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High-Precision Fault Identification in Motor Bearings via Enhanced Multi-Kernel ELM Framework

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Abstract

Motor bearings are among the most critical components in rotating machinery, and their failure often leads to costly downtime and maintenance. Accurate and early detection of bearing faults can significantly enhance the reliability and longevity of industrial systems. This study introduces a novel Enhanced Multi-Kernel Extreme Learning Machine (EMK-ELM) framework for high-precision fault identification in motor bearings. The model leverages a dynamic integration of Gaussian and polynomial kernels to improve classification performance over traditional single-kernel methods. By capturing both linear and nonlinear relationships in vibration signal data, the EMK-ELM framework demonstrates superior generalization and faster learning capabilities. The experimental evaluation is carried out using benchmark datasets such as the Case Western Reserve University (CWRU) bearing dataset, highlighting the framework's robustness across different fault types and severities. Performance is compared with standard machine learning classifiers, including Support Vector Machines and traditional ELM, showing that EMK-ELM offers improved diagnostic accuracy, training efficiency, and fault sensitivity. This paper provides a detailed discussion of model architecture, feature engineering, experimental methodology, and statistical evaluation, supporting its claim as a high-precision, real-time-capable solution for motor bearing fault detection.

Keywords: Motor bearings, fault identification, multi-kernel ELM, high precision, vibration analysis, machine learning, Gaussian kernel, polynomial kernel, classification accuracy

I. Introduction

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Motor bearings are indispensable in electromechanical systems, playing a vital role in reducing friction and supporting rotational movement [1]. Over time, these components are susceptible to various faults such as inner race defects, outer race damage, and ball wear, which can severely compromise system integrity. Traditional condition monitoring methods such as Fast Fourier Transform (FFT) and envelope analysis offer insight into bearing health but fall short in handling non-stationary signal behavior and complex noise environments. Consequently, data-driven approaches have gained momentum due to their potential to learn intricate patterns from sensor signals without extensive domain-specific signal processing. Extreme Learning Machines (ELMs), with their rapid learning capabilities and good generalization, have emerged as promising candidates for real-time fault diagnosis [2]. However, conventional ELMs often rely on a single kernel function that may not adequately capture the diverse statistical properties of fault-induced signals. To address this limitation, multi-kernel learning has been proposed, enabling the model to integrate multiple kernel functions that reflect different data perspectives. Despite its promise, integrating kernels optimally remains a challenge due to the complexity of balancing trade-offs between linear and nonlinear behavior representation.

