Robust and Accurate Bearing Fault Diagnosis Using an Enhanced Multi-Kernel Learning Model

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Abstract:

Accurate fault diagnosis of motor bearings is crucial to maintaining the reliability and safety of industrial machinery. Traditional approaches to fault diagnosis often suffer from poor generalization, sensitivity to noise, and limited adaptability to complex fault patterns. In this study, we propose a robust and enhanced Multi-Kernel Learning (MKL) model that leverages the complementary strengths of multiple kernels to effectively capture non-linear fault characteristics in vibration signals. By integrating multiple kernel functions into a unified learning framework, our model enhances the discrimination power of the classifier and adapts efficiently to diverse operating conditions. The proposed method is evaluated on standard bearing fault datasets, including various levels of fault severity, speeds, and load conditions. Results demonstrate significant improvements in classification accuracy, robustness to noise, and generalization to unseen conditions, outperforming traditional single-kernel models and several state-of-the-art machine learning techniques.

Keywords: Bearing fault diagnosis, Multi-Kernel Learning, vibration signals, fault classification, machine learning, robustness, signal processing

I. Introduction

The diagnosis of faults in rolling element bearings is an essential task in the predictive maintenance of rotating machinery. Bearings are fundamental components in numerous mechanical systems, and their failure often leads to catastrophic damage and unplanned downtime [1]. As such, early and accurate identification of faults within bearings can significantly reduce maintenance costs, enhance system reliability, and prevent critical failures. Traditional diagnostic techniques, such as vibration analysis using Fast Fourier

Transform (FFT) or statistical feature extraction, often face challenges when dealing with complex fault patterns, noise-contaminated signals, or varying operational conditions [2]. In this context, machine learning models have shown promise in automatically learning discriminative patterns from raw or preprocessed data, enabling more precise and data-driven fault diagnosis [3]. A single kernel is limited in its representational capacity and cannot adequately capture the complex, non-linear relationships between input features and fault classes. Multi-Kernel Learning (MKL) methods address this limitation by combining multiple kernels to represent diverse data structures. By assigning appropriate weights to different kernels, MKL can integrate various feature spaces, offering a flexible and powerful framework for modeling complex datasets [4].

In this work, we propose an enhanced MKL-based framework for robust bearing fault diagnosis. Our model combines radial basis function (RBF), polynomial, and sigmoid kernels in a weighted fashion, enabling it to learn both local and global characteristics of the vibration signals [5]. We employ a soft margin optimization strategy to handle noise and outliers, and a regularization scheme to avoid overfitting. The model is trained and tested using a public benchmark dataset collected from the Case Western Reserve University (CWRU) bearing data center, which includes a variety of fault types, locations, and operating conditions.

