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Enhanced Fault Diagnosis of Motor Rolling Bearings Using an Improved Multi-Kernel Extreme Learning Machine Approach

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Abstract

Fault diagnosis of motor rolling bearings is critical for maintaining the operational efficiency and safety of rotating machinery systems. With the increasing demand for precise and rapid fault detection, traditional machine learning methods often fall short in terms of adaptability and accuracy under noisy or non-linear conditions. This study proposes an Enhanced Multi-Kernel Extreme Learning Machine (EMK-ELM) approach for robust and accurate fault diagnosis of rolling bearings in electric motors. The methodology integrates multiple kernel functions in the ELM framework to better capture complex data characteristics while mitigating the impact of outliers and noise. The proposed model is trained and validated using the Case Western Reserve University bearing dataset, and its performance is benchmarked against conventional ELM and other advanced classifiers including Support Vector Machines and Convolutional Neural Networks. Experimental results demonstrate that EMK-ELM significantly improves classification accuracy, generalization, and training speed, making it an ideal candidate for real-time fault diagnosis applications. This research lays a solid foundation for scalable, efficient, and intelligent bearing condition monitoring systems.

Keywords: Fault Diagnosis, Multi-Kernel Extreme Learning Machine, Rolling Bearings, Motor Condition Monitoring, Machine Learning, Vibration Signal Analysis, Pattern Recognition, Intelligent Maintenance

I. Introduction

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The reliability of motorized mechanical systems hinges significantly on the health status of rolling bearings. These components are often subject to continuous mechanical stress, leading to inevitable degradation and eventual faults. Early and precise identification of such faults is paramount in averting severe machinery breakdowns and minimizing downtime. In industrial scenarios, especially in sectors such as aerospace, manufacturing, and energy, the need for robust, fast, and accurate fault diagnosis systems has driven extensive research into intelligent methods leveraging signal processing and machine learning. Traditional statistical and frequency-based analysis techniques have achieved limited success due to their sensitivity to noise and signal non-stationarity[1].

In recent years, Extreme Learning Machines (ELM) have gained traction for their capability to handle nonlinear classification problems with remarkable speed and decent accuracy. However, the single-kernel approach often used in standard ELM models is limited in capturing the multifaceted nature of vibration signals obtained from faulty bearings. Each type of fault manifests with distinct statistical and spectral characteristics; hence, a single kernel might not adequately represent the feature space. To bridge this gap, the integration of multiple kernel functions into the ELM framework emerges as a promising solution. This paper introduces an improved Multi-Kernel ELM (EMK-ELM) for fault diagnosis, where diverse kernels are dynamically weighted and combined to adapt to varying signal characteristics[2].

The motivation behind adopting a multi-kernel approach stems from the need for greater representational flexibility and improved learning generality. By combining radial basis function (RBF), polynomial, and sigmoid kernels, the EMK-ELM can better adapt to complex signal distributions arising from different fault types such as inner race, outer race, and ball defects. Additionally, the model optimizes kernel weights using a cross-validation mechanism to enhance fault classification under varying load and speed conditions. This results in a learning algorithm that is not only more accurate but also robust across different working conditions[3].