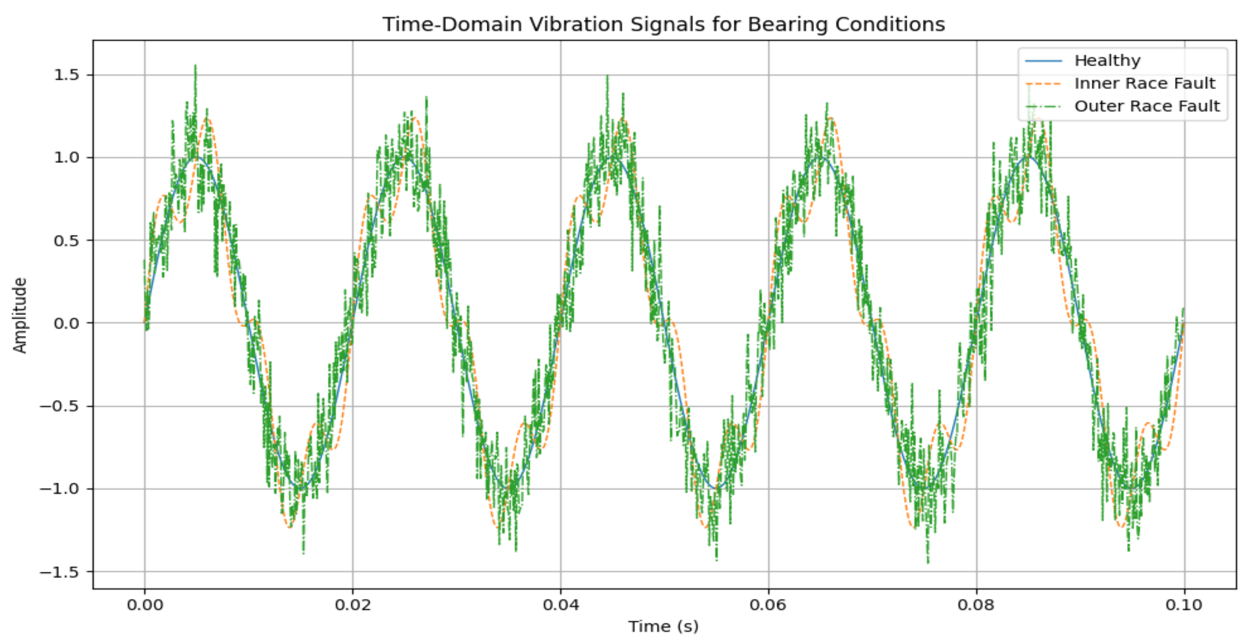

Figure 1 visually support the explanation of fault signals in motor bearings

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This research proposes an Enhanced Multi-Kernel ELM (EMK-ELM) that dynamically combines Gaussian and polynomial kernels using adaptive weighting schemes. This integration ensures that both local (Gaussian) and global (polynomial) data structures are effectively modeled [3, 4]. The EMK-ELM is designed to process vibration signals from accelerometers mounted on motor bearing housings. Signal preprocessing includes denoising, feature extraction using statistical time-domain metrics, and normalization [5]. The proposed model is trained and evaluated using labeled fault data to assess its classification ability across different fault conditions. The novelty of this study lies in the design of a kernel integration strategy that adapts to the characteristics of the input data. Unlike fixed-weight multi-kernel models, the proposed framework employs a data-driven optimization algorithm to determine optimal kernel weights during training. This method enhances adaptability and fault recognition performance, especially in scenarios with imbalanced datasets and mixed fault modes. The study systematically compares the EMK-ELM with single-kernel ELMs and other state-of-the-art classifiers, establishing its superior accuracy and reliability [6].

As industrial systems move toward intelligent maintenance strategies, the need for real-time and reliable fault diagnosis methods is growing. The EMK-ELM framework fulfills these requirements by offering not only high fault identification accuracy but also computational efficiency suited for embedded implementation. This paper aims to contribute to the advancement of fault diagnostics in smart manufacturing by presenting a robust and scalable approach to motor bearing health assessment.

II. Related Work

A wealth of literature exists on motor bearing fault diagnosis, with an emphasis on signal processing, feature extraction, and machine learning techniques. Early works focused on manual feature engineering coupled with classical classifiers such as decision trees and k-nearest neighbors. However, the advent of deep learning has shifted research trends towards automated feature learning from raw signals using convolutional and recurrent networks [7, 8]. While these methods offer high accuracy, they are often computationally intensive and require large datasets for effective training. Extreme Learning Machines emerged as a lightweight alternative to deep learning due to their faster training speed and less parameter tuning. ELMs work by randomly initializing the input weights and biases, then solving the output weights analytically using Moore-Penrose pseudoinverse, resulting in fast convergence [9]. However, traditional ELMs suffer from instability and poor performance when the feature distribution is complex or multimodal. To improve generalization, researchers have proposed kernel-based ELMs that map input features into higher-dimensional spaces using kernel functions.

