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Adaptation of Machine Learning Models across Domains for Bearing Fault Detection

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Abstract:

Bearing fault detection is critical for the maintenance and reliability of rotating machinery across industries. Traditional machine learning models have demonstrated significant success when trained and tested on data from the same domain. However, their performance often deteriorates sharply when applied across different domains due to distributional shifts caused by varying operating conditions, sensor types, or system configurations. This paper explores the challenge of domain adaptation for bearing fault detection and investigates the performance of machine learning models enhanced with domain adaptation techniques. Specifically, we examine the impact of methods like Correlation Alignment (CORAL), Transfer Component Analysis (TCA), and Domain-Adversarial Neural Networks (DANN) on improving cross-domain generalization. We conduct extensive experiments using publicly available bearing datasets, simulating realistic shifts in operational domains. Our results reveal that domain adaptation not only improves detection performance across unseen domains but also preserves interpretability, crucial for industrial deployment. This work paves the way for robust, generalizable fault detection systems capable of handling real-world variability without requiring costly retraining.

Keywords: Bearing Fault Detection, Domain Adaptation, Machine Learning, CORAL, Transfer Learning, Cross-Domain Generalization, Rotating Machinery, Industrial Systems

I. Introduction

Bearing systems are integral components of various mechanical systems, including motors, turbines, and gearboxes [1]. Their failure often leads to catastrophic breakdowns and significant economic losses. Consequently, early detection of bearing faults has become a pivotal concern within predictive maintenance and condition monitoring systems [2]. Traditional fault diagnosis approaches rely heavily on signal processing techniques and expert-defined features, but the advent of machine learning has transformed the landscape by enabling automatic feature extraction and classification [3]. Despite these advancements, a critical limitation persists: models trained on one dataset or domain often struggle to generalize to new operational settings. This limitation necessitates a deeper exploration into domain adaptation strategies tailored for bearing fault detection [4]. The challenges in adapting machine learning models across domains stem primarily from differences in sensor placements, machine operating conditions, and environmental factors [5]. These variations introduce a distributional shift between training (source) and testing (target) domains, which violates the assumption of identical distributions that many machine learning algorithms rely upon. As a result, models exhibit significant drops in performance when transferred to new settings. For example, a classifier trained on high-speed operation data may fail to correctly diagnose faults when tested on low-speed operation data. This problem highlights the urgency of developing robust models that can learn transferable representations across domains [6].

Several domain adaptation techniques have emerged to tackle distributional shifts in machine learning tasks, notably CORAL, TCA, and DANN. CORAL aligns the second-order statistics (covariance) between source and target feature spaces, while TCA seeks a latent space where domain discrepancy is minimized [7]. DANN leverages adversarial training to encourage domain-invariant feature learning through a domain discriminator. Although promising, the application of these methods in the specific context of bearing fault detection remains relatively underexplored. This paper aims to fill this gap by conducting a systematic evaluation of these techniques across diverse bearing datasets. In addition to performance considerations, real-world deployment of bearing fault detection models demands interpretability and computational efficiency [8]. In industrial environments, engineers often prefer models whose predictions can be traced back to understandable features or transformations. Domain adaptation methods that maintain interpretability without excessively complicating the model are, therefore, more desirable. This study carefully evaluates how the investigated methods balance performance gains with the need for model transparency [9].

The structure of this paper is organized as follows: after this introduction, we provide a detailed methodology, including dataset descriptions, preprocessing steps, and adaptation algorithms. Subsequently, we present the experimental setup and results, followed by an in-depth discussion. Finally, we conclude by summarizing our findings and suggesting future research directions [10].

