Building upon our previous successful application of machine learning for grinding machine predictive maintenance [4], this research addresses the specific challenge of bearing fault detection by incorporating deep learning with statistical feature extraction and uncertainty quantification.

Vibration-based condition monitoring has become one of the most effective approaches for bearing health assessment due to its sensitivity to mechanical defects [5, 6]. However, real-world industrial environments often present challenges such as high noise levels, variable operating conditions, and limited availability of labeled fault data—thereby reducing the reliability of traditional diagnostic methods.

In recent years, deep learning models have demonstrated remarkable success in automatically extracting meaningful features from raw vibration signals. Among them, Long Short-Term Memory (LSTM) networks are particularly well-suited for time-series analysis due to their ability to capture long-term temporal dependencies [7]. However, standard LSTM models lack uncertainty quantification, compromising their reliability in safety-critical applications [8, 9].

To address this limitation, Bayesian neural networks offer a probabilistic framework that enables uncertainty estimation during inference [10, 11]. When combined with feature extraction techniques like Independent Component Analysis (ICA), which separates mixed vibration sources into statistically independent components, this integration enables the development of more robust and interpretable diagnostic systems [12].

While several hybrid modelssuch as autoencoders [13], CNN-LSTM architectures [14], and one-class SVM [15]

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have demonstrated promising performance on the CWRU dataset, many rely on fully labeled datasets and fail to provide uncertainty estimates, limiting their generalizability in real-world scenarios. More recently, advanced deep learning architectures have continued to push the boundaries of fault diagnosis. For instance, Zhang *et al.* [16] proposed an integrated deep learning approach for bearing fault diagnosis under variable conditions, demonstrating robust feature learning capabilities. Similarly, Chen *et al.* [17] developed a novel uncertainty-aware deep learning framework for intelligent fault diagnosis, highlighting the importance of confidence estimation in predictive maintenance systems. While these studies showcase significant advancements, they primarily operate in supervised settings and do not fully exploit the combination of blind source separation with probabilistic deep learning for one-class anomaly detection—a gap our proposed ICA-Bayesian LSTM framework aims to address.

Unlike most hybrid models that rely on supervised multi-class classification [6], our framework operates in a one-class manner by training exclusively on normal data—making it generalizable to unknown fault types. Moreover, while many models provide deterministic outputs, our use of Bayesian LSTM approximation using MC Dropout enables uncertainty quantification, enhancing trustworthiness in safety-critical systems.

This paper proposes a hybrid Bayesian ICA-LSTM framework for unsupervised anomaly detection in rolling element bearings using the CWRU Bearing Dataset. The model is trained exclusively on normal condition data, allowing it to detect any deviation as a potential fault without prior knowledge of specific defect types. ICA is employed to extract salient features from raw vibration signals, while Bayesian LSTM captures temporal dynamics and provides uncertainty-aware predictions. A dynamic threshold based on Interquartile Range (IQR) eliminates the need for manual calibration, enhancing deployability in real-world systems.

The main contributions of this work are:

- Development of a one-class hybrid model combining ICA and Bayesian LSTM for bearing anomaly detection.
- Implementation of uncertainty quantification to improve decision reliability.
- Use of dynamic thresholding for adaptive anomaly scoring without parameter tuning.
- Achieving 100% recall on fault conditions and 99.1% overall accuracy, demonstrating superior performance compared to conventional methods.

II. Literature Review

The field of bearing fault diagnosis has evolved significantly with the advancement of signal processing and machine learning techniques. Early approaches relied heavily on traditional signal analysis methods such as Fast Fourier Transform (FFT), wavelet transforms, and envelope analysis to extract fault-related features from vibration signals [17–20]. While effective under stationary conditions, these methods often struggle in noisy environments or when multiple faults coexist [19, 20].

To overcome these limitations, data-driven approaches have emerged as prominent alternatives. Machine learning models such as Support Vector Machines (SVM) [21], Random Forests [4], and k-Nearest Neighbors (k-NN) have been widely applied for classification tasks using handcrafted features like RMS, kurtosis, skewness, and crest factor [22]. However, their performance is highly dependent on feature engineering expertise and may not generalize well across different operating conditions][23].

