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Hybrid Kernel-Driven ELM for Intelligent Fault Detection in Motor Rolling Bearings

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Abstract

Motor rolling bearings are critical components in industrial machinery, and their failure can lead to significant downtime and financial losses. Therefore, developing robust and intelligent fault detection systems is essential for ensuring operational reliability. This study presents a novel approach utilizing a Hybrid Kernel-Driven Extreme Learning Machine (HK-ELM) for intelligent fault detection in motor rolling bearings. The hybridization of multiple kernel functions enhances the learning capability and generalization of ELM by capturing complex nonlinear features from vibration signals. The proposed model integrates Gaussian and polynomial kernels to construct a composite kernel function, enabling adaptive feature extraction. The experimental evaluation was conducted on publicly available bearing datasets, where the hybrid kernel model was benchmarked against traditional ELM and other standard machine learning models. Results demonstrate that the HK-ELM model outperforms its counterparts in classification accuracy, training time, and fault recognition robustness, especially in the presence of noise and overlapping classes. This paper also discusses the impact of kernel parameter tuning and the hybridization strategy on diagnostic performance, concluding that the hybrid approach offers a highly scalable and efficient solution for real-time industrial fault detection applications.

Keywords: Hybrid Kernel, Extreme Learning Machine, Fault Detection, Motor Bearings, Intelligent Diagnostics, Vibration Analysis, Machine Learning

I. Introduction

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The reliability of rotating machinery hinges significantly on the health of motor rolling bearings, which are prone to various types of mechanical faults such as inner race defects, outer race defects, and ball faults [1]. Detecting these faults at an early stage is crucial to avoid unscheduled downtimes and catastrophic failures. Traditional diagnostic methods, including manual inspections and threshold-based techniques, are often inadequate due to their reliance on prior knowledge and limited adaptability to complex conditions [2]. With the advancement of machine learning, data-driven techniques have gained momentum, offering automated and intelligent fault diagnosis capabilities. Extreme Learning Machine (ELM), a single-hidden layer feedforward neural network, has emerged as a popular tool for classification and regression tasks due to its fast learning speed and good generalization ability. However, conventional ELM suffers from performance limitations when applied to nonlinear and high-dimensional problems such as vibration signal analysis in bearing diagnostics. The inherent linearity of the basic ELM architecture restricts its effectiveness in capturing the underlying nonlinear relationships present in real-world fault patterns. To address this, kernel-based ELM models have been proposed, which map the input features into a high-dimensional space using kernel functions.