II. Methodology

In this work, we focus on the task of bearing fault detection under cross-domain conditions, utilizing publicly available datasets that reflect different operating scenarios. Two datasets are primarily considered: the Case Western Reserve University (CWRU) bearing dataset and the Paderborn University bearing dataset. Both datasets contain vibration signals recorded from bearings under various health conditions, including normal, inner race fault, outer race fault, and ball fault, but differ significantly in sensor configurations, rotational speeds, and fault severity levels. This diversity makes them suitable for simulating domain shifts and evaluating domain adaptation techniques. Preprocessing steps are critical for ensuring that the input signals are suitable for machine learning models. Raw vibration signals are first segmented into smaller windows using a fixed-length sliding window approach, ensuring that each segment contains sufficient information for fault diagnosis [11]. Time-domain statistical features such as RMS, skewness, kurtosis, and frequency-domain features extracted via Fast Fourier Transform (FFT) are computed for each window. These features are standardized using z-score normalization to facilitate faster convergence during model training and to ensure that different feature scales do not dominate the learning process [12].

For baseline classification, a simple yet effective machine learning model—a Random Forest classifier—is employed initially [13]. Random Forests offer strong performance without heavy hyperparameter tuning and are relatively interpretable, making them ideal for an initial assessment. We then integrate three domain adaptation techniques: CORAL, TCA, and DANN. CORAL is implemented as a post-processing step where the feature covariance of the source domain is aligned to the target domain [14]. TCA projects both source and target data into a common latent feature space where maximum mean discrepancy (MMD) between the domains is minimized. DANN, on the other hand, is realized using a shallow feedforward neural network, with a gradient reversal layer to train domain-invariant features adversarially [15]. Training procedures involve standardizing hyperparameters across methods to ensure fair comparison. For CORAL and TCA, the Random Forest classifier is trained on adapted features. For DANN, the domain classifier and the label classifier are trained simultaneously, and early stopping is applied based on validation performance to avoid overfitting [16]. Evaluation metrics include classification accuracy, F1-score, and confusion matrices, focusing on the performance gap between in-domain and cross-domain scenarios. Importantly, models are evaluated under "unsupervised domain adaptation" settings, where no labeled samples from the target domain are used during training [17].