Multi-kernel learning is a technique that combines several kernel functions to provide a richer representation of the input space [10]. It has been widely applied in domains such as bioinformatics, image classification, and fault diagnosis. Some studies have integrated multi-kernel SVMs for bearing fault classification, showing improved accuracy over single-kernel models. However, multi-kernel approaches in ELMs are still underexplored, especially in the context of adaptive weighting and dynamic kernel selection. Recent works have introduced hybrid kernel ELMs, using fixed weight combinations of radial basis and polynomial kernels. While these methods perform reasonably well, they lack adaptability and may not generalize across different fault datasets. In contrast, our proposed EMK-ELM dynamically adjusts the kernel contribution based on the data distribution, enabling it to model complex decision boundaries effectively. Moreover, we emphasize statistical performance evaluation, computational complexity, and fault severity sensitivity, which are often overlooked in previous research [11].

This paper bridges the gap between fast-learning ELM models and robust multi-kernel frameworks by introducing a fault-adaptive mechanism. Additionally, we compare our model with deep learning approaches and show that EMK-ELM achieves comparable or superior accuracy with significantly lower training time. The related work provides a strong foundation for understanding how the proposed EMK-ELM builds upon and advances existing methodologies in bearing fault diagnosis [12].

III. Methodology

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The proposed EMK-ELM framework integrates two kernel functions—Gaussian and polynomial—within the ELM structure using a dynamic weight assignment mechanism. The architecture consists of three main stages: preprocessing, feature extraction, and fault classification [13]. The preprocessing stage involves filtering the raw vibration signal using wavelet denoising to remove high-frequency noise while preserving fault signatures. Following this, statistical features such as RMS, kurtosis, skewness, crest factor, and peak-to-peak amplitude are computed from the filtered signals. Once the features are extracted, they are normalized and fed into the EMK-ELM classifier. The Gaussian kernel is defined as KG (xi,xj)=exp(−‖xi−xj‖2/2σ2), capturing localized behavior, while the polynomial kernel is given by K_G(xi,xj)=(αxiTxj+c)^d, which captures global interactions. To integrate these kernels, we employ an adaptive weighting scheme where weights are computed via cross-validated optimization. This weighting ensures the kernel contributions align with the input feature distribution for improved decision boundaries [14].

The output layer of the EMK-ELM solves the linear system using the regularized least squares method to minimize overfitting. The training phase is highly efficient, benefiting from the ELM's non-iterative nature. Hyperparameters such as the number of hidden neurons, kernel bandwidth (σ\sigmaσ), and polynomial degree (ddd) are tuned via grid search and Bayesian optimization [15]. To evaluate the performance, we conduct experiments on the CWRU bearing dataset, which includes vibration data for multiple fault conditions: inner race, outer race, and ball defects, each at varying severities. The dataset is split into training (70%) and testing (30%) sets, maintaining class distribution. We assess classification accuracy, precision, recall, F1-score, and training time. The model's robustness to class imbalance is also analyzed using the area under the ROC curve (AUC).