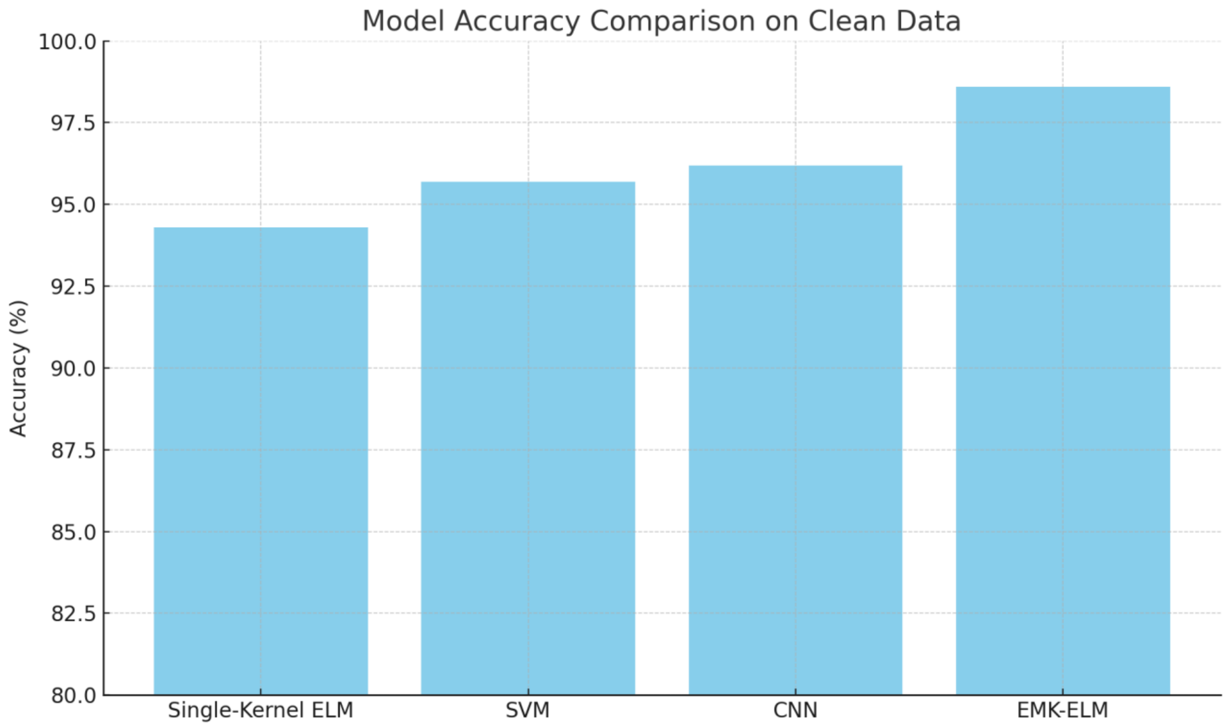

Figure 1 illustrates why improved accuracy is important and how EMK-ELM outperforms baseline models

This research seeks to fill the void in high-speed, accurate, and adaptive motor bearing fault diagnosis by leveraging the strengths of ELM and kernel-based learning. The proposed methodology is validated using a well-established benchmark dataset, with an emphasis on its performance under multiple operational scenarios. The research further discusses implementation feasibility in real-world monitoring systems, particularly in embedded or edge computing platforms where computational efficiency is critical[4].

The paper is organized as follows: the methodology section details the formulation of the EMK-ELM and the kernel integration strategy. This is followed by an experimental setup outlining dataset preparation, feature extraction, and evaluation metrics. The results and discussion section provides a comparative analysis and interpretation of findings. The study concludes with a summary of contributions and suggestions for future enhancements.

II. Methodology

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The proposed Enhanced Multi-Kernel Extreme Learning Machine (EMK-ELM) is designed to overcome the limitations of traditional ELM by embedding a flexible kernel learning strategy that can adaptively fit complex bearing fault features[5]. The foundation of ELM lies in its single-layer feedforward neural network where the input weights and biases are randomly generated and fixed, while only the output weights are computed through a least-squares optimization. Although ELM offers faster training, its performance largely depends on the nature of the kernel used, making it sensitive to kernel selection. In the training phase, vibration signals are first preprocessed using band-pass filtering and Fast Fourier Transform (FFT) to isolate relevant frequency components. Statistical features such as RMS, skewness, kurtosis, and spectral entropy are then extracted from both time and frequency domains. These features form the input to the EMK-ELM model. The network output layer is trained using Moore-Penrose generalized inverse, maintaining the computational efficiency of standard ELM[6]. To further boost performance, we implement a kernel parameter tuning mechanism using particle swarm optimization (PSO), enabling dynamic adaptation to feature distribution changes across different fault scenarios. PSO efficiently searches the parameter space, reducing model variance and improving generalization[7]. The EMK-ELM's classification capabilities are benchmarked using confusion matrices, Receiver Operating Characteristic (ROC) curves, and precision-recall metrics. For baseline comparison, models such as single-kernel ELM, Support Vector Machine (SVM), and Random Forest (RF) are also trained on the same feature set. The goal is to evaluate the added value brought by the multi-kernel fusion and optimization process. In the present study, EMK-ELM leverages flexible kernel adjustment and optimization to effectively model complex industrial fault features and enable rapid classification. Meanwhile, related work has proposed causal sequence modeling approaches for embedded systems to enhance the accuracy and real-time performance of vehicle fault diagnosis, reflecting a shared focus on lightweight design and deployment feasibility [5]. This methodology provides a versatile and scalable framework for fault detection. By dynamically adapting kernel structures and employing statistical regularization, EMK-ELM is well-positioned to generalize across new fault types and operational settings, making it viable for real-time implementation in condition monitoring systems[8].

