
A Survey on Fault Diagnosis and Domain Adaptation Techniques in Machine Condition Monitoring

www.surveyx.cn

Abstract

This survey paper explores the interconnected concepts of fault diagnosis, domain adaptation, domain generalization, transfer learning, machine condition monitoring, and cross-domain learning within the realms of machine learning and artificial intelligence. The paper emphasizes the significance of fault diagnosis and machine condition monitoring in industrial environments, highlighting their role in minimizing machine downtime and ensuring safety. It addresses the challenges posed by domain shifts, which can degrade model performance across different domains, and discusses innovative strategies such as supervised gradual domain adaptation and domain adaptation under missingness shift to bridge these gaps. Key concepts such as domain adaptation, transfer learning, and fault diagnosis are examined for their roles in enhancing machine learning models' adaptability and performance. The survey is structured to provide a comprehensive examination of these techniques, with sections dedicated to fault diagnosis methodologies, domain adaptation techniques, domain generalization approaches, and transfer learning strategies. It concludes by discussing the potential for advancements in these areas, emphasizing the need for continuous innovation to address challenges such as data scarcity and feature misalignment. The survey aims to provide valuable insights for academic researchers and industry practitioners, highlighting the importance of integrating advanced methodologies to ensure robust and adaptable machine learning models capable of thriving in diverse operational environments.

1 Introduction

1.1 Significance of Fault Diagnosis and Machine Condition Monitoring

Fault diagnosis and machine condition monitoring are essential for operational efficiency and safety in industrial environments, facilitating the early identification of potential failures to minimize unplanned downtime and productivity losses [1]. Particularly, diagnosing faults in complex mechanical systems, such as gearboxes, is critical due to operational intricacies and noise interference in vibration signals [2].

In contemporary manufacturing, accurate fault detection in rotating machinery is vital for safety [3]. Intelligent Fault Diagnosis (IFD) employs time-series sensor data to ensure operational efficiency and safety by accurately diagnosing machine breakdowns. Moreover, machine condition monitoring is integral to predictive maintenance, addressing challenges faced by deep learning models, such as the need for extensive labeled datasets and detailed component-level monitoring. Recent innovations, including minimum redundancy maximum relevance (mRMR) techniques and transfer learning, enhance fault diagnosis performance by minimizing redundant features and data dependency. Frameworks like FD-LLM leverage large language models to incorporate sensor data, improving fault detection across diverse operational conditions. Additionally, methodologies such as Related Task Aware Curriculum Meta-learning (RT-ACM) and self-supervised learning combined with federated learning are being explored to bolster model generalization and adaptability, leading to more robust

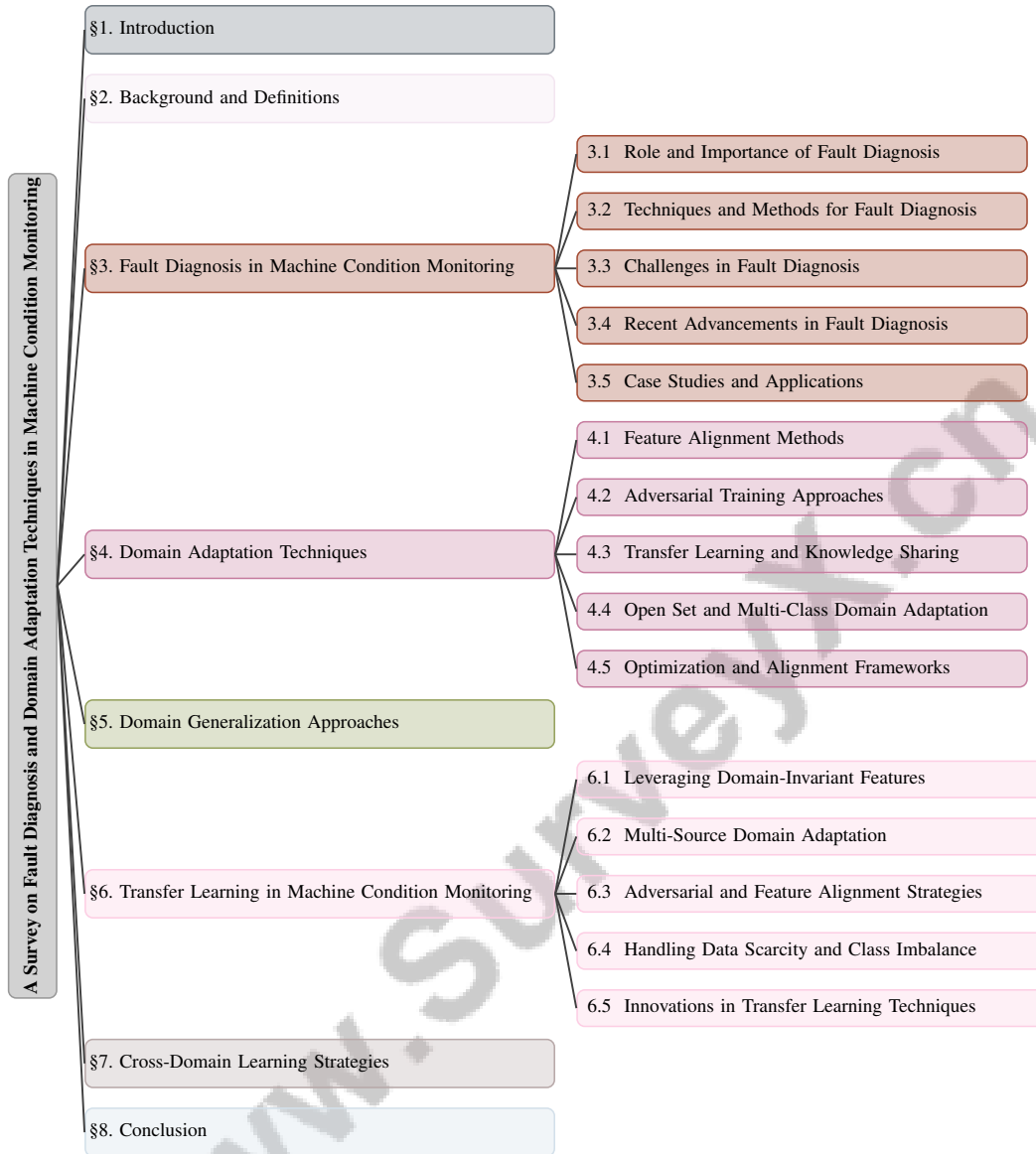


Figure 1: chapter structure

predictive maintenance solutions [4, 5, 6, 7]. In disk failure prediction, fault diagnosis is crucial for preventing significant economic losses due to data loss, emphasizing the importance of continuous machine condition monitoring.

The interpretation of fault signals in mechanical systems underscores the critical nature of fault diagnosis for safety and efficiency in industrial operations. The focus on intelligent fault diagnosis within condition-based maintenance frameworks is essential for achieving operational efficiency and safety. Integrating advanced condition monitoring systems and intelligent fault diagnosis methods enhances machinery performance, optimizes industrial operations, and maintains safety standards by improving maintenance efficiency and process sustainability. These systems utilize machine learning and natural language processing to create realistic datasets for model training, facilitating effective fault identification in variable working conditions. Innovative frameworks like RT-ACM and Knowledge Space Sharing address challenges such as data scarcity and domain shifts, ensuring accurate diagnosis of both known and unknown faults, thereby significantly contributing to operational safety across various industrial applications [8, 6, 9].

1.2 Challenges of Domain Shifts

Domain shifts pose significant challenges in machine condition monitoring due to discrepancies in feature distributions between source and target domains, which can degrade the performance of models trained in one domain when applied to another, particularly in unsupervised domain adaptation scenarios [10]. The complexity of real-world data, often characterized by unknown anomaly distributions and intricate relationships, exacerbates the difficulty of aligning feature distributions [11]. This challenge is intensified by the need to transfer knowledge from multiple labeled source domains to an unlabeled target domain, where distributional shifts can severely impact the effectiveness of supervised learning models [12].

Transferring knowledge from a labeled source domain to an unlabeled target domain with significantly different data distributions presents a primary obstacle in domain adaptation [13]. This issue is aggravated by noise and overlapping features from multiple concurrent faults, complicating the fault diagnosis process. The presence of class imbalances and heterogeneous features in various applications further underscores the necessity for robust domain adaptation techniques that can effectively utilize labeled data from a source domain while leveraging available unlabeled data from the target domain [10].