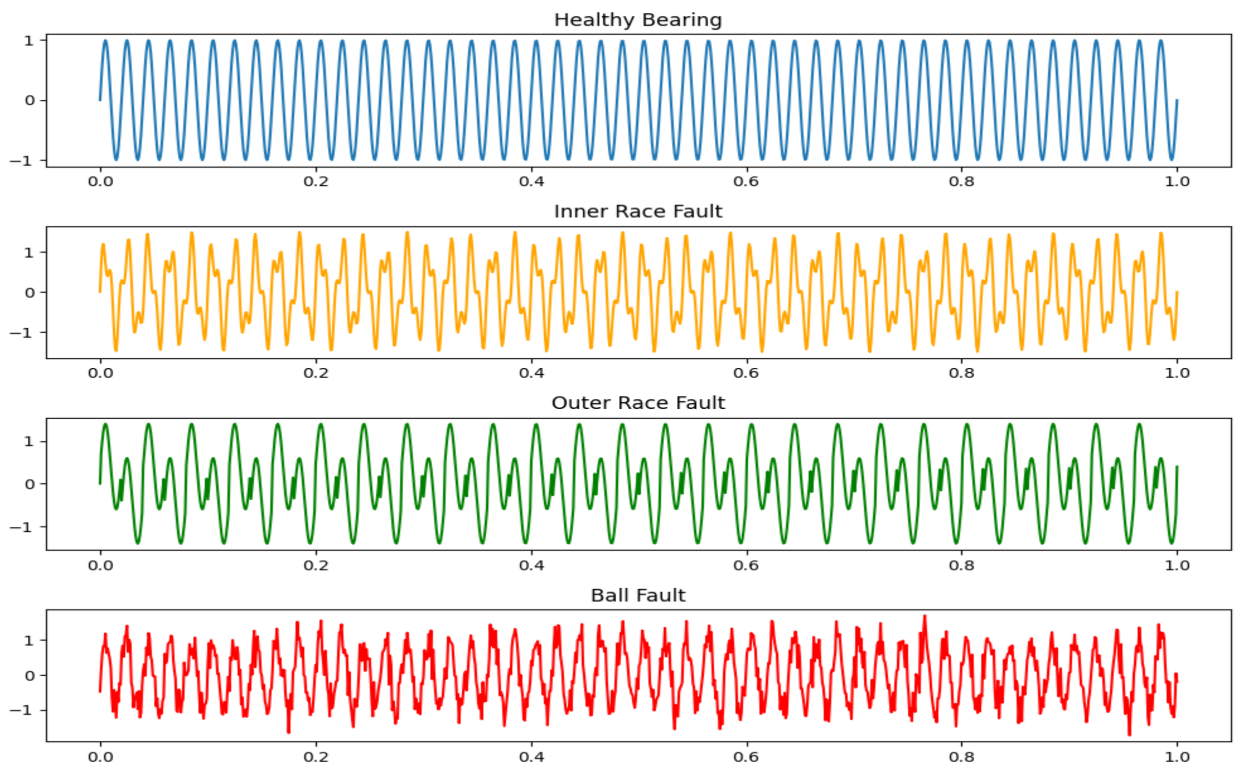

Figure 1 Illustrate different types of motor bearing faults (healthy, inner race, outer race, ball fault).

While single-kernel approaches provide some improvement, they often fail to generalize across various fault scenarios due to their rigidity in capturing only specific aspects of data distributions. This paper proposes a Hybrid Kernel-Driven ELM (HK-ELM) model that combines multiple kernels—specifically, Gaussian and polynomial kernels—to better extract both local and global patterns from raw vibration signals [3]. The hybrid kernel approach enables the ELM to adapt to a wider range of fault characteristics, making it a more powerful diagnostic tool for industrial applications. This work aims to demonstrate that the HK-ELM model can achieve superior fault classification performance over existing techniques. The research includes comprehensive experiments using benchmark datasets such as the Case Western Reserve University bearing dataset [4]. Evaluation metrics include accuracy, precision, recall, F1-score, and computational efficiency, all of which are crucial for real-time deployment. Furthermore, the influence of kernel parameters and the hybridization weighting scheme is explored to optimize the model for diverse operating conditions.

In essence, this paper contributes to the field of intelligent fault detection by presenting a scalable, high-performance solution suitable for industrial implementation [5]. The HK-ELM framework offers a promising direction for future research in intelligent machinery monitoring, with potential extensions to other rotating components and complex systems beyond motor bearings.

II. Related Work

Numerous research efforts have been made in the field of fault detection for rolling bearings using machine learning and signal processing techniques [6]. Traditional approaches such as Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), and Wavelet Transform have been widely employed for feature extraction from vibration signals. These methods, while useful, often require expert knowledge to select appropriate parameters and lack adaptability to diverse fault types and operating environments [7]. Additionally, they can be computationally intensive, limiting their applicability in real-time scenarios. Machine learning models such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees (DT) have shown promising results in bearing fault classification [8]. However, these models often struggle with high-dimensional data and complex feature interactions, which are common in vibration

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The hybrid kernel is formulated as a convex combination of the individual kernels:

$$K_{hybrid}(x_i, x_j) = \alpha K_{Gaussian}(x_i, x_j) + (1 - \alpha) K_{Polynomial}(x_i, x_j)$$

where α is a weighting factor that balances the contribution of each kernel function.

The Gaussian kernel is defined as:

$$K_{Gaussian}(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$$

and the polynomial kernel as:

$$K_{Polynomial}(x_i, x_j) = (x_i \cdot x_j + c)^d$$

with σ, c, and d being kernel parameters.

signal datasets. Deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) have recently gained popularity due to their ability to learn hierarchical features automatically. While effective, they require large amounts of labeled data and computational resources, which are not always feasible in industrial settings [9]. Extreme Learning Machines have gained attention due to their simplicity and training efficiency. Kernel-based ELMs (KELMs) were introduced to enhance the nonlinear modeling capabilities of the standard ELM by mapping input features into high-dimensional spaces using kernel functions. However, single-kernel KELMs often show suboptimal performance in diverse fault detection scenarios due to their limited adaptability. Multi-kernel learning (MKL) techniques attempt to address this by combining multiple kernels to capture a broader range of data characteristics [10].

Recent studies have demonstrated that hybrid kernel methods can significantly enhance model generalization and performance in complex classification tasks. Hybrid kernel approaches, especially those integrating Gaussian and polynomial kernels, offer complementary strengths—Gaussian kernels are effective at capturing local structures, while polynomial kernels excel at modeling global patterns. Despite their potential, hybrid kernel strategies remain underexplored in the context of ELMs for fault diagnosis in rolling bearings [11]. This paper builds upon these insights by proposing a hybrid kernel mechanism tailored for ELM, optimizing both the kernel combination strategy and the ELM architecture for superior fault detection. The proposed model is evaluated extensively and compared with state-of-the-art techniques, providing a clear understanding of its advantages and limitations [12].