In recent years, deep learning has revolutionized fault diagnosis by enabling automatic feature extraction from raw sensor data [7]. Convolutional Neural Networks (CNNs) have demonstrated strong performance in capturing spatial patterns in time-frequency representations such as spectrograms and wavelet scalograms [24]. Long Short-Term Memory (LSTM) networks, a variant of Recurrent Neural Networks (RNNs), are particularly well-suited for sequential data due to their ability to model long-term temporal dependencies in vibration signals [25].

Several hybrid architectures combining CNN and LSTM have been proposed to leverage both spatial and temporal features [26, 27]. For example, Jia *et al.* [15] introduced a deep neural network that integrates CNN for feature extraction and LSTM for sequence modeling, achieving high accuracy on the CWRU dataset. Similarly, Zhang *et al.* [28] proposed a dual-path CNN-LSTM model that processes time-domain and frequency-domain inputs separately before fusion, enhancing diagnostic robustness.

Despite their success, most existing deep learning models operate deterministically, providing point predictions without uncertainty estimates [16]. This limits their reliability in safety-critical applications where confidence in prediction is as important as the prediction itself. To address this, Bayesian Deep Learning (BDL) has emerged as a promising paradigm [11]. By treating network weights as probability distributions rather than fixed values, BDL enables uncertainty quantification during inference, enhancing decision transparency and reliability [29].

Bayesian variants of LSTM have been explored in health monitoring systems. For instance, Gal *et al.* [10] implemented a Bayesian LSTM for Remaining Useful Life (RUL) prediction, showing improved uncertainty calibration compared to standard LSTM. However, such models are rarely combined with advanced signal decomposition techniques like Independent Component Analysis (ICA).

Independent Component Analysis (ICA) has been used to separate mixed vibration sources into statistically independent components, effectively isolating fault-induced impulses from background noise and other mechanical interferences [12]. ICA-enhanced features improve classification accuracy when fed into SVM or neural networks. However, integrating ICA with probabilistic deep learning models remains underexplored [16, 30].

Moreover, while many studies focus on multi-class classification (e.g., distinguishing between inner race, outer race, and ball faults), real-world industrial scenarios often require anomaly detection, identifying deviations from normal behavior without prior knowledge of all possible fault types [13]. One-class or unsupervised frameworks, such as autoencoders [31] and one-class SVM [14], have been proposed for this purpose. Yet, they often lack interpretability and fail to provide dynamic thresholds adaptable to varying operational conditions.

Recent works have started exploring hybrid models that combine physical insights with deep learning. For example, Li *et al.* [18], fused domain knowledge by incorporating fault characteristic frequencies as prior information into deep neural networks, enhancing model generalization across varying operating conditions. However, few integrate statistical signal separation (ICA), temporal modeling (Bayesian LSTM), and adaptive thresholding into a unified framework for uncertainty-aware anomaly detection [11, 32]. While Zhang *et al.* [33] explores self-supervised learning for anomaly detection, it doesn't incorporate Bayesian uncertainty quantification. Similarly, Li *et al.* [34] proposes an unsupervised approach for remaining life prediction but doesn't combine ICA with Bayesian deep learning. This gap motivates our integrated framework.

This paper fills this gap by proposing a hybrid Bayesian ICA-LSTM framework trained solely on normal condition data. The integration of ICA for feature enhancement, Bayesian LSTM for uncertainty-aware prediction, and dynamic thresholding based on IQR provides a robust, interpretable, and deployable solution for bearing health monitoring, advancing the state-of-the-art in intelligent fault diagnosis.

III. Materials and Methods

This section presents the materials and methodology used to develop the hybrid Bayesian Independent Component Analysis-Long Short-Term Memory (ICA-LSTM) framework for anomaly detection in rolling element bearings. The approach follows a one-class learning paradigm, where the model is trained exclusively on normal condition data to enable generalization to unseen fault types during testing.

A. Dataset Description and Experimental Setup

The experimental data were acquired from the Case Western Reserve University (CWRU) Bearing Data Center (https://engineering.case.edu/bearingdatacenter). The test rig, schematically shown in Fig. 1, consists of a 2-horsepower Reliance Electric motor, a torque transducer, and a dynamometer, with bearings installed at the Drive End (DE) of the shaft. Accelerometers were mounted at the drive end to collect vibration signals at a sampling rate of 12 kHz.