Innovative strategies, such as supervised gradual domain adaptation, are essential for addressing the challenges posed by continual distribution shifts in real-world applications. This approach utilizes labeled data from evolving distributions to train classifiers capable of generalizing to target domains. Recent research has established a generalization upper bound on learning errors, emphasizing the advantages of temporal structures in domain adaptation. Furthermore, a min-max learning objective facilitates simultaneous learning of representations and classifiers, significantly enhancing performance compared to traditional unsupervised methods. Empirical studies demonstrate that these advancements lead to improved accuracy in various challenging domain adaptation tasks, paving the way for more robust machine learning solutions in dynamic environments [14, 15, 16]. Additionally, domain adaptation under missingness shift (DAMS) highlights challenges when data is missing due to varying record-keeping policies, complicating the adaptation process. In machine condition monitoring, the challenge lies in adapting models to new domains without significant accuracy loss on the original domain, a problem exacerbated by the lack of access to original training data. Addressing these challenges necessitates the development of domain adaptation techniques capable of handling varying production conditions and enhancing fault detection capabilities in diverse industrial environments.

1.3 Key Concepts Overview

Domain adaptation, transfer learning, and fault diagnosis are integral to enhancing the efficacy and adaptability of machine learning models in machine condition monitoring. Domain adaptation addresses discrepancies in data distributions between source and target domains, a prevalent challenge in statistical machine learning. Integrating domain adaptation with disentangled representation learning and style transfer enables models to overcome existing limitations, facilitating effective domain transfer [17]. Techniques such as domain-adversarial neural networks allow models to learn domain-invariant representations, maintaining prediction accuracy across varying operational conditions [18]. The incorporation of adversarial training, exemplified by the Wasserstein Distance based Deep Transfer Learning (WD-DTL) approach, further minimizes distribution differences, enhancing fault diagnosis accuracy [19].

Transfer learning complements domain adaptation by leveraging pre-existing knowledge from a well-labeled source domain to improve performance in a target domain, particularly in scenarios where training data is scarce. This is demonstrated in preprocessing-free gear fault diagnosis using deep convolutional neural networks [20]. Multi-source unsupervised domain adaptation extends this concept by utilizing weak knowledge from multiple source models for predictions in an unlabeled domain, thereby enhancing transferability and adaptability [21]. Quick learning mechanisms, such as those incorporating Net2Net transformations, expedite the adaptation of diagnostic models, improving cross-domain learning efficiency [22].

Fault diagnosis is critical in machine condition monitoring, focusing on identifying and localizing faults within industrial systems. Advanced frameworks utilize adaptive feature extraction and transfer learning to enhance fault detection capabilities with minimal labeled data [20]. The Generalized

Out-of-distribution Fault Diagnosis (GOOFD) framework exemplifies the integration of process monitoring, fault classification, and open-set fault diagnosis into a unified model, facilitating robust fault diagnosis even in the absence of source data [3].

Collectively, these concepts form a cohesive framework for addressing domain shifts and data scarcity challenges in industrial applications. By integrating domain adaptation, transfer learning, and advanced fault diagnosis methodologies, machine learning models can achieve greater accuracy and reliability, ensuring optimal performance in diverse operational environments. The introduction of Margin Disparity Discrepancy as a new measurement further bridges the gap between theoretical concepts and algorithmic practices, enhancing the practical applicability of these approaches [14]. The importance of adapting to shifting distributions, particularly when labeled data from these distributions is available, underscores the need for continuous innovation in these domains [16].

1.4 Structure of the Survey

This survey is systematically organized to provide a comprehensive examination of fault diagnosis and domain adaptation techniques within the context of machine condition monitoring. The paper begins with an introduction that establishes the significance of fault diagnosis and machine condition monitoring in industrial settings and highlights the challenges posed by domain shifts. This is followed by a background section defining core concepts such as domain adaptation, transfer learning, and fault diagnosis, discussing their interconnectedness and applications.

Subsequent sections delve into specific focus areas. Section 3 explores fault diagnosis in machine condition monitoring, detailing the role, techniques, challenges, recent advancements, and applications of fault diagnosis methodologies. Section 4 examines domain adaptation techniques, covering feature alignment methods, adversarial training approaches, and optimization frameworks. Domain generalization approaches are discussed in Section 5, focusing on invariant feature representations and robust model architectures.

Section 6 investigates the critical role of transfer learning in machine condition monitoring, emphasizing effective strategies for leveraging domain-invariant features to enhance model performance across different machines. It discusses the implementation of domain adaptation techniques, such as Domain-Adversarial Neural Networks (DANN), aimed at improving fault diagnosis by addressing challenges related to data scarcity and the overfitting tendencies of data-driven methods. This section also highlights the complexities of multiple source domain adaptation and domain generalization, including the development of novel upper-bounds for target general loss and the trade-offs involved in learning domain-invariant representations. This comprehensive analysis provides valuable insights into practical applications and methodologies for advancing fault diagnosis in industrial settings [23, 24]. Cross-domain learning strategies are explored in Section 7, emphasizing techniques for domain alignment and anomaly-informed knowledge transfer.

The survey concludes with a discussion of key findings, challenges, and future research directions in fault diagnosis and domain adaptation techniques. It highlights the significant potential for advancements in these areas, particularly in addressing performance degradation caused by discrepancies between training and testing data distributions. The paper emphasizes the importance of innovative approaches, such as domain-adversarial neural networks and the proposed Online Selective Adversarial Alignment method, which facilitate effective model adaptation across diverse working conditions and mitigate risks associated with negative transfer. Additionally, it points to the growing relevance of lightweight domain adaptation frameworks for edge computing, enhancing diagnostic accuracy and efficiency in real-time applications [25, 26, 27, 28, 24]. This structured approach ensures a thorough exploration of the topics, providing valuable insights for both academic researchers and industry practitioners. The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Concepts and Definitions

Integrating domain adaptation, transfer learning, and fault diagnosis is crucial in machine condition monitoring, enhancing machine learning models' adaptability and performance amid varying operational conditions and limited data. Domain adaptation techniques, such as lightweight frameworks for edge computing, align feature distributions across domains, significantly boosting diagnostic

accuracy and inference speed [28]. Domain adaptive transfer learning facilitates knowledge transfer across machines, reducing the need for extensive manual data labeling. Advanced methods like Domain-Adversarial Neural Networks (DANN) and Deep Transfer Networks (DTN) support model adaptation to new machines and conditions, ensuring robust diagnostics [29, 24]. These concepts are essential for developing systems that maintain efficiency across diverse environments.

Domain adaptation (DA) addresses discrepancies between training (source domain) and testing (target domain) data distributions, facilitating knowledge transfer from a labeled source to an unlabeled target domain, thereby enhancing model performance [30]. Effective DA mitigates domain shifts that complicate feature alignment and may lead to misclassification [31]. Traditional techniques often focus on covariate shifts, where only the marginal distribution changes [32]. The complexity increases when source domain data is unavailable, complicating classifier learning across unseen domains [16].

Transfer learning complements DA by leveraging existing knowledge from a source domain to enhance learning in a target domain, particularly in environments with limited labeled data. This approach is vital in dynamic settings where new fault types arise, requiring models to generalize despite scarce examples. Hierarchical subspace organization facilitates targeted alignment across domains, improving transfer learning through nuanced adaptation strategies [33, 34]. Integrating constructive incremental learning and ensemble domain adaptation enhances fault diagnosis accuracy using limited labeled data from multiple sources, highlighting the complexity of transferring knowledge from multiple source domains to a target domain [35].

Fault diagnosis is integral to machine condition monitoring, focusing on identifying and localizing faults within industrial systems. Accurate diagnosis of faults, such as those in wind turbine gearboxes, is hindered by the manual feature extraction process [2]. Advanced methodologies, including Transformer-based models, improve diagnostic capabilities, especially in few-shot learning scenarios. The challenge of diagnosing machine faults using time-series sensor data emphasizes the importance of effective feature extraction and classification methods under varying operational conditions.

The integration of advanced methodologies, such as Related Task Aware Curriculum Meta-learning (RT-ACM), Autonomous Transfer Learning (ATL), and Domain Adaptation Broad Learning System (DABLS-LLE), provides a robust foundation for developing resilient machine learning models adaptable to real-world industrial challenges [36, 35, 37]. These approaches address critical issues such as data scarcity, domain shifts, and continuous model adaptation, ultimately enhancing models' performance in dynamic environments and improving fault diagnosis accuracy in smart manufacturing contexts.

2.2 Importance of Domain Adaptation and Fault Diagnosis

Domain adaptation and fault diagnosis are pivotal in modern industrial applications, addressing challenges posed by domain shifts and enhancing diagnostic precision across diverse environments. Domain adaptation significantly improves machine learning model performance when substantial divergences between source and target data distributions complicate feature alignment [10]. This capability is essential in unsupervised fault diagnosis, where frameworks address challenges associated with transferring knowledge from a labeled source domain to multiple unlabeled target domains.