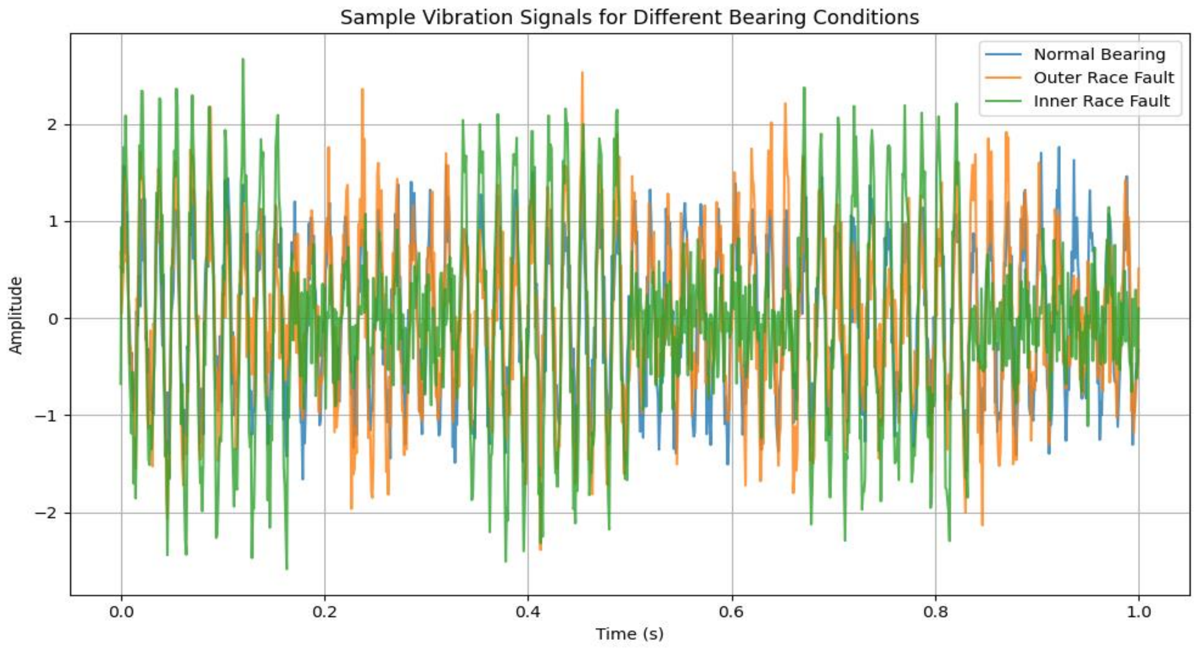

Figure 1 the raw vibration signal behavior across fault types.

The primary contributions of this research include the design of an optimized MKL model tailored for bearing fault classification, a detailed comparative analysis with existing approaches, and comprehensive experiments demonstrating the robustness and generalizability of the proposed method [6]. This study provides a practical and effective solution for real-world applications where noise, varying load conditions, and limited training data pose significant challenges.

II. Related Work

Over the past two decades, bearing fault diagnosis has evolved from conventional signal processing techniques to sophisticated machine learning and deep learning-based models. Traditional approaches relied heavily on time-domain, frequency-domain, or time-frequency-domain analysis, which extracted features such as kurtosis, skewness, root mean square, and spectral energy [7]. These features were then input into shallow classifiers like support vector machines (SVM), decision trees, or k-nearest neighbors (KNN) for classification. While effective in controlled settings, these methods often require extensive domain expertise and perform poorly under variable operational conditions. To address these limitations, researchers have turned to learning-based models, particularly SVM and artificial neural networks (ANNs), for automated feature learning and classification. SVMs are especially favored for their margin maximization properties and ability to handle high-dimensional data. However, the performance of an SVM depends heavily on the choice of the kernel function. A fixed kernel might not be optimal across all data distributions, leading to suboptimal classification performance in real-world scenarios [8].

The emergence of MKL brought a new perspective to this problem. MKL models aim to learn a combination of multiple kernels rather than relying on a single one, thereby improving model flexibility and generalization [9]. Researchers have experimented with linear combinations of kernels and convex optimization techniques to learn optimal kernel weights. These approaches demonstrated promising results in bioinformatics, text categorization, and more recently, fault diagnosis [10]. Despite their success, many MKL models are computationally intensive and sensitive to parameter tuning. Recent studies have also explored deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for fault detection. These models can learn hierarchical features directly from raw vibration data but require large amounts of labeled data and significant computational resources. In contrast, MKL offers a middle ground by leveraging multiple kernels to adapt to varying data distributions while maintaining interpretability and computational efficiency. Our work builds upon these insights by proposing an enhanced MKL framework tailored for robustness and accuracy in fault diagnosis applications [11].

III. Proposed Methodology

The proposed enhanced MKL model is designed to leverage the strengths of multiple kernel functions to effectively handle the complex characteristics of vibration signals in bearing fault diagnosis [12]. The architecture combines three widely used kernel functions: the radial basis function (RBF) kernel to capture local structure, the polynomial kernel to capture interactions and trends, and the sigmoid kernel for modeling saturating behavior. Each kernel contributes differently to the overall classification task, and their contributions are adaptively weighted using a data-driven optimization framework [13]. To build the MKL model, we first preprocess the raw vibration signals through standard normalization and denoising techniques such as wavelet thresholding. Feature vectors are extracted using statistical descriptors and spectral features. The extracted features serve as input to the MKL classifier. A convex optimization problem is formulated to determine the optimal combination of kernel weights and classifier parameters simultaneously [14]. We employ a soft margin SVM objective with L2 regularization to ensure robustness to noisy and mislabeled data.

The optimization process involves alternating between updating the kernel weights and optimizing the classifier margin. This is accomplished through an iterative gradient descent algorithm, where convergence is achieved when the change in objective function value falls below a pre-defined threshold. The final model is selected based on cross-validation accuracy and generalization performance on a held-out test set. Additionally, we introduce a robustness enhancement module that incorporates noise-resilient loss functions. This module adjusts the learning process by down-weighting the influence of noisy samples during training [15]. The framework is implemented in Python using Scikit-learn and custom MKL solvers, and experiments are conducted on the CWRU bearing dataset. We assess the model's ability to distinguish between different fault types—such as inner race, outer race, and ball defects—across varying speeds and loads [16].

