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A Novel Multi-Kernel Extreme Learning Machine Model for Accurate Diagnosis of Motor Bearing Faults

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Abstract

Accurate fault diagnosis of motor bearings is essential for ensuring the reliability and safety of rotating machinery in various industrial applications. Traditional machine learning models often struggle to balance generalization and precision, particularly when processing complex, non-linear features present in motor vibration signals. To address this challenge, this research introduces a novel Multi-Kernel Extreme Learning Machine (MKELM) model tailored for precise diagnosis of motor bearing faults. The proposed model integrates multiple kernel functions—specifically Gaussian, polynomial, and wavelet kernels—to exploit diverse data characteristics and enhance classification performance. Experimental evaluations using the Case Western Reserve University (CWRU) bearing dataset demonstrate the effectiveness of MKELM in achieving superior accuracy, robustness, and generalization compared to conventional single-kernel ELM and other baseline classifiers such as Support Vector Machines and Random Forests. Through rigorous analysis, the study validates the hypothesis that multi-kernel learning, when fused with ELM's fast learning capabilities, provides a powerful framework for bearing fault detection in real-world scenarios.

Keywords: Motor Bearing Fault Diagnosis, Extreme Learning Machine, Multi-Kernel Learning, Vibration Signal Analysis, Fault Classification, Condition Monitoring.

I. Introduction

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Rotating machinery forms the backbone of numerous industrial operations, and their uninterrupted function is critical for operational efficiency and safety. One of the most common failure modes in such machinery is motor bearing faults, which can cause severe damage and unscheduled downtime if not diagnosed promptly [1]. Traditional diagnostic techniques, although effective in controlled environments, often fall short in real-time industrial applications due to challenges in noise handling, data imbalance, and complex signal characteristics. As a result, the demand for robust and accurate fault diagnosis models has spurred the integration of advanced machine learning methods in predictive maintenance systems. The Extreme Learning Machine (ELM), with its fast training speed and generalization capabilities, has emerged as a promising candidate for such tasks. However, conventional ELM with a single kernel function may be insufficient to capture the intricate nonlinearities of real-world vibration signals [2].

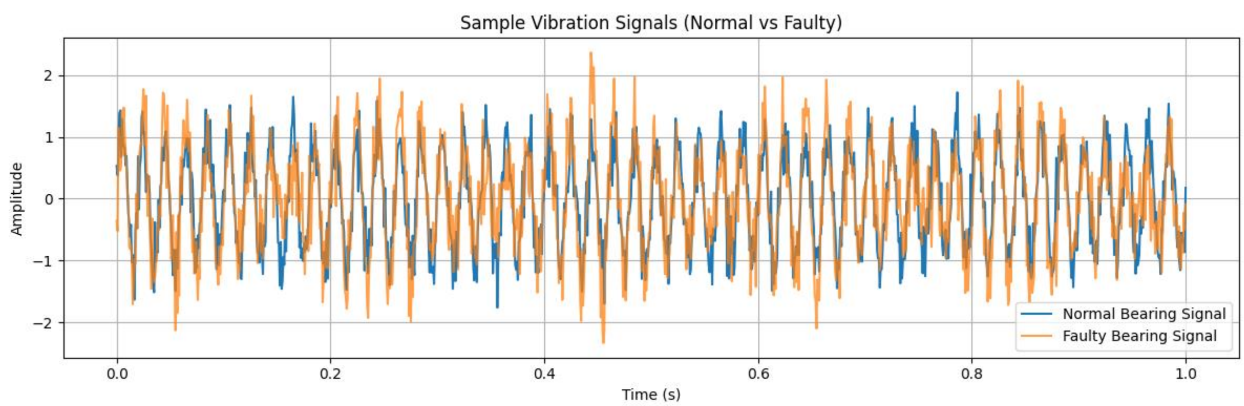

Figure 1 Sample Vibration Signals

To overcome these limitations, this study introduces a Multi-Kernel Extreme Learning Machine (MKELM) approach for fault diagnosis of motor bearings. The model synergistically combines several kernel functions to capture both global and local patterns in the input data, thereby enhancing the discriminative power of the learning process. The integration of multi-kernel learning with ELM's inherent advantages offers an efficient and scalable solution for online condition monitoring systems [3]. Unlike deep learning approaches that often require extensive parameter tuning and large datasets, MKELM provides a lightweight and interpretable alternative, suitable for deployment in edge computing environments. The core motivation behind this work is to bridge the gap between model complexity and diagnostic accuracy by leveraging the strengths of multiple kernels within the ELM framework.