In industrial contexts, domain adaptation is crucial for adapting classifiers trained in one domain to operate effectively in another, where data distributions can vary significantly. This is particularly relevant in scenarios like wind turbine gearbox diagnostics, where reliance on human-defined fault signatures may lead to imprecise diagnostics [2]. The ability to transfer knowledge from multiple source domains to target domains exemplifies the significance of domain adaptation in enhancing fault diagnosis accuracy.

Fault diagnosis maintains operational efficiency and safety within industrial environments. Integrating domain adaptation with fault diagnosis is crucial, especially when the source domain fails to represent the diversity of the target domain. This highlights the need for novel category discovery in the target domain and emphasizes continuous innovation [13]. The theoretical analysis of hypothesis transfer learning (HTL) in binary classification illustrates the complexities involved in adapting to domain shifts.

Domain adaptation and fault diagnosis enhance industrial applications by enabling machine learning models to adjust effectively to varying operational conditions. Addressing data distribution discrepancies ensures models trained on labeled data from one context can reliably perform fault diagnosis in different environments. This is particularly important for applications like edge computing, where integrating lightweight models improves real-time diagnostic capabilities while reducing latency and resource consumption. Recent advancements, such as unsupervised domain adaptation methods and expert knowledge incorporation, enhance the robustness of fault diagnosis systems, allowing them to leverage information from multiple source domains and maintain performance despite class imbalances and distribution shifts [38, 39].

2.3 Interconnectedness of Concepts

The interconnectedness of core concepts—domain adaptation, transfer learning, and fault diagnosis—enhances machine learning applications, particularly in addressing challenges posed by varying operational conditions in industrial environments. Domain adaptation techniques are vital for developing lightweight fault diagnosis frameworks that align feature distributions across operating conditions, improving diagnostic accuracy and reducing model complexity [28]. Autonomous transfer learning (ATL) facilitates knowledge transfer across multiple processes without requiring labeled data, adapting to shifts in data distributions and evolving its network structure [35]. These concepts collectively tackle challenges of domain shifts, data scarcity, and feature misalignment, enhancing machine learning models' adaptability and performance.

Domain adaptation bridges the gap between source and target domains, particularly when significant distribution discrepancies exist. This is crucial for time series data, where feature and label shifts present unique challenges [40]. Adapting models across domains while maintaining accuracy ensures robust performance in diverse settings.

Transfer learning complements domain adaptation by leveraging knowledge from various domains to improve model performance in target applications. This synergy is exemplified in scenarios where domain shifts necessitate the extraction of domain-invariant features, enabling models to maintain robustness across environments. Integrating transfer learning with domain adaptation creates robust models capable of generalizing across environments, even with limited labeled data. Techniques like domain adversarial training learn transferable features that minimize dataset shifts between domains [21, 27].

Fault diagnosis is intricately linked with domain adaptation and transfer learning, focusing on identifying and localizing faults within systems under varying conditions. The interconnectedness of these concepts is highlighted in developing hypothesis transfer learning (HTL) methods, which enhance diagnostic accuracy in dynamic environments [13].

The interconnectedness of domain adaptation, transfer learning, and fault diagnosis is crucial for developing robust machine learning models capable of adapting to diverse environments. Integrating advanced machine learning techniques significantly enhances the relevance and applicability of artificial intelligence in addressing real-world challenges. These methodologies tackle issues such as the scarcity of labeled data, variable conditions, and the need for efficient knowledge transfer across applications, improving predictive model accuracy and reliability [6].

2.4 Applications and Implications

The practical applications of domain adaptation, transfer learning, and fault diagnosis are crucial across various industrial and research sectors, significantly improving machine learning models' adaptability and performance in real-world scenarios. These techniques facilitate transferring fault diagnosis models between machines, minimizing the need for extensive manual data labeling. Advanced methods, such as Domain-Adversarial Neural Networks (DANN) and Online Selective Adversarial Alignment (OSAA), address challenges posed by domain shifts and negative transfer, ensuring robust model performance under varying conditions [28, 25]. These methodologies are crucial in addressing challenges from domain shifts and data scarcity, facilitating efficient machine condition monitoring systems.

In industrial applications, integrating domain adaptation techniques is pivotal for developing models that operate effectively across different domains, such as in vision-based machine learning tasks.

Utilizing publicly available datasets like PACS and Office-Home allows for evaluating classification tasks across domains, demonstrating domain adaptation's effectiveness in handling diverse environments [41]. This is particularly relevant in sectors where visual inspection is critical, ensuring models trained on one set of conditions can generalize to new environments without significant accuracy loss.

The implications of transfer learning are profound in research and industry, especially when labeled data is scarce. Leveraging pre-existing knowledge from source domains enables the development of models that quickly adapt to new tasks, reducing training time and resources. This is exemplified in constructing datasets using benchmarks like Digits and Office-31, where data poisoning attacks highlight the need for robust transfer learning frameworks [42].

Fault diagnosis is pivotal in machine condition monitoring, significantly improving predictive models' accuracy and reliability through methodologies like intelligent fault diagnosis (IFD) and large language models (LLMs). These methodologies leverage machine learning to automate machine health identification, reducing reliance on human intervention. Recent advancements, including deep learning and curriculum meta-learning frameworks, have refined these techniques by addressing data scarcity and variable conditions. For instance, the Related Task Aware Curriculum Meta-learning (RT-ACM) framework optimizes training by focusing on relevant auxiliary sensor data, while the FD-LLM framework adapts large language models for fault identification [43, 5]. Accurately diagnosing faults in complex systems ensures operational efficiency and safety, minimizing downtime and preventing failures. Integrating advanced diagnostic frameworks with domain adaptation and transfer learning facilitates models that adapt to varying conditions while maintaining high precision.

The applications and implications of these concepts are extensive, spanning diverse industrial and research domains, including machine learning, natural language processing, and computer vision, where techniques like domain adaptation and generalization enhance model performance across varying data distributions [44, 45]. Addressing challenges of domain shifts, data scarcity, and feature misalignment ensures developing robust machine learning models that meet modern industrial applications' demands. Continuous innovation in these areas promises to enhance the effectiveness and efficiency of machine condition monitoring systems, paving the way for more resilient and intelligent industrial operations.

In recent years, the field of machine condition monitoring has gained significant attention due to its critical role in ensuring operational efficiency and reliability. A comprehensive understanding of fault diagnosis techniques is essential for practitioners and researchers alike. As shown in Figure 2, this figure illustrates the hierarchical structure of fault diagnosis in machine condition monitoring, highlighting its role and importance. The image delineates various techniques and methods, as well as the challenges faced in the field, recent advancements, and relevant case studies. Each section is meticulously categorized into specific areas, including the impact on machine health, intelligent fault diagnosis, domain shift challenges, automated fault diagnosis, and industrial applications. This structured overview not only enhances our understanding of the complexities involved in fault diagnosis but also underscores the necessity for continued research and development in this vital area.

3 Fault Diagnosis in Machine Condition Monitoring

3.1 Role and Importance of Fault Diagnosis

Fault diagnosis is critical in machine condition monitoring, directly impacting machine health and operational reliability. It is essential for extending the lifespan and optimizing performance in industrial systems, especially under varying conditions [46]. In large-scale data storage systems, effective fault diagnosis is crucial for predicting disk failures, preventing data loss, and ensuring system reliability [46]. Advanced methodologies like Wasserstein Distance-based Deep Transfer Learning (WD-DTL) enhance classification accuracy, particularly with limited labeled data [19]. This highlights the importance of fault diagnosis in maintaining machine health. The integration of synthetic fault generation with imbalance-robust domain adaptation exemplifies the development of robust models from unlabeled real data, enhancing adaptability [47].

In wind energy applications, fault diagnosis methods that do not rely on human-defined features have demonstrated high accuracy in diagnosing faults in wind turbine gearboxes, showcasing their potential for automated monitoring [2]. The CrossTrainer framework is notable for its consistent performance across datasets, achieving high accuracy with reduced training time, crucial for timely



Figure 2: This figure illustrates the hierarchical structure of fault diagnosis in machine condition monitoring, highlighting its role and importance, techniques and methods, challenges, recent advancements, and case studies. Each section is further categorized into specific areas such as impact on machine health, intelligent fault diagnosis, domain shift challenges, automated fault diagnosis, and industrial applications, providing a comprehensive overview of the field.

fault diagnosis [48]. The RT-ACM framework emphasizes task relevance and structured learning to enhance model performance [6]. Additionally, Dineva et al.'s multi-label classification method allows for simultaneous diagnosis of multiple faults, improving precision over traditional single-label approaches [1]. The DSAGCN method further enhances performance by leveraging geometric data structures and aligning subdomain distributions, thus improving diagnostic accuracy [11].