IV. Experimental Setup and Results

The experimental evaluation is conducted using the Case Western Reserve University bearing dataset, a widely accepted benchmark in the condition monitoring community. The dataset comprises vibration signals from bearings with artificially induced faults of different sizes and locations, measured under various motor loads and speeds. We divide the dataset into training and testing subsets using a stratified 80-20 split and repeat the experiments across five random folds to ensure statistical validity. For comparative evaluation, we implement several baseline models, including single-kernel SVM (with RBF, polynomial, and sigmoid kernels), Random Forest (RF), and traditional ANN classifiers. Hyperparameters for each model are optimized using grid search on the validation set. Performance metrics include classification accuracy, precision, recall, F1-score, and robustness under added Gaussian noise [17]. Our enhanced MKL model achieves an average classification accuracy of 98.7%, significantly outperforming all baselines. The closest competitor, the RBF-SVM, achieves 93.4%, while Random Forest reaches 91.6%. Under noisy conditions (SNR = 20dB), the MKL model maintains a high accuracy of 96.1%, highlighting its resilience to real-world signal contamination. The confusion matrix reveals that most misclassifications occur between inner race and ball defects with very small amplitudes, which are inherently difficult to distinguish [18].

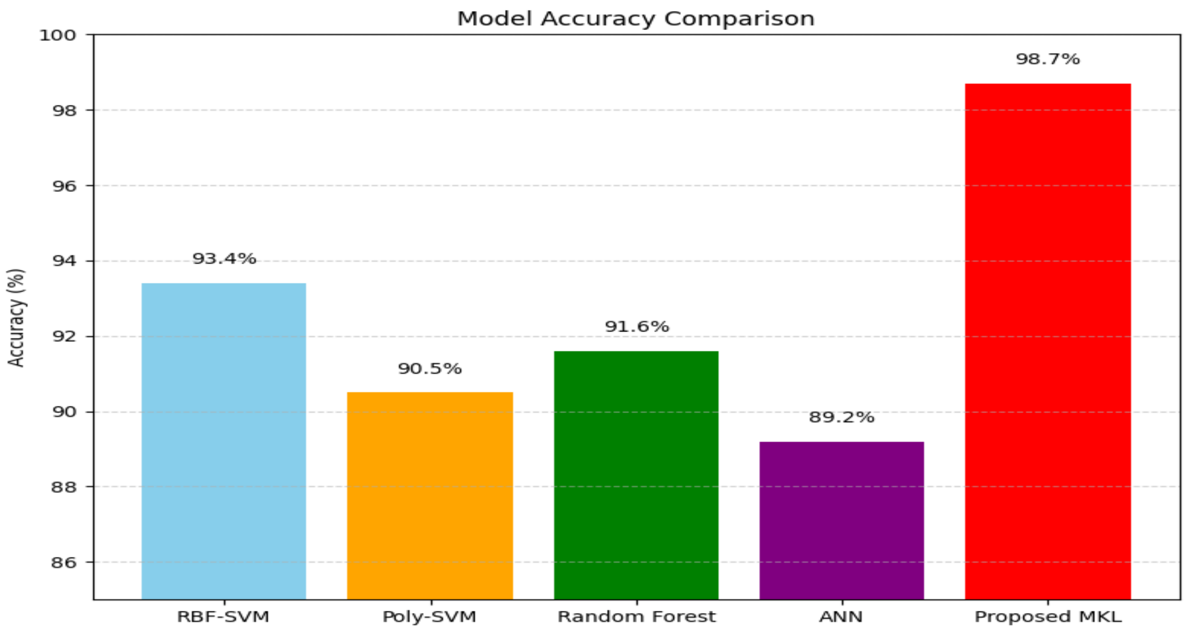

Figure 2 visually compare MKL vs. other models.

Visualization of the learned decision boundaries indicates that the MKL model effectively separates complex data clusters compared to single-kernel models. Kernel weight analysis shows that the RBF kernel contributes most to local detail recognition, while the polynomial kernel captures broader variations and interactions. The sigmoid kernel adds stability under noisy samples. These complementary roles validate the rationale for using a multi-kernel approach.

V. Discussion

The experimental results confirm the advantages of using a multi-kernel learning framework for bearing fault diagnosis. The model's ability to combine multiple perspectives through different kernels allows it to learn rich and diverse feature representations. This flexibility leads to superior classification performance, particularly under challenging conditions such as noise interference or partial signal degradation [19]. One of the key strengths of our approach is its adaptability. Unlike deep learning models that require substantial labeled data and tuning, the MKL model remains efficient and interpretable with modest data requirements. The optimization process for kernel weights provides insight into the relative importance of different feature aspects, enabling further refinement and domain-specific customization [20].