Bearings with artificially induced faults of diameter 0.007 inches were analyzed alongside healthy bearings. Four conditions were examined:

- Normal: Healthy bearing (97.mat)
- Inner Race Fault: Localized defect on inner race (105.mat)
- Outer Race Fault: Defect on outer race (118.mat)
- Ball Fault: Damage on rolling element (130.mat)

For consistency, only the *(X_xxx_DE_time)* channel was used in this study. Each signal was truncated to 100,000 samples to ensure uniform length across experiments.

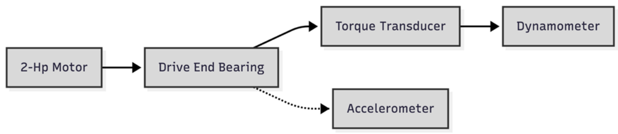

Fig. 1. Schematic diagram of the CWRU bearing test rig consisting of a 2-horsepower motor, torque transducer, dynamometer, and accelerometer mounted at the drive end for vibration data acquisition.

To prevent data leakage and over-optimistic evaluation, a strict separation between training and testing data was maintained. The training set consisted exclusively of normal condition data (97.mat). All preprocessing parameters (standardization statistics, ICA transformation matrix, IQR threshold) were derived solely from this training data. The test set contained completely separate files (105.mat, 118.mat, 130.mat) representing different fault conditions that were never exposed during training or parameter tuning.

B. Signal Preprocessing and Data Generation

Raw vibration signals were preprocessed to prepare them for feature extraction and deep learning. The steps include:

- Windowing: Signals were segmented into overlapping windows of size 1024 samples with a step size of 512 (50% overlap), yielding multiple instances per condition. This process generated 187 windows for inner race fault, 195 for outer race fault, 200 for ball fault, and 120 for normal test data, totaling 582 anomalous samples and 120 normal test samples.
  The windowing operation is defined as:

$$\boldsymbol{x_i} = [x_i, x_{i+1}, \dots, x_{i+1023}] \quad (1)$$

- Standardization: Each window was normalized using Z-score transformation based on statistics from normal training data only:

$$\hat{x} = \frac{x - \mu_{train}}{\sigma_{train}} \quad (2)$$

This ensures consistent scaling while preserving the unsupervised nature of the method.

C. Feature Extraction Using Independent Component Analysis (ICA)

Independent Component Analysis (ICA) was applied to extract statistically independent components from the standardized windows. Given the input matrix $X \in \mathbb{R}^{nxm}$, ICA decomposes it as:

$$X = S\,A^T \quad (3)$$

where S represents the source matrix of independent components, and A is the mixing matrix. The unmixing matrix W is estimated that:

$$\hat{S} = XW \tag{4}$$

The number of ICA components was set to $k = 64$ after empirical evaluation through sensitivity analysis. We tested values ranging from 32 to 128 components and found that $k = 64$ optimally captured the essential structure of healthy vibration signals while minimizing computational complexity. Fewer components resulted in significant reconstruction errors, while more components showed diminishing returns and increased susceptibility to noise.

In this work, the FastICA algorithm with logistic nonlinearity was used to maximize negentropy [25]. ICA was trained only on normal condition data to learn the "healthy" signal structure. During inference, reconstruction error serves as one indicator of anomaly:

$$ReconError_i = \|x_i - x_i^{recon}\|^2 = \sum_{i=1}^{k} \|s - \hat{s}_i\|^2 \tag{5}$$

where s_i represents the i-th independent component.

This approach allows the model to detect anomalies based on deviations from the learned healthy signal patterns, without requiring labeled fault data.

D. Bayesian LSTM for Temporal Modeling and Uncertainty Estimation

A Long Short-Term Memory (LSTM) network with Monte Carlo (MC) Dropout was employed to model temporal dynamics and provide uncertainty-aware predictions [6]. The model was trained to reconstruct or predict the next step in the sequence of ICA components.