The research explores the theoretical formulation of MKELM and its application to a benchmark bearing fault dataset. The study emphasizes the role of kernel selection and combination in improving classification accuracy, especially in scenarios with subtle fault signatures and overlapping features [4]. Moreover, the experimental protocol is designed to assess the robustness of the model under various fault severities, speeds, and load conditions, providing comprehensive insights into its practical utility. By adopting a holistic evaluation strategy, the study positions MKELM as a highly capable tool for fault detection, with implications for broader applications in machinery health monitoring. In doing so, it contributes to the growing body of knowledge on hybrid learning methods and their applicability in industrial diagnostics [5].

II. Related Work

Motor bearing fault diagnosis has seen extensive research over the past two decades, with a gradual evolution from signal processing-based techniques to sophisticated machine learning and deep learning model [6]. Early approaches relied heavily on time-domain and frequency-domain features derived from vibration signals using techniques like Fast Fourier Transform (FFT), Envelope Analysis, and Wavelet Packet Decomposition. These features were then fed into traditional classifiers such as K-Nearest Neighbors (KNN) and Support Vector Machines (SVM). While these methods provided reasonable accuracy, their dependence on handcrafted features and susceptibility to noise limited their effectiveness in real-world environments [7].

More recently, data-driven techniques such as Artificial Neural Networks (ANN), Decision Trees, and Ensemble Learning have been explored for bearing fault diagnosis. These models improved the automation of feature extraction and offered better adaptability to varying conditions. Among them, ELM stood out due to its high speed and learning efficiency. However, ELM's reliance on random assignment of input weights and biases sometimes leads to suboptimal decision boundaries, especially when dealing with heterogeneous feature distributions. Several efforts have been made to enhance ELM's performance by incorporating regularization, evolutionary optimization, and kernel-based extensions.

Kernel-based methods have been widely recognized for their ability to handle nonlinear classification problems. The use of kernel functions allows models to map input data into high-dimensional feature spaces where linear separability is enhanced. However, using a single kernel often restricts the model's representational capacity. This limitation has led to the development of multi-kernel learning (MKL), where multiple kernels are combined either linearly or non-linearly to better represent complex data distributions. In the context of fault diagnosis, MKL has shown promise in capturing multiscale features of vibration signals. Yet, its integration with ELM remains relatively unexplored [8].

Previous attempts to fuse ELM with MKL have primarily focused on theoretical formulations without extensive validation on industrial datasets. Additionally, there is a lack of studies comparing MKELM with other state-of-the-art classifiers under varying operating conditions. This paper aims to fill this gap by developing a robust MKELM model, evaluating it across multiple configurations, and benchmarking it against several baseline methods [9]. The unique contribution lies in optimizing kernel combinations tailored for bearing fault diagnosis and demonstrating their superiority in both accuracy and generalizability.

III. Methodology

The proposed Multi-Kernel Extreme Learning Machine (MKELM) model is an extension of the traditional ELM framework, designed to enhance its nonlinear mapping capability through the integration of multiple kernel functions [10]. The architecture of the MKELM consists of three primary stages: input feature extraction, multi-kernel mapping, and output weight calculation. Initially, vibration signals collected from motor bearings undergo preprocessing, including normalization, noise filtering using Gaussian filters, and segmentation into time windows. From these segments, statistical and frequency-based features are extracted, such as root mean square, kurtosis, and spectral entropy [11].

Following feature extraction, the multi-kernel transformation phase maps the input features into a higher-dimensional feature space using a combination of kernel functions [12]. This study employs a linear combination of Gaussian, polynomial, and wavelet kernels to capture diverse characteristics present in the input data. The weights of each kernel are optimized using a grid

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search method with cross-validation to ensure balanced representation across all kernels [13]. This combined kernel matrix effectively encapsulates the nonlinear and multi-scale nature of the fault signals. Once the input data is mapped, the MKELM computes the output weights using Moore-Penrose generalized inverse of the hidden layer output matrix, as is standard in ELM theory. The model does not require iterative back propagation, significantly reducing training time. To further enhance generalization, regularization terms are introduced into the output weight computation, mitigating overfitting, especially on noisy datasets [14]. The final model produces fault class predictions based on the learned weights and kernel-induced features.