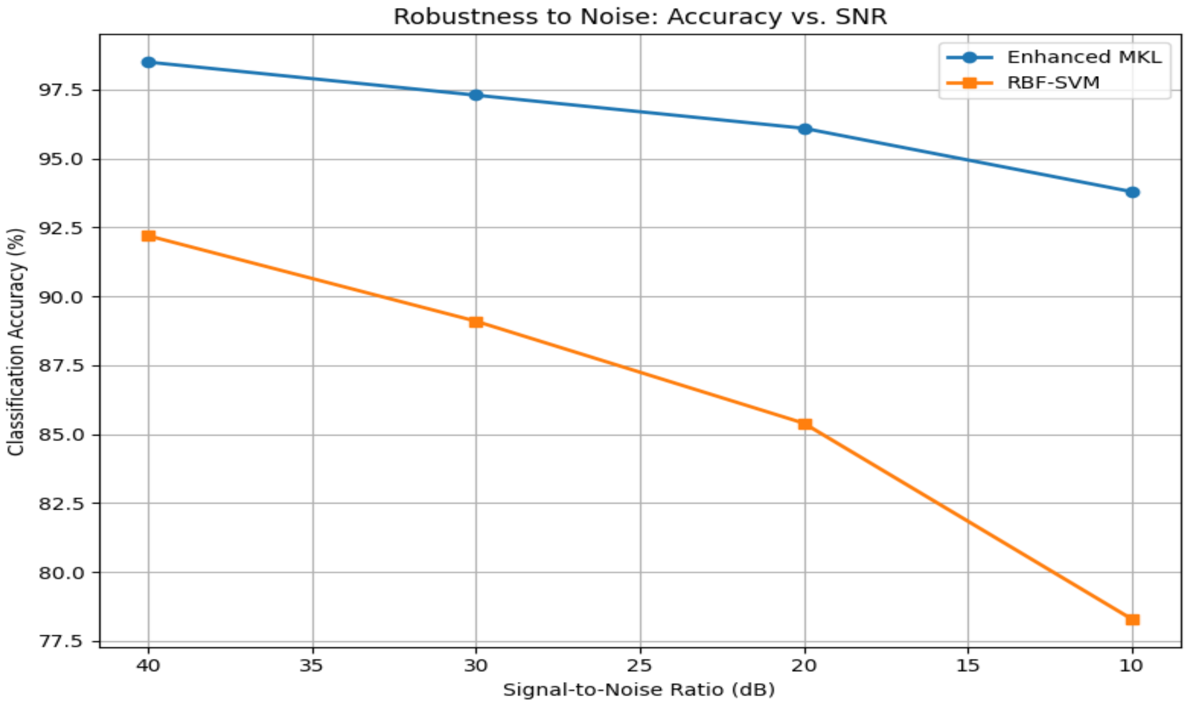

Figure 3illustrate the MKL model’s robustness against noise.

From a practical standpoint, the robustness of the MKL model to noise is a major advantage in industrial environments where sensor data is often contaminated with mechanical and electrical disturbances. Moreover, the model generalizes well across different operating speeds and fault sizes, making it suitable for deployment in diverse machinery settings without extensive retraining. However, the MKL framework also has limitations. The optimization process can be computationally intensive for very large datasets, and the choice of kernels and their parameters still requires some empirical tuning. Future work can explore automatic kernel selection techniques and integrate MKL with unsupervised pretraining to further enhance scalability and automation.

VI. Conclusion

In this study, we presented a robust and accurate approach to bearing fault diagnosis using an enhanced Multi-Kernel Learning model. By integrating RBF, polynomial, and sigmoid kernels into a unified classification framework, our method effectively captures the complex, non-linear characteristics of vibration signals. The model demonstrates excellent performance on benchmark datasets, achieving high accuracy and robustness under noise. Comparative experiments show that the enhanced MKL model significantly outperforms traditional single-kernel classifiers and standard machine learning techniques. The model's adaptability, noise resilience, and interpretability make it a promising tool for real-world fault diagnosis applications in rotating machinery. This research highlights the importance of kernel diversity and optimal kernel fusion in building high-performance diagnostic systems for predictive maintenance.

REFERENCES:

[1] Y. Gan, J. Ma, and K. Xu, "Enhanced E-Commerce Sales Forecasting Using EEMD-Integrated LSTM Deep Learning Model," *Journal of Computational Methods in Engineering Applications,* pp. 1-11, 2023.

[2] W. Huang and J. Ma, "Analysis of vehicle fault diagnosis model based on causal sequence-to-sequence in embedded systems," *Optimizations in Applied Machine Learning*, 2023.