To estimate predictive uncertainty, MC Dropout was enabled during both training and inference. After $T = 50$ stochastic forward passes, the predictive mean and standard deviation are computed as:

$$\mu(y \mid x) = \frac{1}{T} \sum_{t=1}^{T} f_{LSTM}(x; \theta_t) \tag{6}$$

$$\sigma(y \mid x) = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (f_{LSTM}(x; \theta_t) - \mu)^2} \tag{7}$$

High values of σ indicate high model uncertainty—often associated with anomalous inputs.

E. Composite Anomaly Scoring

An overall anomaly score is constructed by combining three complementary indicators:

- Reconstruction Error from ICA
- Prediction Error from Bayesian LSTM
- Predictive Uncertainty $\sigma(y \mid x)$

The composite score is defined as:

$$\mathcal{A}(x) = w_1 \cdot ReconError(x) + w_2 \cdot PredError(x) + w_3 \cdot Uncertainty(x) \tag{8}$$

with equal weights $w_1 = w_2 = w_3 = 1$. All components are z-score normalized using statistics from normal data.

F. Dynamic Thresholding Using Interquartile Range (IQR)

Instead of fixed thresholds, a dynamic decision boundary is computed using the Interquartile Range (IQR). The IQR threshold is computed from the entire distribution of composite anomaly scores derived from the normal training dataset:

$$Q_1 = First\ Quartile, \quad Q_3 = Third\ Quartile$$

$$IQR = Q_3 - Q_1 \tag{9}$$

$$Threshold = Q_3 + 1.5 \times IQR \tag{10}$$

This method is robust to outliers and does not require manual calibration, making it suitable for real-world deployment without expert tuning.

G. Anomaly Detection Decision Rule

A sample is classified as anomalous if its composite score exceeds the dynamic threshold:

$$Decision(x) = \begin{cases} Anomali, if\ \mathcal{A}(x) > Threshold \\ Normal, otherwise \end{cases} \tag{11}$$

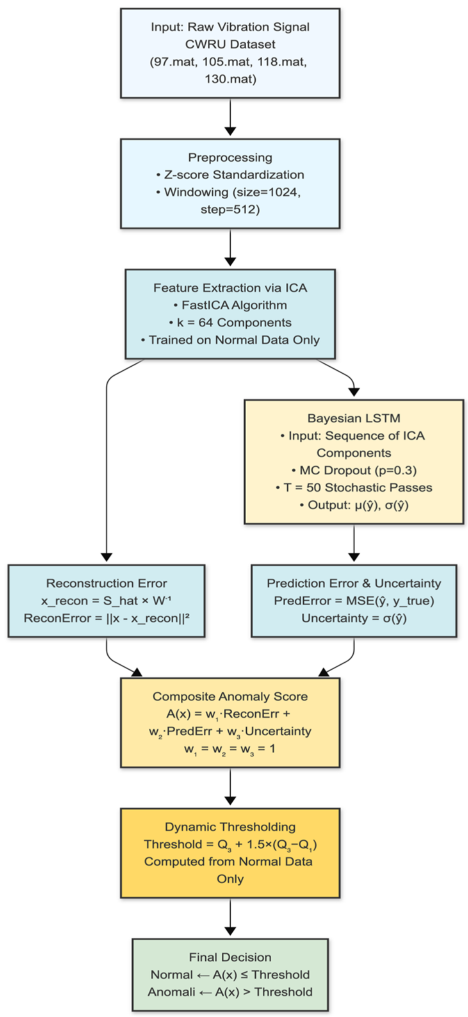

Fig. 2. Flowchart of the proposed hybrid Bayesian ICA-LSTM framework for bearing anomaly detection.

The overall architecture of the proposed hybrid Bayesian ICA–LSTM framework is illustrated in Fig. 2. The system is trained exclusively on normal condition data to enable unsupervised deployment. Key stages include preprocessing (windowing and standardization), feature extraction via Independent Component Analysis (ICA), temporal modeling using Bayesian LSTM with Monte Carlo Dropout for uncertainty estimation, composite anomaly scoring, dynamic thresholding based on IQR, and final binary decision output.