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III. Methodology

The proposed Hybrid Kernel-Driven Extreme Learning Machine (HK-ELM) combines two kernel functions—Gaussian and polynomial—into a unified learning framework [13]. The core idea is to leverage the strengths of both kernels to improve the ELM's ability to capture complex and nonlinear relationships in vibration signals. In the ELM architecture, the hidden layer output is computed using the hybrid kernel matrix, and output weights are determined analytically through least squares optimization. Unlike traditional ELMs that require random initialization of weights and biases, kernel ELMs bypass this step, making the learning process more stable and less dependent on initial conditions [14, 15].

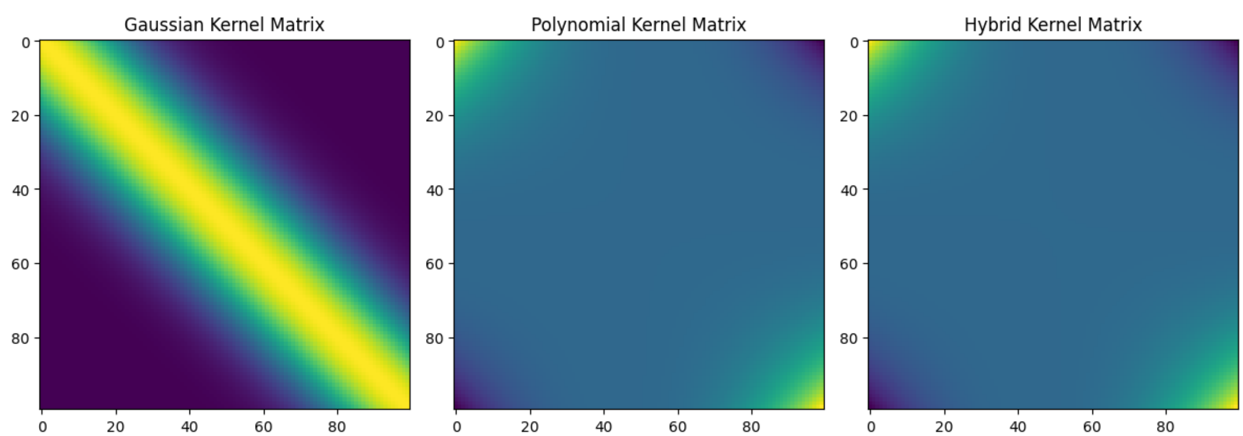

Figure 2 Show how the hybrid kernel combines the Gaussian and polynomial kernels.

The dataset used for training and evaluation is preprocessed using standard techniques including normalization and segmentation. Time-domain statistical features such as RMS, kurtosis, skewness, and peak-to-peak amplitude are extracted, along with frequency-domain features derived through FFT. These features are then fed into the HK-ELM for classification [16]. To optimize the model, a grid search approach is employed to tune kernel parameters and the weighting factor α\alphaα. Cross-validation ensures the robustness and generalizability of the results. The classification task involves identifying different fault types: healthy, inner race fault, outer race fault, and ball fault. In terms of generalization performance, recent studies have shown that incorporating structural fusion and multi-kernel coordination mechanisms can effectively mitigate overfitting to localized patterns, even in high-volatility tasks such as quantitative

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financial modeling. For instance, a framework developed for U.S. education fund trading demonstrated that integrating multiple learning strategies across agents significantly improved model stability and adaptability under dynamic input conditions. This strategy design concept aligns with the hybrid kernel fusion and coordinated hyperparameter optimization adopted in our work, further supporting the methodological validity of multi-kernel integration for complex classification tasks[13]. Performance is evaluated using standard metrics, and computational complexity is assessed to gauge suitability for real-time deployment [17].

IV. Experimental Results and Analysis

The performance of the HK-ELM was evaluated using the Case Western Reserve University bearing dataset, which includes vibration signals recorded under various fault conditions and load levels. The dataset provides a comprehensive benchmark for testing the generalization capabilities of diagnostic models in practical settings [18]. The experiments involved classification of four fault categories using extracted time-domain and frequency-domain features. Initial results showed that the HK-ELM significantly outperformed conventional ELM and single-kernel ELM models in terms of accuracy and robustness. With an optimal weighting factor α=0.6\alpha = 0.6α=0.6, the hybrid model achieved an average classification accuracy of 98.6%, compared to 94.2% for single Gaussian kernel ELM and 92.5% for polynomial kernel ELM. These results indicate that the hybrid kernel effectively balances local and global pattern extraction.