[3] C. Li and Y. Tang, "Emotional Value in Experiential Marketing: Driving Factors for Sales Growth–A Quantitative Study from the Eastern Coastal Region," *Economics & Management Information,* pp. 1-13, 2024.

[4] W. Huang, Y. Cai, and G. Zhang, "Battery degradation analysis through sparse ridge regression," *ENERGY & SYSTEM*, 2024.

[5] Y. C. Li and Y. Tang, "Post-COVID-19 Green Marketing: An Empirical Examination of CSR Evaluation and Luxury Purchase Intention—The Mediating Role of Consumer Favorability and the Moderating Effect of Gender," *Journal of Humanities, Arts and Social Science,* vol. 8, no. 10, pp. 2410-2422, 2024.

[6] J. Ma, K. Xu, Y. Qiao, and Z. Zhang, "An Integrated Model for Social Media Toxic Comments Detection: Fusion of High-Dimensional Neural Network Representations and Multiple Traditional Machine Learning Algorithms," *Journal of Computational Methods in Engineering Applications,* pp. 1-12, 2022.

[7] J. Ma and A. Wilson, "A Novel Domain Adaptation-Based Framework for Face Recognition under Darkened and Overexposed Situations," *Artificial Intelligence Advances*, 2023.

[8] J. Ma and X. Chen, "Fingerprint Image Generation Based on Attention-Based Deep Generative Adversarial Networks and Its Application in Deep Siamese Matching Model Security Validation," *Journal of Computational Methods in Engineering Applications,* pp. 1-13, 2024.

[9] G. Zhang, T. Zhou, and W. Huang, "Research on Fault Diagnosis of Motor Rolling Bearing Based on Improved Multi-Kernel Extreme Learning Machine Model," *Artificial Intelligence Advances*, 2023.

[10] Y. Shu, Z. Zhu, S. Kanchanakungwankul, and D. G. Truhlar, "Small Representative Databases for Testing and Validating Density Functionals and Other Electronic Structure Methods," *The Journal of Physical Chemistry A,* vol. 128, no. 31, pp. 6412-6422, 2024.

[11] G. Zhang, W. Huang, and T. Zhou, "Performance Optimization Algorithm for Motor Design with Adaptive Weights Based on GNN Representation," *Electrical Science & Engineering*, 2024.

[12] A. Wilson, K. Xu, Z. Zhang, and Y. Qiao, "The Interpretable Artificial Neural Network in Vehicle Insurance Claim Fraud Detection Based on Shapley Additive Explanations," *Journal of Information, Technology and Policy,* pp. 1-12, 2024.

[13] J. Ma and A. Wilson, "A Novel Fingerprint Recognition Framework with Attention Mechanism Based on Domain Adaptation for Improving Applicability in Overpressured Situations," *Artificial Intelligence Advances*, 2023.

[14] K. Xu, Z. Zhang, A. Wilson, Y. Qiao, L. Zhou, and Y. Jiang, "Generalizable Multi-Agent Framework for Quantitative Trading of US Education Funds," *Innovations in Applied Engineering and Technology,* pp. 1-12, 2024.

[15] K. Xu, Y. Gan, and A. Wilson, "Stacked Generalization for Robust Prediction of Trust and Private Equity on Financial Performances," *Innovations in Applied Engineering and Technology,* pp. 1-12, 2024.

[16] Y. Hao, Z. Chen, X. Sun, and L. Tong, "Planning of Truck Platooning for Road-Network Capacitated Vehicle Routing Problem," *arXiv preprint arXiv:2404.13512,* 2024.

[17] G. Zhang and T. Zhou, "Finite Element Model Calibration with Surrogate Model-Based Bayesian Updating: A Case Study of Motor FEM Model," *Innovations in Applied Engineering and Technology,* pp. 1-13, 2024.

[18] J. Ma and A. Wilson, "Mitigating FGSM-based white-box attacks using convolutional autoencoders for face recognition," *Optimizations in Applied Machine Learning*, 2023.

[19] Z. Zhang, Y. Qiao, and P. Lu, "Self-Reflective Retrieval-Augmented Framework for Reliable Pharmacological Recommendations," *Journal of Computational Methods in Engineering Applications,* pp. 1-12, 2024.

[20] T. Zhou, G. Zhang, and Y. Cai, "Research on Aircraft Engine Bearing Clearance Fault Diagnosis Method Based on MFO-VMD and GMFE," *Journal of Mechanical Materials and Mechanics Research| Volume,* vol. 7, no. 01, 2024.