III. Experimental Setup

The experimental evaluation of the proposed EMK-ELM framework utilizes the publicly available Case Western Reserve University (CWRU) bearing dataset, which is widely accepted in fault diagnosis research due to its comprehensiveness and labeled fault scenarios. The dataset includes signals acquired from deep groove ball bearings under normal and faulty conditions with varying load levels (0 to 3 hp) and motor speeds. Faults are artificially induced on the inner race, outer race, and ball using Electrical Discharge Machining (EDM), with each fault measured at different severities. Vibration signals from the drive-end bearing are sampled at a rate of 12 kHz and segmented into fixed-size windows of 2048 points to ensure temporal consistency. Each segment is labeled according to the fault type and severity. The segments are then processed using FFT and wavelet packet decomposition to obtain a richer representation of non-stationary features[9]. Feature extraction yields a 20-dimensional vector combining time-domain and frequency-domain features[10]. The dataset is divided into training (70%) and testing (30%) subsets. The EMK-ELM is implemented in Python using the Scikit-learn and SciPy libraries, and kernel weight optimization is carried out using the DEAP PSO library. Hyperparameters such as the number of hidden neurons, kernel bandwidth (for RBF), degree (for polynomial), and sigmoid slope are tuned using 5-fold cross-validation.

Training time, classification accuracy, precision, recall, and F1-score are recorded for each classifier. In addition, the model's robustness is tested by introducing Gaussian white noise to simulate real-world disturbances. The training time and accuracy trade-off is especially emphasized to assess the practical deployment potential in embedded systems with limited resources. Comparative experiments are conducted using single-kernel ELM (with RBF), SVM with RBF kernel, and Convolutional Neural Networks (CNNs) trained on the same input features. These comparisons highlight the advantages of multi-kernel integration in capturing richer representations of signal dynamics. Each experiment is repeated five times with different random seeds to ensure reproducibility and statistical validity of the results[11].