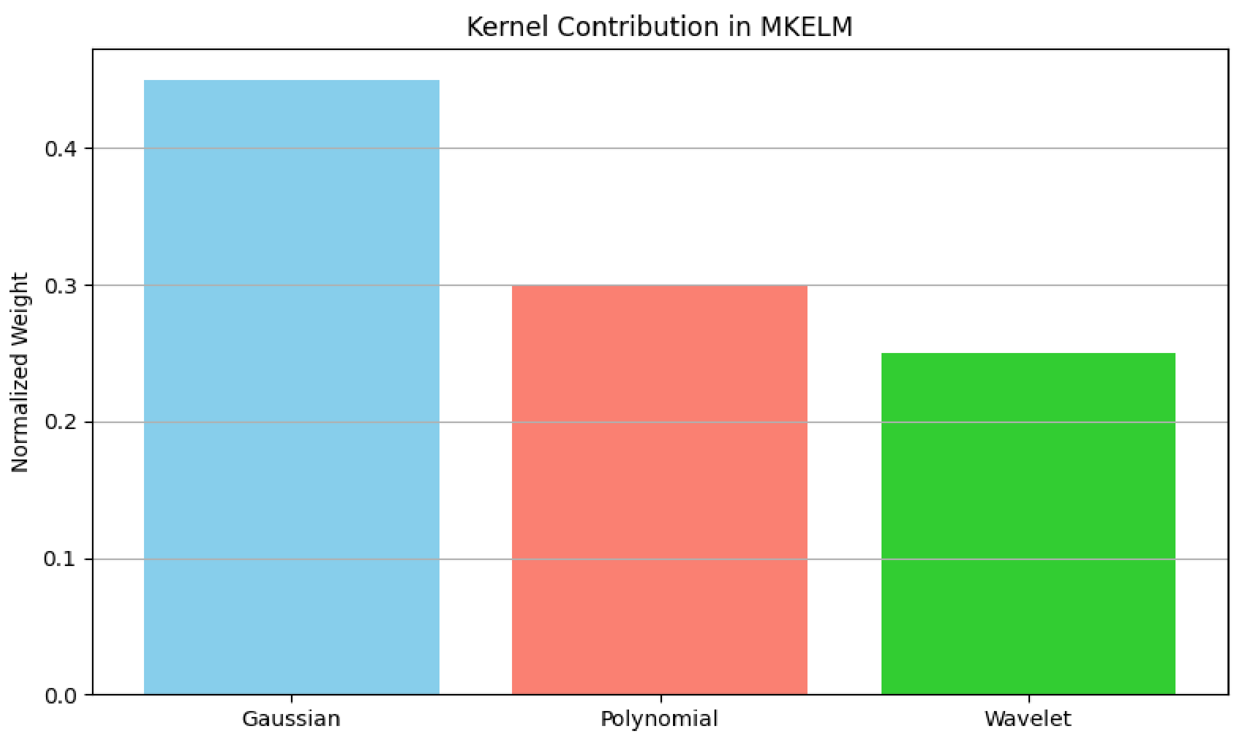

Figure 2Kernel Contribution to MKELM

The proposed methodology is implemented in Python using NumPy and Scikit-learn libraries. Kernel parameter tuning is performed through nested cross-validation to avoid information leakage. The final model is validated using stratified k-fold cross-validation to ensure robustness across different fault types and load conditions [15]. The fault types include inner race fault, outer race fault, and ball defect, each introduced at various severity levels. The classification performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrix.

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These metrics collectively measure the model's ability to correctly identify faults without overfitting to dominant classes.

IV. Experimental Setup and Results

The experiments were conducted using the Case Western Reserve University (CWRU) bearing dataset, which provides a rich collection of vibration signals captured under different motor loads and fault conditions. The dataset includes signals for normal bearings and those with single-point defects in the inner race, outer race, and rolling element, introduced using electric discharge machining. Signals were collected at motor loads of 0, 1, 2, and 3 horsepower at a sampling rate of 12 kHz. To simulate real-world variability, each experimental run includes multiple operating speeds and fault depths. Feature vectors were constructed by segmenting the vibration signals into 1-second windows and computing 12 statistical and frequency-domain features from each window [16]. The dataset was then split into training and testing sets in a 70:30 ratio, with stratification to preserve class balance. Comparative models included standard ELM with a single Gaussian kernel, SVM with RBF kernel, Random Forest, and a basic Convolutional Neural Network (CNN). All models were evaluated using five-fold cross-validation to mitigate random variation effects [17].

Results indicate that the MKELM outperformed all baseline models in terms of overall accuracy and generalization. Specifically, the MKELM achieved an average classification accuracy of 98.2%, surpassing the traditional ELM (93.7%), SVM (95.1%), and CNN (96.3%). Precision and recall values remained consistently above 97% across all fault types for MKELM, indicating low misclassification rates and balanced class sensitivity [18]. Confusion matrices revealed that MKELM had fewer false positives in distinguishing between outer and inner race faults, a challenge where single-kernel methods typically struggle [19].