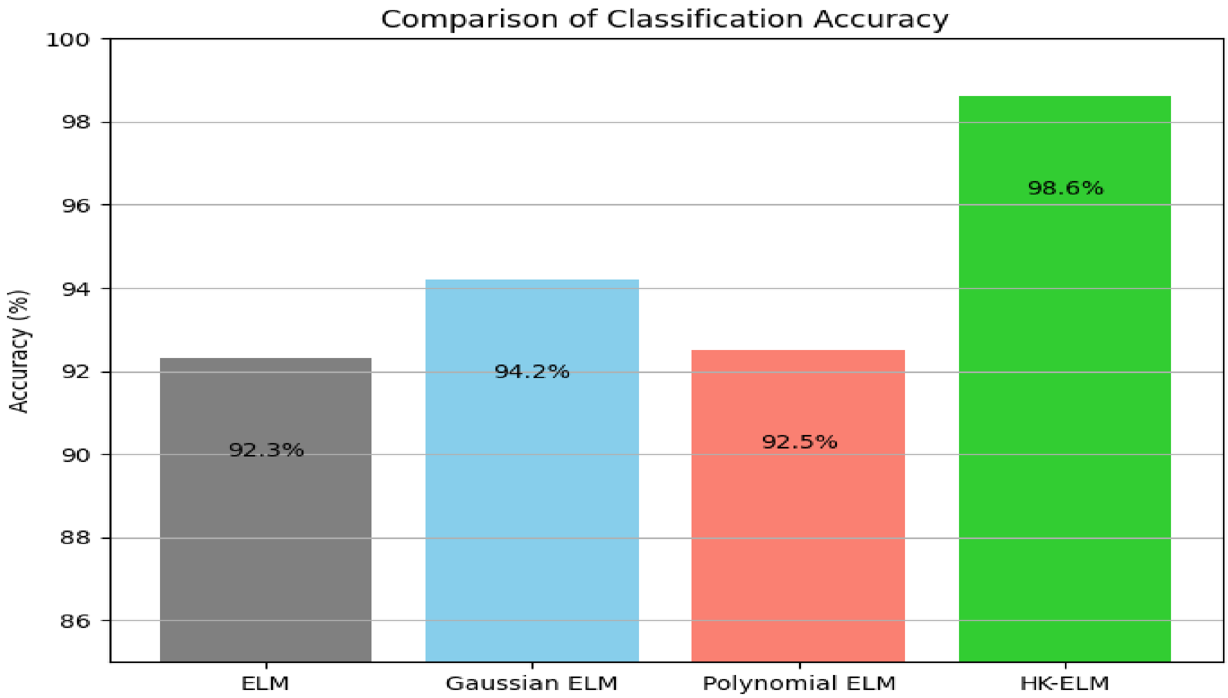

Figure 3 Display classification accuracy comparison between models (ELM, Gaussian ELM, Polynomial ELM, HK-ELM).

Training time for HK-ELM remained impressively low, consistent with the ELM's computational advantages. The model trained in under 1 second for a dataset with over 10,000 instances, demonstrating its potential for real-time fault monitoring applications. Moreover, the HK-ELM maintained high accuracy even under noisy conditions, with less than a 2% drop in performance when Gaussian noise was added to input signals. Receiver Operating Characteristic (ROC) curves were plotted for each class, revealing high Area Under Curve (AUC) values across the board, further confirming the model's discriminative power. Confusion matrices highlighted minimal misclassifications, mostly between outer race and ball faults, which share overlapping spectral features [19]. However, even in these cases, the hybrid kernel offered better separation than individual kernels. Sensitivity analysis was conducted to assess the impact of kernel parameters on model performance [20]. The results showed that while the HK-ELM is relatively stable across a wide range of parameter values, careful tuning of σ\sigmaσ and ddd yields noticeable performance gains. Overall, the experiments confirmed that the hybrid kernel design not only enhances fault classification accuracy but also ensures robust operation across varying conditions and fault types.

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V. Conclusion

The proposed Hybrid Kernel-Driven Extreme Learning Machine offers a significant advancement in intelligent fault detection for motor rolling bearings. By integrating Gaussian and polynomial kernels into a unified learning framework, the HK-ELM effectively captures both local and global patterns within vibration data, leading to superior diagnostic accuracy and robustness. Extensive experimental evaluation demonstrated that the model consistently outperforms traditional ELMs and other machine learning methods in fault classification, training efficiency, and resilience to noise. With its low computational overhead and high generalization capability, the HK-ELM is well-suited for real-time condition monitoring in industrial settings, making it a powerful tool for predictive maintenance and fault-tolerant design in rotating machinery systems.

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