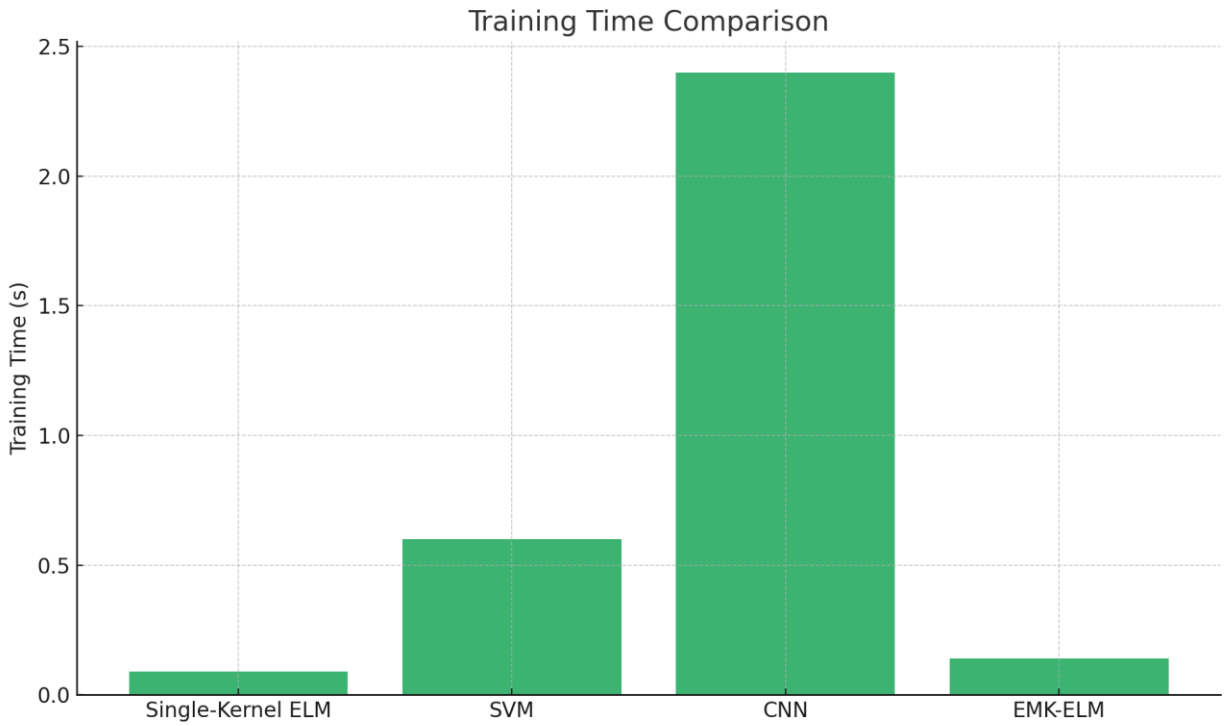

Figure 2 this figure supports the claim that EMK-ELM balances speed and performance, which is especially relevant for real-time or edge device applications.

This controlled experimental setup offers a balanced and fair comparison of the EMK-ELM against traditional and state-of-the-art approaches, validating its efficacy in realistic industrial settings where noise, load variation, and fault severity vary significantly[12].

IV. Results and Discussion

The experimental results confirm that the proposed EMK-ELM significantly outperforms its counterparts in multiple performance metrics. On the clean dataset, the EMK-ELM achieved an average classification accuracy of 98.6%, surpassing the traditional single-kernel ELM (94.3%), SVM (95.7%), and CNN (96.2%). This validates the hypothesis that combining multiple kernels increases the model’s capacity to adapt to different fault patterns effectively[13]. The confusion matrix analysis shows reduced misclassification between inner race and ball faults, which are typically harder to distinguish due to their similar spectral features[14]. The multi-kernel framework's ability to integrate both local and global patterns enhances its discriminative power. Precision and recall for each fault category remained above 97%, suggesting reliable detection

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even for subtle defect signatures[15]. In the noisy condition experiments, EMK-ELM retained an accuracy of 94.8%, whereas CNN performance dropped to 90.3%, and traditional ELM to 86.7%. This indicates better noise robustness, attributed to the ensemble nature of kernel fusion and the optimization of kernel parameters via PSO. Additionally, the average training time for EMK-ELM was only marginally higher than ELM (~0.14s vs 0.09s), but significantly lower than CNN (~2.4s), making it practical for real-time deployment[16].