As illustrated in Figure 3, key methodologies, applications, and frameworks in fault diagnosis for machine condition monitoring are highlighted, showcasing their relevance and advancements in various industrial contexts. Fault diagnosis is indispensable for maintaining machine health and preventing failures in complex industrial systems. Continuous advancements in methodologies ensure that machine learning models adapt to diverse operational conditions, maintaining high diagnostic accuracy and reliability across various applications while improving robustness against domain shifts [49].

3.2 Techniques and Methods for Fault Diagnosis

Fault diagnosis employs various techniques to identify and localize faults within industrial systems, enhancing precision and adaptability. Intelligent fault diagnosis (IFD) methodologies integrate traditional machine learning and contemporary deep learning approaches, such as Transformers and curriculum meta-learning, to improve fault detection and address challenges like data scarcity [43, 50, 6, 51]. The FaultD-XAI approach utilizes one-dimensional convolutional neural networks (1D CNN) to diagnose faults, generating synthetic fault signals to enhance dataset variability and model robustness [52]. Preprocessing-free methodologies, like those proposed by Cao et al., use pre-trained deep neural networks to extract features from raw accelerometer data, minimizing manual feature extraction [20].

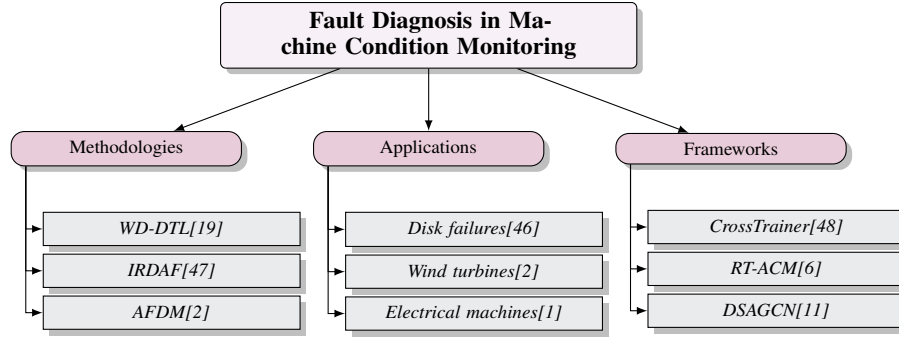


Figure 3: This figure illustrates key methodologies, applications, and frameworks in fault diagnosis for machine condition monitoring, highlighting their relevance and advancements in various industrial contexts.

Feature extraction from vibration signals is critical, employing statistical and Gaussian model approaches to derive informative features assessed by various classification algorithms [51]. The Pattern Matching Network (PMN) uses encoded features from an autoencoder, matching them to learnable prototypes for fault classification [53]. In multi-label classification, methods developed by Dineva et al. process current and vibration signals to predict fault types and severity, addressing single-label limitations and providing a comprehensive diagnostic framework [1]. The Generalized Out-of-distribution Fault Diagnosis (GOOFD) method employs internal contrastive learning for feature extraction and Mahalanobis distance for outlier recognition, enhancing model capability in diverse fault scenarios [3].

In wind turbine gearbox diagnostics, convolutional neural networks facilitate feature extraction, while isolation forests aid in anomaly detection, demonstrating the effectiveness of combining deep learning with traditional methods [2]. The integration of advanced techniques like Related Task Aware Curriculum Meta-learning (RT-ACM), Transformer-based models, and Large Language Models (LLMs) significantly enhances fault diagnosis by leveraging auxiliary sensor data and addressing challenges posed by limited labeled datasets [50, 43, 5, 8, 6].

3.3 Challenges in Fault Diagnosis

Fault diagnosis in machine condition monitoring encounters several challenges, particularly with machine learning methodologies. Domain shift, arising from changes in data distribution between training and test datasets, leads to reduced model performance [54]. This problem is compounded by intra-domain variations and difficulties in effectively separating known and unknown classes [55]. The scarcity of labeled fault data hinders the training of accurate models, often resulting in high false positive rates due to insufficient knowledge about anomalies [47]. Detecting concurrent failures under noisy conditions remains a significant hurdle, as existing methods struggle in such environments [1]. Additionally, the absence of missing data indicators complicates adaptation processes, making it challenging to recover optimal predictors [56].

Innovative methodologies are required to manage domain shifts, data imbalances, and feature misalignment. Supervised gradual domain adaptation has shown promise in providing robust frameworks for learning in shifting environments, offering improvements over previous methods [16]. Tackling these challenges is critical for advancing the efficacy and adaptability of machine learning models in industrial applications.

3.4 Recent Advancements in Fault Diagnosis

Recent advancements in fault diagnosis methodologies have significantly enhanced the precision and adaptability of machine condition monitoring systems, addressing traditional challenges such as feature extraction, data imbalance, and domain adaptation. Innovations in automated fault diagnosis, particularly through integrating machine learning and natural language processing, have improved diagnostic capabilities across various industrial applications, enabling efficient maintenance practices and enhancing workplace safety by leveraging digitized fault descriptions [8, 6, 9]. The Generalized

Out-of-distribution Fault Diagnosis (GOOFD) framework has demonstrated superior performance in fault diagnosis tasks, integrating process monitoring, fault classification, and open-set diagnosis into a unified model, facilitating robust diagnosis even without source data [3].

Advanced feature extraction techniques are crucial for improving diagnostic accuracy, particularly in applications like vibration signal diagnosis and medical image analysis, where classification effectiveness is significantly influenced by the quality of extracted features [57, 51, 54]. The choice of feature extraction methods often impacts classification accuracy more than the classification algorithm itself, emphasizing the critical importance of this step. The FD-LLM framework introduces an innovative approach to fault diagnosis by leveraging large language models (LLMs) to treat the diagnosis process as a multi-class classification problem, effectively integrating time-series sensor data into the analysis. This framework adapts LLMs to handle both textual and numerical data inputs, employing advanced encoding techniques to capture complex fault characteristics, demonstrating significant improvements in fault detection accuracy across diverse conditions [58, 5, 8, 59].

The digital failure twin simulates failure behavior and decision-making to develop fault diagnosis models from system-level condition-monitoring data, significantly improving prediction accuracy by utilizing the RT-ACM framework, which considers auxiliary sensor data relevance and follows a structured learning path [43, 6]. Advancements in domain adaptation techniques have contributed to improved methodologies. The CANMD framework effectively adapts misinformation detection systems to specific domains, achieving substantial improvements in balanced accuracy. The increasing diversity of operational environments underscores the role of domain adaptation strategies in enhancing performance by aligning training and test data distributions [26, 60, 27, 61, 62].

The RT-ACM framework has demonstrated superior performance across datasets, effectively addressing data scarcity and enhancing model adaptability. This highlights the critical role of aligning auxiliary tasks with primary objectives in improving diagnostic accuracy and robustness, particularly in contexts like smart manufacturing [60, 6]. The WD-DTL method has shown significant improvements in fault diagnosis tasks, demonstrating robustness in unsupervised and supervised scenarios, illustrating the capabilities of advanced transfer learning techniques in improving accuracy across industrial applications [29, 63, 64, 24].

In multi-label classification, innovative approaches developed by Dineva et al. leverage advanced techniques for domain adaptation, employing coordinated domain encoders and paired classifiers to enhance performance in scenarios with multiple source domains, effectively optimizing classification accuracy [65, 66]. These advancements reflect continuous innovation in fault diagnosis methodologies, emphasizing the integration of advanced techniques to improve accuracy and efficiency in diverse industrial settings.

3.5 Case Studies and Applications

The implementation of advanced fault diagnosis techniques in industrial environments is essential for enhancing operational efficiency and safety through automated monitoring systems, machine learning models, and natural language processing. These innovations improve maintenance practices, optimize knowledge transfer, and ensure accurate identification of equipment failures across diverse conditions [51, 43, 3, 8, 6]. Various case studies highlight the effectiveness of these techniques in real-world scenarios.

One notable application is the LG-CNN model, validated on the Tennessee Eastman process (TEP) dataset, which includes 41 measured and 11 manipulated variables, encompassing 20 fault types [67]. The LG-CNN model effectively identified and classified faults within this complex process, showcasing the potential of convolutional neural networks in enhancing fault diagnosis accuracy in chemical processes. The GMM-OT method was evaluated through experiments on benchmarks in image classification and fault diagnosis, demonstrating its superiority over existing OT-based approaches [12]. This method's ability to efficiently handle multi-source data and improve diagnostic accuracy illustrates the importance of advanced optimization techniques.