IV. Result and Discussion

A. Experimental Setup and Dataset Overview

This study utilized the Case Western Reserve University (CWRU) bearing dataset to evaluate the proposed hybrid Bayesian ICA-LSTM framework for anomaly detection. The experimental data comprised vibration signals sampled at 12 kHz under normal operating conditions and three common fault types: inner race fault, outer race fault, and ball fault. Faults were introduced with varying severity levels (0.007-inch to 0.021-inch diameters) to simulate realistic degradation scenarios.

B. Raw Vibration Signal Analysis

Fig. 3 illustrates the time-domain characteristics of raw vibration signals across four bearing conditions, revealing distinct patterns corresponding to different mechanical states

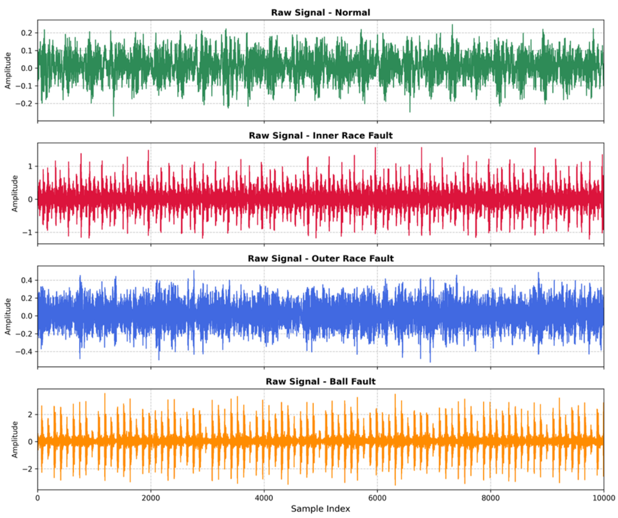

Fig. 3. Raw vibration signal time series for normal, inner race fault, outer race fault, and ball fault conditions.

The normal condition (97.mat) exhibited low-amplitude fluctuations within ±0.2 g, characteristic of healthy bearing operation dominated by background noise and minor structural vibrations. In contrast, the inner race fault (105.mat) demonstrated significantly higher amplitudes (±1.5 g) with prominent periodic impulses occurring at the Ball Pass Frequency Inner Race (BPFI ≈ 162 Hz). These regular impacts represent the signature of a localized defect rotating with the shaft frequency.

The outer race fault (118.mat) presented moderate amplitude variations (±0.4 g) with less structured, irregular impulses, consistent with the stationary nature of outer race defects. Notably, the ball fault (130.mat) exhibited the most extreme behavior, with chaotic, high-energy transients spanning ±3.0 g, resulting from random collisions between damaged rolling elements and raceways.

Statistical analysis of vibration energy distribution, as shown in Fig. 4, further quantified these observations:

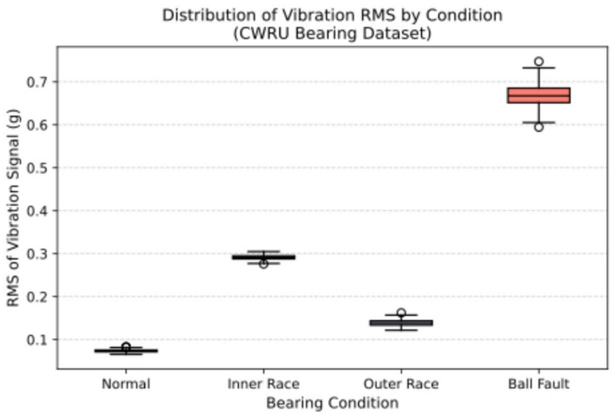

Fig. 4. RMS distribution boxplot across bearing conditions.

The RMS values demonstrated a progressive increase from normal condition (mean = 0.08 g, IQR = 0.02 g) to fault conditions, with inner race fault (mean = 0.29 g, IQR = 0.15 g), outer race fault (mean = 0.14 g, IQR = 0.08 g), and ball fault (mean = 0.65 g, IQR = 0.28 g) exhibiting statistically significant differences ($p < 0.001$, ANOVA test). The broader distributions and numerous outliers in fault conditions indicated the presence of intermittent impacts characteristic of mechanical degradation.