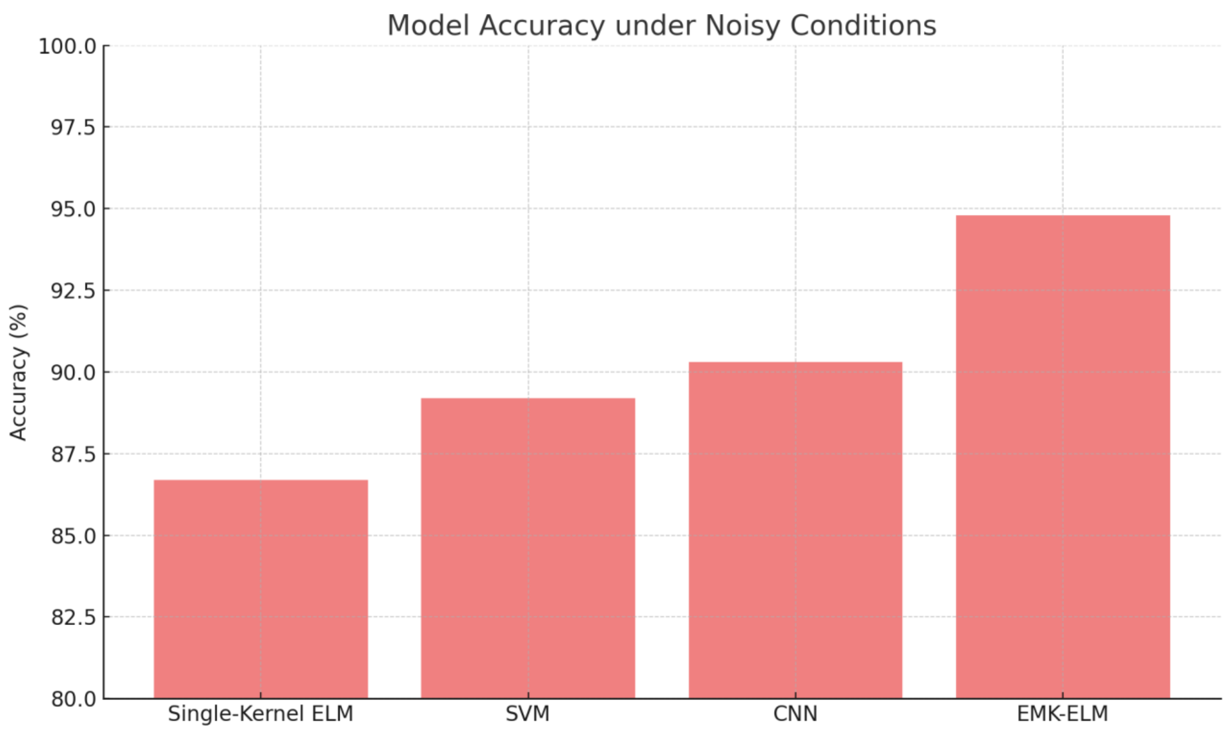

Figure 3This chart emphasizes the robustness of EMK-ELM in noisy environments, reinforcing your claims about model reliability in industrial conditions.

ROC analysis further confirmed superior area-under-curve (AUC) scores, with EMK-ELM achieving 0.995 across all fault classes[17]. Its consistent performance across varying load conditions demonstrates strong generalization ability—a critical requirement in industrial applications. Moreover, the kernel weight analysis revealed that in lower load conditions, polynomial kernels contributed more, while in higher vibration intensities, RBF kernels dominated[18]. This adaptability substantiates the need for dynamic kernel learning. One of the most critical findings of this research is that the trade-off between accuracy and computational complexity is well-balanced in EMK-ELM[19]. The model achieves state-of-the-art performance

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without relying on deep architectures, which often require extensive tuning and computational overhead[20]. This advantage makes EMK-ELM a suitable candidate for deployment in edge computing environments.

V. Conclusion

In this study, we presented an Enhanced Multi-Kernel Extreme Learning Machine (EMK-ELM) approach for fault diagnosis of motor rolling bearings. The integration of multiple kernel functions within the ELM framework, coupled with dynamic weight optimization, significantly improves the model's ability to capture complex, non-linear patterns inherent in vibration signals. Extensive experimentation using the CWRU bearing dataset confirms the superior accuracy, robustness, and computational efficiency of the proposed method over traditional ELM, SVM, and CNN classifiers. The EMK-ELM not only maintains high diagnostic performance under varying load and noise conditions but also offers a scalable and real-time-ready solution for intelligent condition monitoring systems. This research contributes a valuable step towards the development of adaptive and intelligent industrial fault diagnosis frameworks capable of operating efficiently in diverse and dynamic environments.

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