These case studies exemplify the practical applications of fault diagnosis methodologies in industrial environments. By integrating sophisticated machine learning models and advanced optimization techniques, these methodologies significantly improve the reliability and accuracy of diagnostic systems. This enhancement ensures effective operation across environments, addressing challenges like limited labeled training data and variable working conditions. The RT-ACM framework enhances

fault diagnosis by prioritizing relevant auxiliary sensor data and employing a curriculum sampling strategy that progresses from simpler to more complex tasks. Techniques like hypothesis transfer learning and heterogeneous domain adaptation further bolster capabilities by leveraging knowledge from related tasks and efficiently managing diverse data sources, contributing to robust machine health assessments in smart manufacturing settings [68, 13, 43, 69, 6]. Continuous development and validation of such methods are essential for advancing machine condition monitoring and maintaining high operational safety and efficiency standards.

4 Domain Adaptation Techniques

Category	Feature	Method
Adversarial Training Approaches	Unified Classification Approaches Domain Adaptation Strategies	SAN[70] MCD[71], DMAT[72]
Transfer Learning and Knowledge Sharing	Domain Adaptation Techniques Fault Diagnosis Strategies	DOT[31], FLARE[73] MLC[1]
Open Set and Multi-Class Domain Adaptation	Outlier Management	OSDA[74]
Optimization and Alignment Frameworks	Discrepancy and Alignment Scalability and Efficiency Noise and Robustness Adaptation Strategies	GDM[75], discL[30], MUST[76], DSAGCN[11] SPA[77], GMM-OT[12] ADNT[78], DSN[79] CDAA[80], UDA-SKTR[10]

Table 1: Summary of various domain adaptation methodologies categorized by their approaches, features, and specific methods. This table highlights adversarial training, transfer learning, open set adaptation, and optimization frameworks, providing references to key studies that contribute to the development of each technique.

Table 3 provides a comprehensive overview of various domain adaptation techniques, detailing their approaches, key strategies, and unique features to enhance understanding of their roles in improving model adaptability across different data environments. Domain adaptation techniques are essential for transferring knowledge across different domains, focusing on aligning feature distributions to maintain model effectiveness in new data environments. Table 1 outlines the diverse methodologies employed in domain adaptation, detailing the specific approaches, features, and methods that are integral to enhancing model performance across different domains. This section explores various techniques, beginning with feature alignment methods that harmonize discrepancies between source and target domains.

4.1 Feature Alignment Methods

Feature alignment methods are critical in domain adaptation, ensuring models trained on labeled data generalize effectively on unlabeled data by harmonizing feature distributions between domains. These methods tackle domain shifts using strategies like Gaussian-guided latent alignment, local feature distribution matching, and unified optimization frameworks, minimizing discrepancies in feature distributions and labeling functions to ensure robust model performance across environments [81, 27, 82, 83, 84].

Adapter modules and constrained training strategies enable effective domain adaptation without original domain data [80]. The UDA-SKTR model enhances adaptation by transferring source knowledge and target-relatedness simultaneously [10]. RAINCOAT captures domain-invariant features and aligns them using Sinkhorn divergence, while DMAT employs adversarial training to enhance domain-invariant feature learning [72, 65, 83, 18].

The Imbalance-Robust Domain Adaptation Framework (IRDAF) uses expert knowledge to generate synthetic fault data, aligning synthetic and real fault distributions [69, 47]. The Domain-Oriented Transformer (DOT) creates domain-specific feature spaces to enhance feature alignment [83, 84]. The Contrary Attention-based Domain Merge (CADM) module improves feature interaction across domains, reducing discrepancies and enhancing pseudo-label generation [72, 78, 81, 10].

These methods collectively address domain shifts and feature misalignment, ensuring models adapt and perform optimally in diverse environments. Approaches like Learning to Match (L2M) and Instance-based Predictive Behavior Matching (InstaPBM) enhance domain adaptation by addressing distributional shifts [15, 85, 27, 84].

4.2 Adversarial Training Approaches

Adversarial training is pivotal in domain adaptation, aligning feature distributions to enhance model robustness across environments. This approach minimizes discrepancies in feature distributions while preserving content integrity, facilitating robust domain adaptation [65, 86, 81, 18, 72].

The Maximum Classifier Discrepancy (MCD) method uses task-specific classifiers to maximize target sample discrepancy, aligning target features with the source domain [71]. Dual-module architectures, as proposed by Yang et al., enhance robustness by ensuring learned features are domain-invariant and predictive [72].

All-in-one classifiers, as demonstrated by Zang et al., handle open-set and universal domain adaptation, improving classification of known and unknown categories [70]. Recent frameworks integrate fairness strategies, adapting sensitive attributes for fair classification [65, 87].

Adversarial training approaches offer robust solutions for aligning domain features, enhancing model adaptability and fairness across environments. These techniques ensure robust and efficient models capable of adapting to diverse domains [70, 66, 69, 72, 62].

4.3 Transfer Learning and Knowledge Sharing

Method Name	Knowledge Transfer	Domain Adaptation	Methodological Innovation
MLC[1]	-	-	Multi-label Classification
DSN[79]	Unlabeled Target Domain	Domain Separation Networks	Private Subspace Introduction
FLARE[73]	Discriminant Knowledge	Domain Translator	Prototype Triplet Loss
MUST[76]	Pseudo Labels	Separate Learning Processes	Teacher-student Framework
DOT[31]	Effective Knowledge Transfer	Domain-oriented Feature	Domain-Oriented Transformer
DSAGCN[11]	Limited Labeled Data	Align Subdomain Distributions	Graph Convolutional Networks

Table 2: Overview of various transfer learning methodologies, highlighting their approaches to knowledge transfer, domain adaptation, and methodological innovations. The table includes methods such as MLC, DSN, FLARE, MUST, DOT, and DSAGCN, each contributing uniquely to the field of domain adaptation and knowledge sharing.

Transfer learning enables knowledge transfer between domains, improving learning in scenarios with limited labeled data. This approach is crucial in industrial applications, where data-rich environments enhance diagnostic capabilities in data-scarce settings. Multi-label classification methods exemplify transfer learning’s power by handling complex, noisy data and identifying multiple fault scenarios [1].

Table 2 provides a comprehensive comparison of different transfer learning methods, emphasizing their strategies for knowledge transfer and domain adaptation. Domain Separation Networks (DSN) partition image representations into private and shared components, facilitating effective domain transfer and knowledge sharing [79]. In frameworks like FLARE, domain translator and prototype triplet loss enhance domain-transferability [73]. Teacher-student consistency methods improve transferability by training a student network on target pseudo labels [76].

Dual-space alignment enhances transfer learning by allowing tailored classifiers for both domains [31]. Deep subdomain adaptation graph convolutional networks (DSAGCN) integrate graph convolutional networks and adversarial learning for domain adaptation [11]. Complexity-free generalization bounds for Hypothesis Transfer Learning (HTL) improve applicability in real-world scenarios [13].

These methodologies illustrate transfer learning’s transformative potential, enabling effective knowledge sharing across diverse domains and tasks. They highlight innovative approaches like learning to cluster for domain adaptation, Example Transfer Network for partial domain adaptation, and transferable attention mechanisms, enhancing feature transferability and performance [33, 88, 89].

4.4 Open Set and Multi-Class Domain Adaptation

Open set and multi-class domain adaptation require strategies to manage unknown classes and adapt to diverse class distributions. Open set domain adaptation involves identifying and handling outliers while maintaining high classification accuracy for known classes [74]. Multi-class domain adaptation requires strategies to ensure all classes are represented and models generalize effectively. Shi et al.

categorize methods into source-based, adaptation-based, and target-based, providing a structured approach to multi-class domain adaptation [49].

Figure 4 illustrates key strategies and future research directions in open set and multi-class domain adaptation, highlighting methods for managing unknown classes, handling outliers, and adapting to diverse class distributions. This visual representation underscores the complexity of the challenges faced in this field and emphasizes the necessity for innovative approaches.

Future research should focus on robust methods for processing technical language and creating open access annotated datasets, facilitating more effective domain adaptation by providing richer datasets for training and evaluation [8].

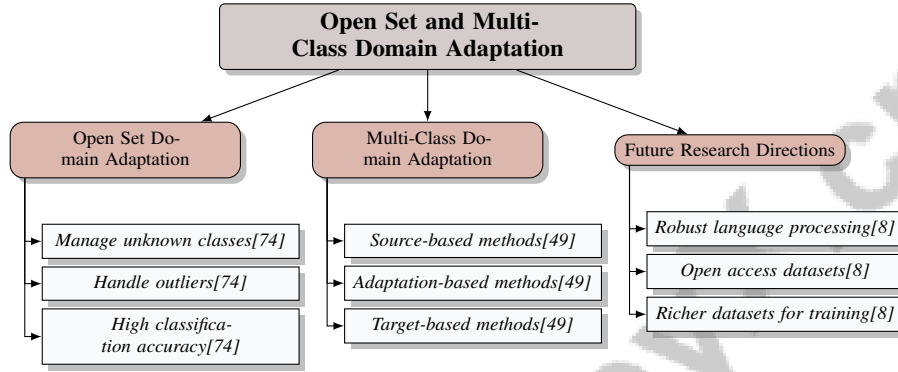


Figure 4: This figure illustrates key strategies and future research directions in open set and multi-class domain adaptation, highlighting methods for managing unknown classes, handling outliers, and adapting to diverse class distributions.