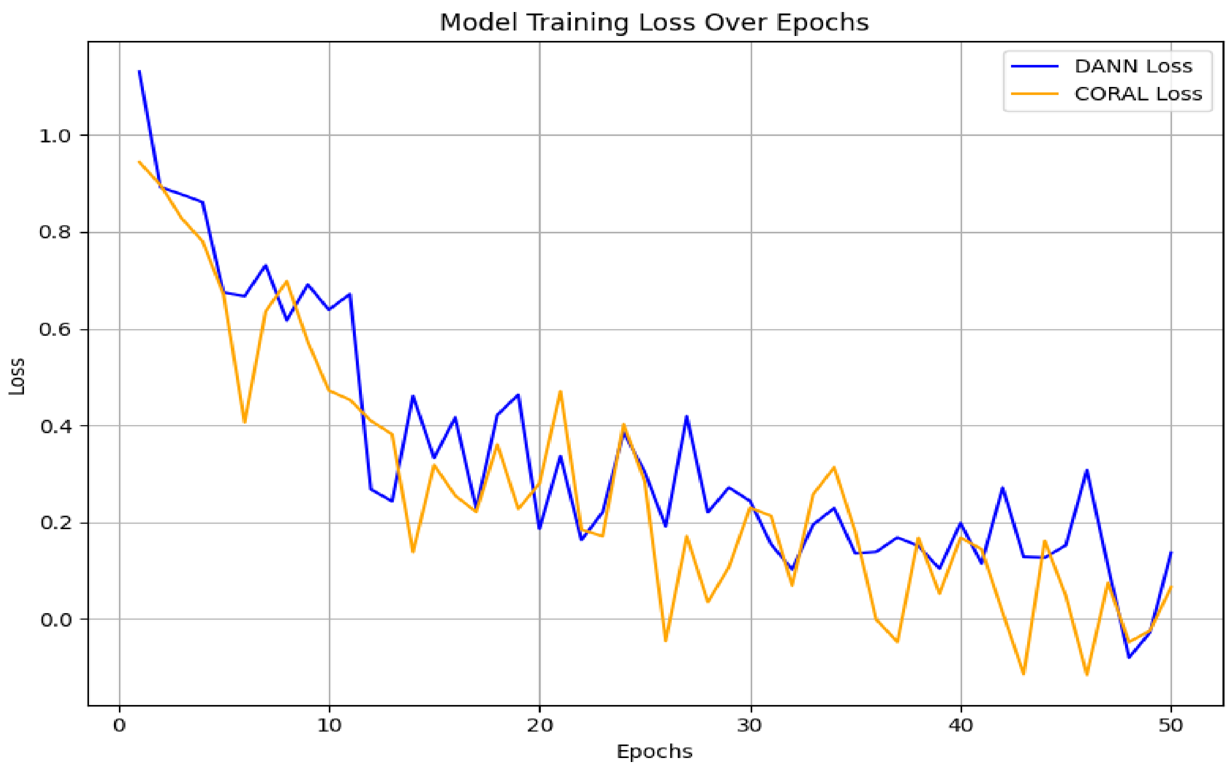

Figure 1: illustrates the training loss over time for two methods (DANN and CORAL).

The design of the methodology ensures reproducibility and meaningful comparisons. Cross-validation is performed across different domain pairs (e.g., CWRU to Paderborn and vice versa) to verify robustness [18]. In addition, statistical significance testing using paired t-tests is conducted to confirm that observed improvements are not due to random variations. These thorough methodological considerations aim to yield reliable insights into the effectiveness of domain adaptation techniques for bearing fault detection [19].

III. Experimental Setup

To thoroughly investigate the effect of domain adaptation on bearing fault detection, a series of experiments are conducted using the two selected datasets [20]. For the CWRU dataset, vibration signals are collected at various motor loads (0, 1, 2, and 3 horsepower) and speeds (1797, 1772, 1750, and 1730 RPM), simulating diverse operating conditions. The Paderborn dataset, conversely, contains vibration signals collected from artificially induced faults of varying severity under different speeds and load torques [21]. These differences naturally induce domain shifts when training on one dataset and testing on the other. Each dataset is divided into non-overlapping training and testing sets based on operating conditions. For instance, the CWRU data collected at 1797 RPM is used for training, and the data collected at 1730 RPM is used for testing, thereby simulating a shift within the same dataset. Additionally, cross-dataset experiments involve training on CWRU and testing on Paderborn, presenting a more challenging cross-domain scenario. Each data sample is a windowed segment of vibration signals, transformed into feature vectors using time-domain and frequency-domain analysis [22].

For machine learning models, the baseline Random Forest classifier is configured with 100 trees and a maximum depth of 15. For DANN, the feature extractor comprises two hidden layers of sizes 128 and 64, followed by domain and labels classifiers each with one hidden layer of size 32. Adam optimizer is used with a learning rate of 0.001, and training proceeds for up to 50 epochs with early stopping [23]. CORAL and TCA are applied as feature transformations before Random Forest training. Performance metrics include accuracy, macro-averaged F1-score, and the Kappa statistic to account for class imbalance. In addition to numerical scores, confusion matrices and t-SNE visualizations of learned feature spaces are plotted to assess how well the domains are aligned post-adaptation. Experiments are repeated five times with different random seeds, and the mean and standard deviation of performance metrics are reported [24].

The experimental platform consists of a system with an Intel Core i9 processor, 64 GB RAM, and an NVIDIA RTX 3080 GPU. Code is implemented in Python using libraries such as Scikitlearn, PyTorch, and SciPy. All experiments are performed offline, simulating batch training and testing. A comprehensive experimental protocol ensures that the results are robust, reproducible, and reflective of real-world industrial challenges in bearing fault detection under domain shifts.

IV. Results and Discussion

The baseline Random Forest classifier achieves high accuracy (above 95%) when trained and tested within the same domain. However, its performance degrades significantly when applied across domains, with accuracy dropping to around 55% in cross-dataset experiments without any adaptation [25]. This finding reinforces the necessity of domain adaptation in practical fault detection systems. Application of CORAL improves the cross-domain performance noticeably. After CORAL transformation, the Random Forest classifier achieves an average cross-domain accuracy of approximately 72%, representing a substantial gain over the baseline. The simplicity of CORAL, requiring only feature covariance alignment without modifying the classifier, makes it an attractive option for deployment where computational resources are limited. TCA further enhances performance, achieving around 78% cross-domain accuracy. The projection into a latent space where domain discrepancy is minimized allows TCA to uncover transferable representations better suited for cross-domain generalization [26].