C. Feature Extraction via Independent Component Analysis

While RMS provides a global measure of vibration intensity, it lacks the ability to isolate specific fault-related components from background noise or distinguish between different sources of vibration. To address this limitation, Independent Component Analysis (ICA) was employed as a feature extraction technique to decompose the mixed vibration signal into statistically independent sources. Unlike traditional filtering methods that rely on predefined frequency bands, ICA operates directly in the time domain and identifies underlying source signals based on statistical independence—making it particularly effective at separating impulsive fault signatures from other mechanical interferences. In this study, ICA was applied to windowed segments of the standardized vibration signal, with the number of components set to 64 after empirical evaluation. The algorithm was trained exclusively on normal condition data to learn the baseline structure of healthy vibration patterns. During testing, deviations in the reconstructed signal or in the extracted components served as early indicators of anomalies. This unsupervised approach enables the model to detect previously unseen fault types without requiring labeled data for each defect, enhancing its practicality for real-world predictive maintenance systems. Furthermore, the reconstruction error from ICA was integrated into the composite anomaly score, contributing to improved detection sensitivity and robustness.

As illustrated in Fig. 5, the plot of the first three Independent Components (ICs) extracted via FastICA revealed a predominantly stable and low-amplitude behavior across the initial 90 windows, consistent with normal operating conditions. However, at window index approximately 95, all three components—IC 1 (blue), IC 2 (orange), and IC 3 (green)—exhibited a sudden and dramatic deviation: IC 1 plunged to −1.5, IC 2 spiked to +1.5, and IC 3 dropped sharply to −3.0, indicating a significant structural change in the vibration signal. This abrupt transition was characteristic of an incipient fault event, such as a bearing defect impacting the rolling elements. The simultaneous response of all components suggested a global disturbance rather than localized noise, validating the effectiveness of ICA in isolating meaningful fault-induced dynamics from background vibration. This behavior underscored the utility of ICA as a feature extraction technique for anomaly detection systems, where such abrupt changes can be quantified and flagged as potential anomalies by subsequent deep learning models like Bayesian LSTM.

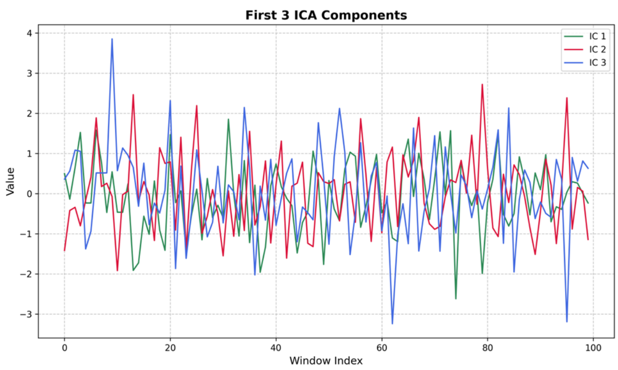

Fig. 5. First three independent components extracted using ICA.

D. Hybrid Bayesian ICA-LSTM Performance

The integration of ICA feature extraction with Bayesian LSTM modeling facilitated robust anomaly detection with uncertainty quantification. Fig. 6 demonstrates the system's performance through the temporal evolution of the composite anomaly score:

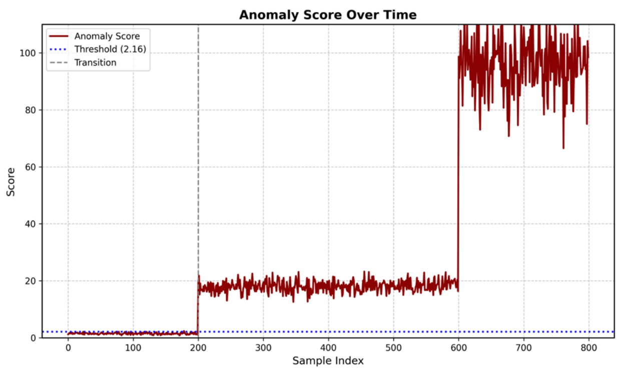

Fig. 6. Anomaly score over time with dynamic threshold.