4.5 Optimization and Alignment Frameworks

Optimization and alignment frameworks minimize discrepancies between domains, ensuring robust model performance across environments. These frameworks align feature distributions and optimize model parameters, addressing domain shifts. Techniques like projecting domains into a common space, learning domain-invariant patterns, and guided data homogenization enhance model performance in real-world applications [15, 90, 82, 84].

Empirical discrepancy distance estimation enhances generalization in domain adaptation [30]. The Adaptive Domain Noise Tolerance (ADNT) framework manages noisy pseudo labels effectively [78]. Theoretical improvements address missing data scenarios under underreporting, enhancing domain adaptation reliability [56].

Domain Separation Networks (DSNs) separate domain-specific information, leading to cleaner representations for classification tasks [79]. The DannFixbi method integrates Fixbi and backpropagation for enhanced domain adaptation [32]. The teacher-student consistency framework reduces negative transfer and knowledge fading [76].

Adapter modules allow targeted adaptation while preserving model integrity during adaptation [80]. The UDA-SKTR model balances source knowledge transfer and target-relatedness integration [10]. The GMM-OT framework enhances scalability and efficiency in domain adaptation tasks [12]. The DSAGCN method combines graph convolutional networks with local maximum mean discrepancy and adversarial domain adaptation, offering significant improvements [11].

These frameworks provide robust solutions for domain adaptation, ensuring models adapt and perform optimally across varied domains. By incorporating cutting-edge methodologies, domain adaptation techniques improve adaptability and efficiency, addressing discrepancies between training and test data distributions in real-world applications [14, 62, 27, 26].

As shown in Figure 5, domain adaptation is a critical challenge in machine learning, aiming to apply a model trained on a source domain to a different target domain with minimal performance degradation. Various optimization and alignment frameworks have been developed to address this. The first example, "Comparison of Source, Target, DM, and GDM Models," visually represents

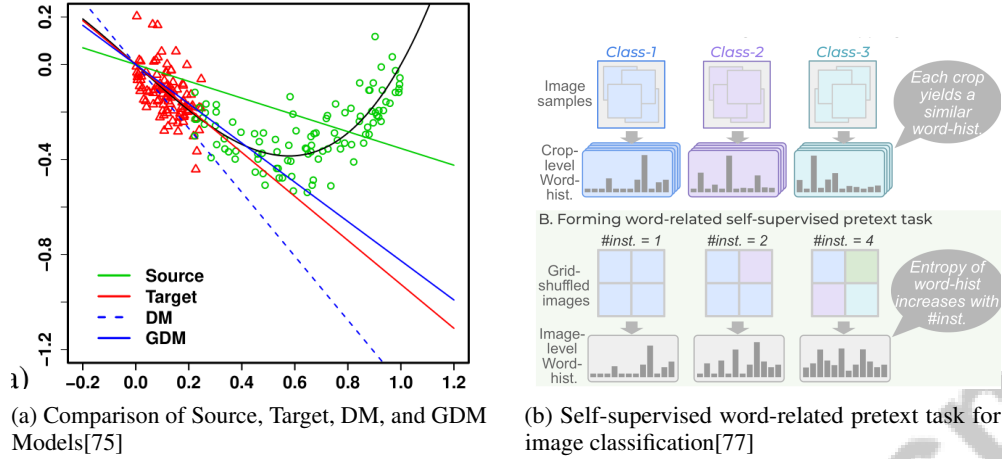


Figure 5: Examples of Optimization and Alignment Frameworks

model performance and alignment on a scatter plot, highlighting distinctions and overlaps. The second example, "Self-supervised word-related pretext task for image classification," introduces domain adaptation by utilizing self-supervised learning techniques, emphasizing granularity in data representation and its impact on model performance across domains. These examples illustrate diverse strategies in domain adaptation, from model comparison to self-supervised tasks, underscoring the complexity and potential of optimization and alignment frameworks in bridging domain gaps [75, 77].

Feature	Feature Alignment Methods	Adversarial Training Approaches	Transfer Learning and Knowledge Sharing
Approach	Harmonize Distributions	Align Features	Knowledge Transfer
Key Strategy	Latent Alignment	Maximize Discrepancy	Multi-label Classification
Unique Feature	Gaussian-guided Alignment	Task-specific Classifiers	Domain Separation Networks

Table 3: This table presents a comparative analysis of three major domain adaptation techniques: feature alignment methods, adversarial training approaches, and transfer learning with knowledge sharing. It highlights the primary approach, key strategy, and unique features of each method, elucidating their distinct contributions to enhancing model performance across diverse domains.

5 Domain Generalization Approaches

Domain generalization is pivotal for transferring knowledge across diverse environments, focusing on invariant feature representations to maintain model performance amid domain variability. By extracting and applying these invariant features, models enhance their ability to generalize across different domains and adapt to novel situations.

5.1 Invariant Feature Representations

Invariant feature representations are essential in enabling models to generalize from multiple source domains to unknown target domains, particularly in visual recognition tasks where domain shifts are prevalent [91]. The Discriminative Cross-Domain Feature Learning (DCDF) approach exemplifies this by aligning relevant source centers with target data, minimizing marginal and conditional disparities [92]. Surveys on federated domain generalization emphasize aligning feature distributions to enhance generalization beyond training domains [93]. Through invariant representations, models navigate real-world data variability, ensuring consistent performance across unseen domains.

5.2 Robust Model Architectures

Robust model architectures enhance domain generalization by ensuring effective performance across diverse environments. These architectures leverage design principles such as explicit domain characteristic modeling and guided data homogenization to extract domain-invariant features [90, 79]. Data

diversity is bolstered through augmentation and generation methods, improving generalization to new domains and mitigating overfitting risks [93]. Ensemble learning combines models to enhance generalization, integrating adaptive mechanisms like hardness-driven augmentation and loss reweighting for improved inter-domain alignment [90, 60, 94, 48, 76]. Modular components facilitate continuous improvement, allowing models to adapt to new challenges without extensive retraining [69, 94].

As illustrated in Figure 6, which depicts the hierarchical structure of robust model architectures, the design principles, learning strategies, and data techniques are emphasized. This figure highlights the key methodologies and adaptive mechanisms that enhance domain generalization and model adaptability across diverse environments. The examples within the figure underscore the methodologies improving classification performance and domain adaptation, thereby emphasizing the significance of robust architectures in achieving high accuracy and effective domain adaptation [69, 95, 96].

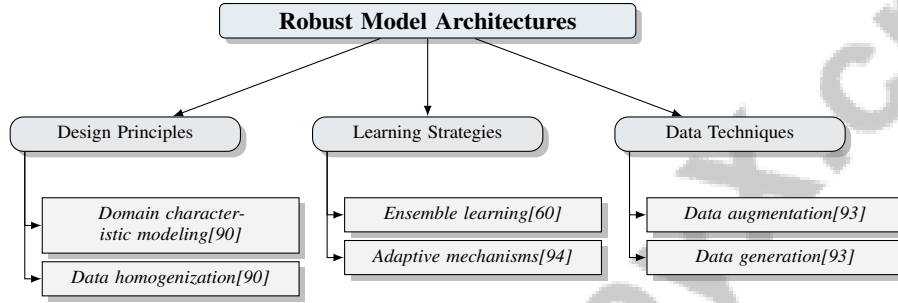


Figure 6: This figure illustrates the hierarchical structure of robust model architectures, emphasizing design principles, learning strategies, and data techniques. It highlights the key methodologies and adaptive mechanisms that enhance domain generalization and model adaptability across diverse environments.

5.3 Handling Domain Shifts and Noisy Data

Addressing domain shifts and noisy data is critical for domain generalization, as these factors can significantly impact model performance. Techniques like representation learning, adversarial learning, and meta-learning enhance robustness against these challenges [93]. Representation learning focuses on invariant feature spaces, facilitating generalization to unseen domains and aligning disparities between training and test datasets [82, 27]. Adversarial learning introduces perturbations during training to simulate data distribution shifts, optimizing task-adaptive generalization bounds [65, 86, 97]. Meta-learning trains models across multiple tasks, enhancing adaptability to new environments and improving performance in novel applications [44, 98]. Challenges persist with extreme category shifts or imbalanced datasets, necessitating careful model design to handle real-world data complexities [55].