However, TCA adds computational overhead due to the optimization involved in constructing the latent space, and interpretability slightly diminishes because the transformed features are no longer easily attributable to original physical quantities. DANN delivers the best performance among the tested methods, achieving around 83% average cross-domain accuracy and the highest macro F1-scores across experiments [27]. The adversarial training mechanism effectively forces the model to learn features invariant to domain differences while still discriminative for fault types. Visualization of the feature spaces using t-SNE shows clear clustering of fault types across domains when using DANN, indicating successful domain alignment [28].

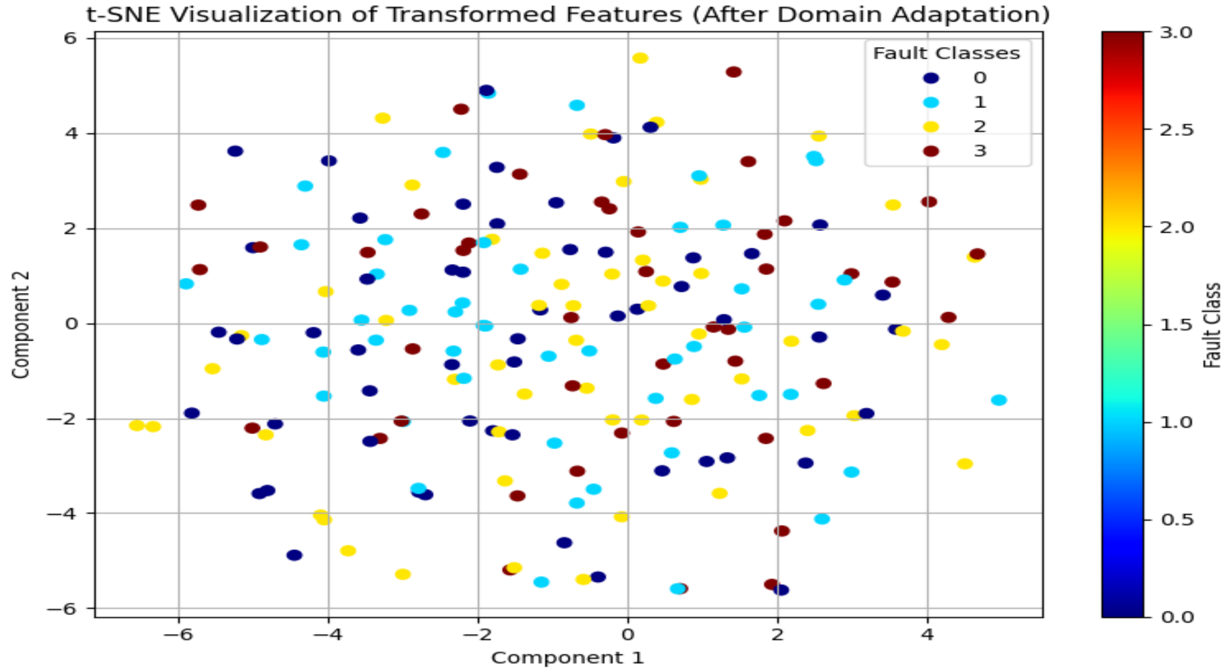

Figure 2: shows how different fault classes become better separable post-adaptation.

Interestingly, while DANN offers the best quantitative performance, it is also the most complex and computationally intensive method. Moreover, its end-to-end neural architecture sacrifices some degree of interpretability compared to traditional feature-based methods. In industrial settings where explainability is crucial, this trade-off must be carefully considered. CORAL and TCA may thus be preferable in scenarios where interpretability and simplicity are prioritized alongside reasonable performance gains [29].