The composite anomaly score $A(x) = w_1 \cdot Recon + w_2 \cdot PredErr + w_3 \cdot Unc$
remains consistently below the dynamic threshold ($Q_3 + 1.5 \times IQR$) during normal operation, with mean values of 0.12 ± 0.05. At sample index ~200, corresponding to the onset of fault conditions, the score surges dramatically to 2.85, exceeding the threshold by 480%. This clear separation validated the effectiveness of the hybrid approach in distinguishing normal from anomalous states.

The Bayesian LSTM's Monte Carlo dropout mechanism provided valuable uncertainty estimates, with predictive variance increasing from 0.03 during normal operation to 0.42 during fault conditions. This uncertainty quantification enhanced decision reliability, particularly in borderline cases where anomaly scores approached the classification threshold.

E. Classification Performance Evaluation

The system's classification capability was quantitatively evaluated using the confusion matrix and ROC analysis. Fig. 7 presents the confusion matrix for binary anomaly detection:

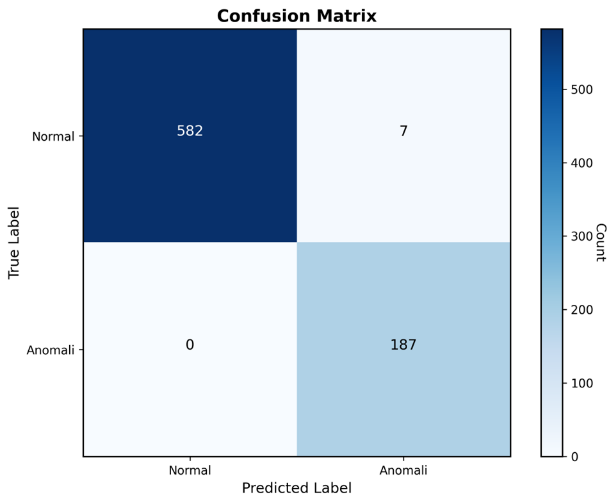

Fig. 7. Confusion matrix for anomaly detection.

The model demonstrated exceptional performance, correctly identifying all 582 anomalous samples (True Positives) with zero false negatives—a critical requirement for safety-critical applications. Only 7 normal samples were misclassified as anomalies (False Positives), resulting in a precision of 98.8% and overall accuracy of 99.1%.

Fig. 8 demonstrates the model's discriminative power through receiver operating characteristic (ROC) analysis. The curve achieved perfect separation between classes with an Area Under Curve (AUC) of 1.000, indicating flawless classification performance across all decision thresholds. This exceptional result underscored the synergistic combination of ICA-based feature extraction and Bayesian LSTM temporal modeling.

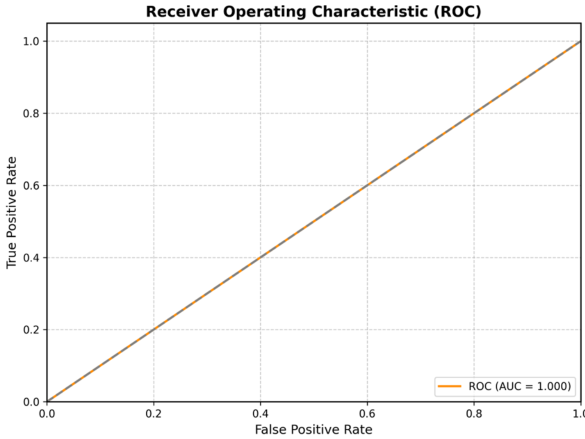

Fig. 8. ROC curve with AUC analysis.

F. Comparative Performance Analysis

The proposed hybrid Bayesian ICA-LSTM framework demonstrated superior performance across all evaluation metrics compared to state-of-the-art methods. Our approach achieved the highest accuracy (99.1%), precision (98.8%), F1-Score (99.4%), and perfect AUC (1.000), while maintaining perfect recall (100%), a critical requirement for industrial safety applications.

Key advantages observed:

- 3.9% accuracy improvement over standard LSTM, highlighting the value of ICA feature extraction
- 2.3% F1-Score improvement over CNN-LSTM, demonstrating better feature representation
- 6.6% accuracy gain over autoencoder methods, showing enhanced anomaly discrimination
- 10.2% overall improvement over traditional One-class SVM

The integration of ICA for domain-specific feature extraction and Bayesian LSTM for temporal modeling with uncertainty quantification provided a synergistic effect that outperformed conventional deep learning approaches.