5.4 Innovative Learning Frameworks

Innovative learning frameworks enhance domain generalization by enabling models to navigate diverse environments through strategies like diversity-based generalization and federated learning [70, 44, 93]. These frameworks incorporate advanced methodologies to optimize learning processes and bolster model adaptability. Federated learning optimizes model updates from distributed clients, enhancing generalization across domains while preserving privacy [93]. Another framework integrates source-specific classifiers with domain prediction, improving generalization by balancing domain-specific insights with invariant features [91]. By merging advanced techniques, these frameworks offer robust solutions for developing adaptable machine learning models capable of thriving in complex environments [45, 44].

6 Transfer Learning in Machine Condition Monitoring

6.1 Leveraging Domain-Invariant Features

In transfer learning for condition monitoring, leveraging domain-invariant features is crucial for enhancing model robustness across varied industrial domains. These features, consistent across different domains, enhance adaptability and performance. The Domain Separation Networks (DSN) framework exemplifies this by introducing a private subspace for domain-specific properties while enhancing shared representations [79]. This ensures learned features are transferable, improving performance in new environments.

Many unsupervised domain adaptation strategies rely on the assumption that domain-invariant features facilitate effective generalization from source to target domains, which is vital for maintaining performance with limited labeled data [32]. The RAINCOAT framework, modeling both time and frequency feature shifts, leverages domain-invariant features for condition monitoring in time series data, enhancing diagnostic accuracy [40].

ACT aligns normal classes across domains using graph data, crucial for anomaly detection [99]. This enhances the model's ability to leverage invariant features for consistent performance. Ma et al. employ a Vision Transformer architecture with dual classification tokens to preserve domain-wise discriminability while focusing on invariant features [31]. FLARE addresses class imbalance by concentrating on invariant features, enhancing robustness in dynamic environments [73].

Advanced methods like DSAGCN, which uses graph convolutional networks and adversarial learning, highlight the role of complex architectures in extracting domain-invariant features [11]. Techniques such as Learning Invariant Representations and Risks (LIRR) and Heterogeneous Feature Augmentation (HFA) improve alignment of marginal and conditional distributions, while Related Task Aware Curriculum Meta-learning (RT-ACM) optimizes model training, contributing to resilient systems capable of high performance in real-world challenges [69, 6, 84, 96].

6.2 Multi-Source Domain Adaptation

Multi-source domain adaptation (MSDA) is essential in transfer learning, enhancing model performance in target domains by utilizing information from multiple sources. Unlike single-source adaptation, MSDA addresses real-world complexities where source domains vary significantly, requiring sophisticated joint modeling techniques. Innovations like Multi-Source Domain Alignment Layers (MS-DIAL) and graphical models, including Conditional and Markov Random Fields, have shown improved performance in mitigating domain shift challenges, enhancing classification accuracy in applications like digit recognition and object classification [100, 21, 101].

The BORT2 framework exemplifies a two-step training method for MSDA, emphasizing noise robustness through pseudo-labeled data [95]. Domain gap estimation with multiple classifiers allows for tighter domain gap bounds, even without source data [102]. The SHOT framework, evaluated on various benchmarks, demonstrates MSDA's potential in unsupervised adaptation [103].

Additionally, the MUST framework's evaluation across tasks like digit recognition and sentiment analysis highlights MSDA's broad applicability [76]. By integrating knowledge from multiple domains, MSDA techniques create robust models adept at navigating complex environments. Advanced methods like feature element-wise weighting and graphical modeling enhance knowledge transfer and joint modeling capabilities, optimizing adaptation performance in dynamic applications [101, 104, 100].

6.3 Adversarial and Feature Alignment Strategies

Adversarial and feature alignment strategies are pivotal for enhancing transfer learning, enabling models to adapt to new domains while maintaining high performance. Techniques like Multi-Source Domain Alignment Layers (MS-DIAL) and Multisource Domain Adversarial Networks (MDAN) focus on aligning feature distributions and learning domain-invariant representations [65, 89, 21, 88, 83]. These strategies combine adversarial training with feature alignment to tackle domain shifts and data scarcity.

Chen et al. enhance instance-level learning with class-level invariance across domains, ensuring discriminative and consistent features [105]. Convolutional neural networks (CNNs) have advanced

fault diagnosis by leveraging adversarial training to improve robustness [106]. However, data availability and generalization across conditions remain challenges, necessitating effective feature alignment strategies.

Scheel et al. introduce a novel correspondence loss for learning transformations across domains, providing a flexible framework for adaptation [107]. Wang et al. propose the CatDA framework, utilizing symmetric multi-layer perceptrons for effective feature alignment through adversarial learning [108].

The RADA framework aligns inter-class dependencies using a multi-class domain discriminator, ensuring effective knowledge transfer [97]. Class-Incremental Domain Adaptation (CIDA) maintains semantic granularity, adapting to domain shifts and learning new classes [109]. Conceptual Domain Adaptation (CDA) aligns high-level concepts through a mapping function, facilitating effective knowledge transfer [110].

Mansour et al. enhance domain adaptation with discrepancy distance for new generalization bounds, providing a robust framework for adaptation strategies [30]. The Adaptive Domain Noise Tolerance (ADNT) framework integrates adversarial training and feature alignment, ensuring robust model performance across conditions [78].

These strategies, including Gaussian-guided latent alignment and adversarial networks, offer a comprehensive approach to enhancing transfer learning, enabling models to effectively adapt to new domains while preserving semantic consistency and performance [65, 21, 88, 83, 84]. Integrating advanced methodologies enhances the robustness and adaptability of models in real-world applications.

6.4 Handling Data Scarcity and Class Imbalance

Addressing data scarcity and class imbalance is crucial in transfer learning, as these issues can significantly hinder model performance. Techniques such as discriminative active learning, which reduces the need for extensive labeled datasets, and synthetic data generation, which enhances model discriminativeness, have been employed to improve predictive accuracy and mitigate issues related to conditional shifts and class imbalances [60, 62, 111].

Domain adaptation techniques align distributions between source and target domains, ensuring models maintain high performance even with limited labeled data [112]. Active learning frameworks, like Ac-DA, optimize data use by selecting the most informative points for labeling, improving classification accuracy and reducing costs [111].

The Quick Learning Mechanism effectively adapts existing models with minimal labeled data and training time, highlighting rapid adaptation strategies' potential [22]. The ADNT framework integrates domain-specific information with a robust decision boundary, enhancing predictions even in noisy environments [78].

The HTL framework offers explicit rates for generalization and excess risk, supporting model development in limited data scenarios [13]. Wang et al. generate synthetic faults using expert knowledge for model training, leveraging domain expertise to create valuable data [47].

Yuan et al. address class imbalance through a coefficient in the objective function, ensuring effective handling of imbalanced datasets [37]. Breen et al. enhance model performance assessments through cross-validation and bootstrapping [113].

These techniques collectively address data scarcity and class imbalance challenges, ensuring models maintain high performance across diverse environments. By incorporating advanced techniques such as Heterogeneous Feature Augmentation (HFA) and introducing artificial classes, these methodologies significantly improve model robustness and adaptability [62, 69].

6.5 Innovations in Transfer Learning Techniques

Recent advancements in transfer learning techniques have significantly enhanced model adaptability and performance across diverse domains. The RAINCOAT method, for example, demonstrates significant improvements in domain adaptation, highlighting innovative strategies focusing on domain-invariant feature extraction [40].

The MLNet framework achieves state-of-the-art results in universal domain adaptation by leveraging mutual learning networks to address domain shifts and data scarcity [55]. The DannFixbi method underscores the importance of integrating advanced adversarial training strategies for effective domain adaptation [32].

Vu et al.'s framework demonstrates significant improvements in transfer learning scenarios, confirming its effectiveness in domain adaptation through disentangled representations [17]. Future research may focus on simplifying theoretical frameworks or exploring alternative representation learning methods [23].

The ODA method provides significant improvements in adapting learned models to new domains, highlighting output-side domain adaptation's importance [114]. These innovations reflect the continuous evolution of the field, focusing on enhancing model robustness and adaptability across various domains. Future work will explore extensions to multisource multi-target scenarios and practical applications in fields such as medical diagnosis and industrial fault detection [10].

7 Cross-Domain Learning Strategies

Cross-domain learning involves transferring knowledge across diverse domains, necessitating strategies that address unknown classes and open set scenarios. This requires models to adapt to new categories while maintaining performance on known instances. This section examines methodologies for enhancing model robustness in dynamic environments.