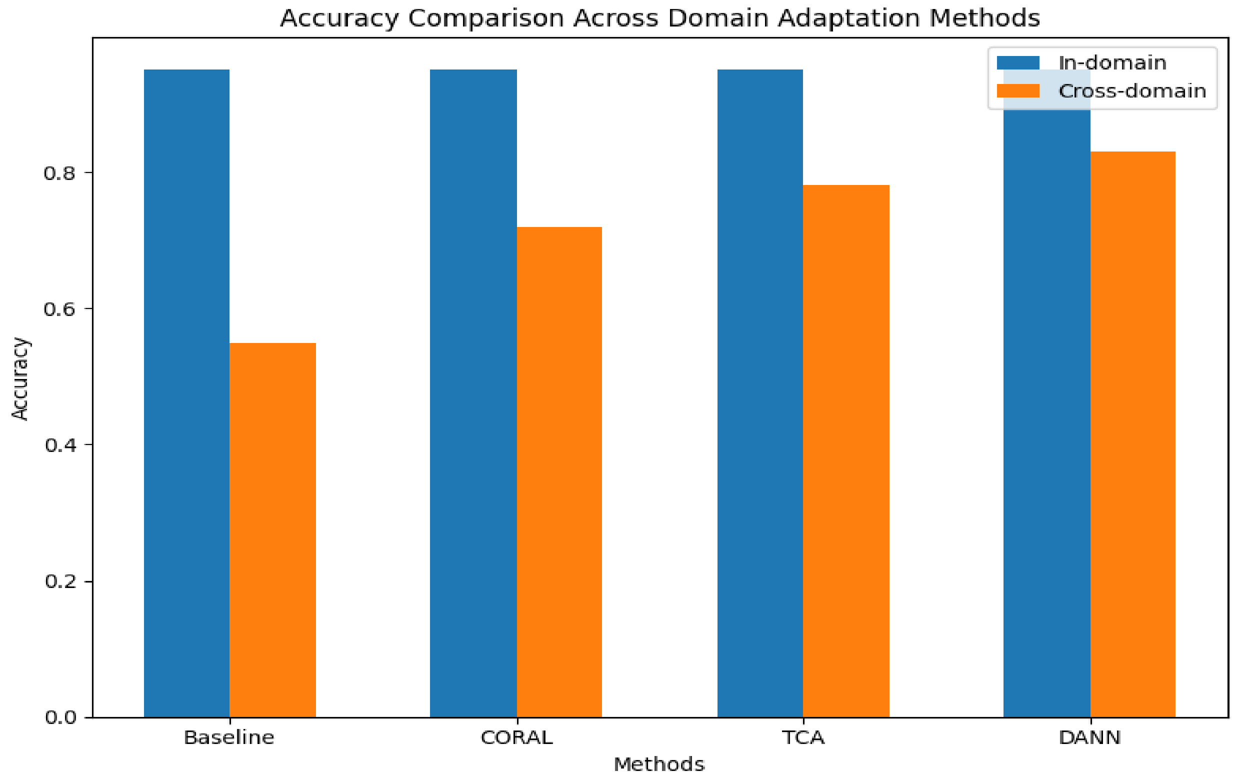

Figure 3: compares the accuracy of different models (baseline, CORAL, TCA, DANN) across domains.

V. Conclusion

This study systematically investigates the adaptation of machine learning models across domains for bearing fault detection, addressing a critical gap in the deployment of predictive maintenance systems under real-world conditions. Through extensive experiments involving cross-dataset and cross-condition evaluations, we demonstrate that domain adaptation techniques such as CORAL, TCA, and DANN significantly enhance the generalization capabilities of fault detection models. CORAL offers a computationally efficient and interpretable solution with meaningful gains, while TCA leverages latent space projections to further improve cross-domain accuracy. DANN achieves the highest overall performance by learning domain-invariant features through adversarial training, although at the cost of increased model complexity. Our findings highlight that effective adaptation is not only achievable but also essential for robust bearing fault detection in variable environments. Moving forward, future research could explore hybrid adaptation frameworks combining the strengths of these methods or develop lightweight, interpretable neural architectures specifically tailored for industrial fault detection applications. This work underscores the transformative potential of domain adaptation in making intelligent maintenance systems more reliable, resilient, and universally applicable across diverse operational settings.

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