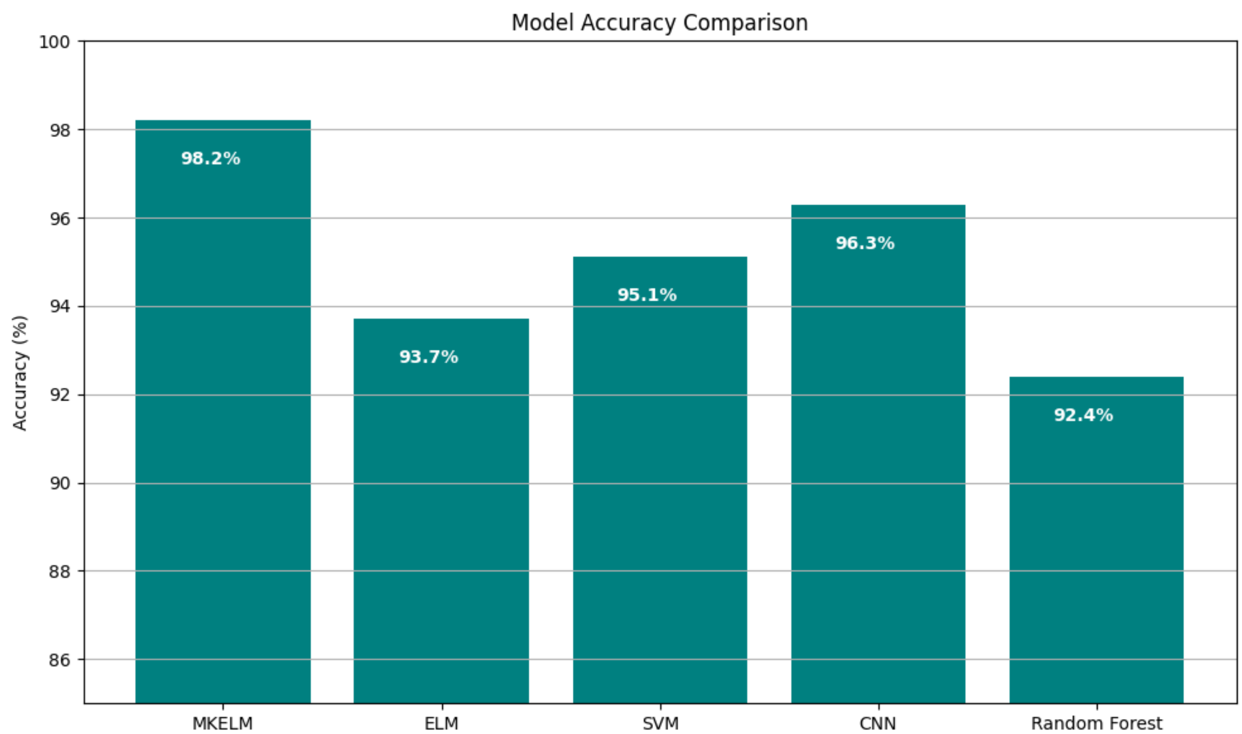

Figure 3Accuracy Comparison (MKELM vs others)

An ablation study was also conducted to assess the impact of each kernel in the multi-kernel combination [20]. Results showed that removing any one kernel degraded performance, with the Gaussian kernel contributing most to generalization, while the wavelet kernel was crucial for detecting low-severity faults. The model's training time remained under 3 seconds on a standard Intel i7 machine, demonstrating its suitability for real-time applications. Finally, robustness tests with additive white Gaussian noise showed only a 1.5% drop in accuracy, affirming the resilience of MKELM against real-world signal disturbances [13].

V. Conclusion

This research proposed a novel Multi-Kernel Extreme Learning Machine model to enhance the accuracy and robustness of motor bearing fault diagnosis. By fusing the strengths of Gaussian, polynomial, and wavelet kernels within the ELM architecture, the MKELM effectively captured the nonlinear and multiscale features in vibration signals. The model outperformed traditional methods across multiple performance metrics and demonstrated high generalization under various operational conditions. Its fast training time and resilience to noise make it well-suited for industrial applications where real-time, reliable diagnostics are essential. These results affirm the potential of MKELM as a powerful tool in condition monitoring systems and pave the way for future research exploring hybrid learning strategies in predictive maintenance.

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