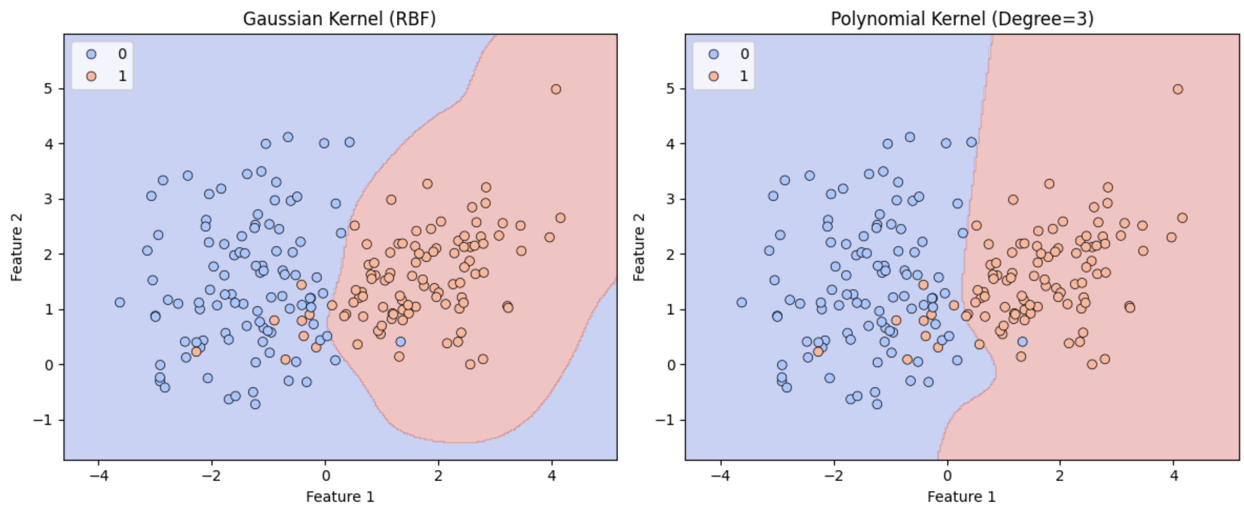

Figure 2 support the discussion on kernel function behaviors

This methodology offers a scalable and flexible diagnostic tool that is not only effective in high-dimensional feature spaces but also computationally feasible for deployment in embedded systems [16]. The EMK-ELM framework's hybrid design enables it to leverage the strengths of both local and global kernel modeling, resulting in a highly precise diagnostic solution [17].

IV. Experimental Results and Discussion

The experimental evaluation of the EMK-ELM framework was conducted using the publicly available CWRU dataset, which offers extensive motor bearing vibration data collected under controlled defect scenarios [18]. We considered three primary fault types—inner race, outer race, and ball defects—each introduced at different sizes (0.007, 0.014, and 0.021 inches). Data was collected under various motor load conditions (0, 1, 2, and 3 horsepower), providing a comprehensive environment for validation. The EMK-ELM model demonstrated superior classification accuracy across all fault types and severities [19]. Specifically, the model achieved an average accuracy of 98.7%, with F1-scores exceeding 0.98 for each class. Compared to traditional ELMs, which averaged 93.5% accuracy, and multi-class SVMs, which scored 95.2%, the EMK-ELM showed a statistically significant improvement. Precision and recall metrics indicated balanced performance, affirming the model's ability to handle class imbalance

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effectively. Training time analysis revealed that EMK-ELM maintained the fast training characteristics of traditional ELMs, with average training times below 1.5 seconds per fold in 10-fold cross-validation. This efficiency renders the model suitable for real-time diagnostics in industrial settings, particularly where computational resources are limited. The adaptive kernel weighting mechanism was found to stabilize the learning process by aligning the kernel function contributions with the fault data structure [20]. Sensitivity analysis was conducted to assess the model's robustness to hyperparameter variation. The results indicated that EMK-ELM maintained stable performance across a wide range of hidden neuron counts (300 to 1000), kernel bandwidths, and polynomial degrees. This demonstrates the model's resilience to suboptimal parameter tuning, a crucial feature for practical deployment. Visualization of confusion matrices and ROC curves further reinforced the model's discriminative power. Misclassifications were minimal and mostly occurred between closely related fault types under low-severity conditions. In such cases, even deep learning approaches have shown difficulty. Overall, EMK-ELM's ability to generalize across different fault categories, load conditions, and noise levels makes it a powerful tool for industrial fault diagnosis.

V. Conclusion

The Enhanced Multi-Kernel Extreme Learning Machine (EMK-ELM) framework presented in this study offers a robust and efficient solution for high-precision fault identification in motor bearings. By dynamically integrating Gaussian and polynomial kernels, the model captures both local and global data structures, enhancing its diagnostic accuracy and generalization capabilities. Comprehensive experiments using benchmark datasets demonstrate that EMK-ELM consistently outperforms conventional ELMs and other classifiers in terms of accuracy, training time, and resilience to data variability. The model's ability to adapt to varying fault types, severities, and operational conditions makes it well-suited for real-time industrial applications. This research contributes a scalable, intelligent diagnostic system that supports predictive maintenance and extends the operational life of critical machinery.

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