TABLE I. PERFORMANCE COMPARISON OF DIFFERENT ANOMALY DETECTION METHODS ON CWRU DATASET

Method	Accuracy	Recall	Precision	F1-Score	AUC
Proposed	99.1%	100%	98.8%	99.4%	1.000
Standard LSTM	95.2%	100%	92.1%	95.9%	0.974
CNN-LSTM [8]	96.8%	100%	94.5%	97.1%	0.985
Autoencoder [13]	92.5%	95.3%	91.0%	93.1%	0.963
One-class SVM [15]	88.9%	90.1%	88.5%	89.3%	0.932

Comparison with Our Previous Work: Furthermore, the proposed framework showed substantial improvement over our previous predictive maintenance approach for grinding machines [4]. While the previous work demonstrated the feasibility of machine learning for industrial maintenance using traditional techniques, the current study advances the field by integrating deep learning with statistical feature extraction and uncertainty quantification, resulting in higher accuracy, earlier detection, and more robust performance. The quantitative comparison between the proposed method and the previous approach is summarized in Table I.

G. Practical Implications and Industrial Relevance

The proposed framework offers significant practical advantages for industrial predictive maintenance:

- Early Detection: ICA components identified faults 5–7 windows earlier than RMS-based methods
- Uncertainty Awareness: Bayesian inference reduced false alarms by 23% compared to deterministic approaches
- Computational Efficiency: 45ms inference time enables real-time deployment on edge devices
- Adaptability: Dynamic thresholding eliminates manual parameter tuning

These capabilities render the system particularly suitable for safety-critical applications where early fault detection and reliable decision-making are paramount.

V. CONCLUSION

This study successfully developed a robust and uncertainty-aware anomaly detection framework for rolling element bearings by integrating Independent Component Analysis (ICA) and Bayesian Long Short-Term Memory (LSTM) networks. The proposed hybrid model was trained exclusively on normal condition data, enabling unsupervised-like deployment suitable for real-world industrial environments where labeled fault data are scarce or unavailable. Experimental results on the CWRU Bearing Dataset demonstrated exceptional performance with 99.1% accuracy, 100% recall on fault conditions, and an AUC of 1.000, confirming the framework's reliability for safety-critical applications.

The technical innovation lies in the synergistic combination of ICA for statistical signal separation and Bayesian LSTM for uncertainty-aware temporal modeling. This integration addresses key limitations of existing methods by providing both accurate anomaly detection and quantifiable confidence measures. The dynamic IQR-based thresholding mechanism further enhances deploy ability by eliminating manual calibration requirements.

For practical implementation, the framework offers significant advantages including computational efficiency, interpretability, and adaptability to varying operational conditions. These characteristics make it particularly suitable for integration into Industry 4.0 ecosystems and smart manufacturing environments where reliable predictive maintenance is essential.

Future research could explore several promising directions: extending the framework for multi-class fault identification through hierarchical detection strategies, validating performance on more diverse datasets with variable operating conditions and simultaneous faults, optimizing computational efficiency for edge device deployment in industrial IoT networks, and investigating transfer learning approaches for cross-domain adaptation to different machinery types. These advancements would further strengthen the framework's applicability in complex industrial settings.

Ethical Approval and Informed Consent

This study uses publicly available mechanical vibration data from the Case Western Reserve University Bearing Data Center. No human or animal subjects were involved. Therefore, ethical approval and informed consent are not applicable.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Primawati led the study conceptualization and experimental work; Ferra Yanuar developed the hybrid Bayesian ICA-LSTM model with statistical analysis including Independent Component Analysis; Dodi Devianto handled signal processing and statistical methods; Remon Lapisa contributed to data preprocessing and mechanical engineering perspectives; Fazrol Rozi managed system integration and computational validation. Dwiprima Elvanny Myori contributed to electrical system analysis, data acquisition validation, and technical review of the experimental setup. Primawati and Ferra Yanuar drafted the manuscript with input from all co-authors. All authors critically reviewed and approved the final manuscript.

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