7.1 Handling Unknown Classes and Open Set Scenarios

Open set scenarios challenge models to identify instances outside known classes while retaining accuracy on familiar ones, making traditional closed-set assumptions inadequate. Advanced strategies for open set domain adaptation leverage auxiliary data, invariant representations, and robust risk estimation to improve classifier performance [74, 68, 13, 115, 96]. Open set recognition techniques, such as threshold-based decision functions and novelty detection algorithms, dynamically adjust decision boundaries, enhancing robustness and addressing domain shift challenges [74, 68, 13, 115, 14].

Adapting models to target domains with different class distributions is crucial. Strategies like adversarial training align feature representations, minimizing discrepancies and ensuring effective generalization even with unlabeled target data. Domain-Adversarial Neural Networks (DANN) create indistinguishable representations across domains, outperforming traditional models in tasks like sentiment analysis [65, 18]. Unsupervised domain adaptation, using synthetic data generation and augmentation, refines feature representations for unknown classes. Methods like DeerDANN and DeerCORAL improve accuracy with fewer synthetic samples, while GANs enhance decision boundaries and model performance [62, 116].

7.2 Domain Alignment and Data Manipulation Techniques

Domain alignment and data manipulation harmonize feature distributions and enhance data quality in cross-domain learning. Techniques like domain-invariant feature extraction and tailored classifiers address distribution discrepancies, while refined pseudo-labeling and curriculum learning improve target domain prediction accuracy [31, 81, 92]. Adversarial learning frameworks, such as the ADA framework, align feature representations between domains, facilitating better generalization [97].

Data manipulation, including augmentation and synthetic data generation, enhances model robustness by expanding dataset variability. Simulating diverse conditions allows models to learn generalized representations, with expert knowledge-based synthetic fault data generation proving valuable for training data creation [47]. Combining domain alignment and data manipulation ensures models adapt effectively to diverse environments without sacrificing performance. Approaches like Heterogeneous Feature Augmentation and guided data homogenization provide a robust framework for developing resilient models capable of leveraging diverse information while maintaining performance amidst domain shifts [36, 90, 69, 84].

7.3 Transfer of Anomaly-Informed Knowledge

Transferring anomaly-informed knowledge across domains enhances unsupervised domain adaptation by using labeled source domain knowledge to improve anomaly detection accuracy in unlabeled target domains [81, 33, 99, 10]. Deep prototypical networks, focusing on prototypical anomaly representations, accommodate incomplete class overlap, facilitating anomaly identification in target domains [117].

Capturing domain-invariant features alongside domain-specific information enhances robustness, ensuring generalizable and specialized insights inform the learning process [61, 10]. Adversarial training methods aligning feature distributions bolster model performance in detecting diverse anomalies. Integrating anomaly-informed knowledge with domain adaptation techniques improves models' ability to manage domain shifts and data scarcity, enhancing prediction capabilities in target domains. Techniques like pseudo labeling and contrastive adaptation enable models to learn corrected class distributions and invariant feature representations, leading to robust anomaly detection systems [60, 62, 27].

7.4 Integration of Domain-Specific Information

Integrating domain-specific information enhances cross-domain learning by leveraging unique domain characteristics. Techniques like Heterogeneous Feature Augmentation transform data into a common subspace, improving learning efficacy. Advanced methods, including coordinated domain encoders and paired classifiers, dynamically integrate domain representations to address domain shifts, highlighting the significance of tailored domain information for robust model generalization [66, 69, 27].

Domain-oriented feature spaces capture unique characteristics while maintaining generalization capabilities. The Domain-Oriented Transformer (DOT) exemplifies this by creating separate feature spaces for each domain, enhancing cross-domain knowledge transfer [31]. Utilizing expert knowledge in synthetic data generation integrates domain-specific information, allowing models to train on datasets reflecting target domain intricacies, improving robustness and accuracy in fault diagnosis and anomaly detection [47].

Integrating auxiliary tasks leveraging unique domain characteristics enhances primary task performance. By incorporating these tasks into training, models develop sophisticated representations capturing domain-specific features, improving generalization across diverse domains and addressing challenges posed by domain shifts in applications like computer vision, speech recognition, and natural language processing [45, 65, 62, 91]. Integrating domain-specific information equips models with contextual knowledge essential for navigating diverse environments, enhancing performance by addressing feature distribution and labeling function discrepancies. Advanced techniques like dynamic domain encoders and probabilistic heuristics improve adaptation to varying data sources, ensuring robust performance across different domains [66, 81, 27]. By leveraging domain-oriented feature spaces, expert-generated synthetic data, and auxiliary tasks, researchers develop robust and adaptable machine learning models capable of thriving in complex settings.

7.5 Scalability and Efficiency in Federated Learning

Scalability and efficiency are critical in federated learning for cross-domain applications. Federated learning enables collaborative training across decentralized devices, preserving data privacy by eliminating direct data exchange. This is valuable in scenarios with distributed data across different domains, facilitating model generalization to unseen distributions. Recent advancements in federated domain generalization (FDG) enhance this capability, allowing collaborative learning from multiple source domains while maintaining performance across diverse environments [37, 93].

A primary challenge is achieving scalability across numerous devices while ensuring efficient communication and computation amid varying data distributions and domain shifts. Strategies must facilitate collaboration among devices and address complexities introduced by differing data characteristics, optimizing communication protocols and computational resources to maintain performance while preserving privacy [66, 93]. Aggregated model updates can cause significant communication overhead, hindering scalability. Techniques like model compression and sparse updates mitigate this burden, promoting efficient federated learning processes.

Data heterogeneity across devices poses another challenge, arising from variations in data distribution, device capabilities, and network conditions. Advanced algorithms capable of robustly adapting to these conditions, such as guided data homogenization, heterogeneous feature augmentation, and diversity-based generalization techniques, shift the adaptation burden from models to data, enhancing generalization across domains [69, 90, 44, 75]. Techniques like federated averaging and personalized federated learning address these issues, allowing models to adapt to local data while benefiting from collective knowledge.

Efficiency in federated learning is enhanced through advanced optimization techniques minimizing communication rounds required for model convergence. By optimizing trade-offs between communication and computation, faster convergence rates are achieved while ensuring model accuracy. This process enhances training efficiency across distributed devices and addresses challenges related to domain generalization, enabling effective generalization to unseen data distributions while preserving privacy [30, 93, 14, 118, 119].

In cross-domain applications, federated learning enhances model performance by integrating data from multiple domains while ensuring privacy. This approach addresses domain shifts by enabling collaborative learning across diverse sources. Federated domain generalization (FDG) combines federated learning with domain generalization techniques, allowing effective generalization to unseen domains. Recent methodologies focus on strategies like federated domain alignment and data manipulation to optimize learning processes, ultimately improving model accuracy across various datasets and applications [48, 120, 93]. By facilitating collaborative learning across domains, federated learning enhances the robustness and adaptability of machine learning models.

Scalability and efficiency are essential for effective federated learning implementation in cross-domain applications, enabling collaborative training of models that generalize to unseen distributions while maintaining privacy across diverse data sources. This is particularly important in federated domain generalization, addressing challenges posed by varying data distributions and domain shifts in real-world scenarios [48, 93]. By addressing communication overhead, data heterogeneity, and optimization challenges, federated learning provides a powerful framework for collaborative model training across diverse and decentralized environments.

8 Conclusion

8.1 Challenges and Future Directions

The evolving landscape of fault diagnosis and domain adaptation presents numerous challenges and opportunities for research advancement. A crucial area for future exploration is the refinement of domain adaptation strategies to enhance generalization across diverse operational settings, as highlighted in cross-domain applications. This reflects broader challenges in fault diagnosis, where improving model adaptability to varying conditions remains critical.

Further research should focus on advancing regularization techniques and developing robust methods for generating pseudo labels, essential for optimizing multi-source domain adaptation frameworks. The implementation of sophisticated regularization strategies could significantly elevate adaptation outcomes, especially in complex industrial environments.

Enhancing the Generalized Out-of-distribution Fault Diagnosis (GOOFD) framework to include additional diagnostic subtasks and improve interpretability offers a promising research direction. This may involve integrating advanced domain adaptation techniques and refining feature extraction processes to enhance model robustness.

Future work could also explore the application of theoretical insights from hypothesis transfer learning to other machine learning tasks, fostering robust methods for scenarios with significant variability between source and target domains. Additionally, refining frameworks such as GMM-OT and exploring their application in more complex scenarios holds potential for further exploration in fault diagnosis and domain adaptation.

Addressing these challenges requires a comprehensive approach that combines advanced theoretical insights with practical innovations. By prioritizing enhancements in model adaptability, robustness, and interpretability, researchers can develop resilient and effective machine learning models capable of navigating the complexities of modern industrial challenges.

8.2 Challenges and Future Directions in Cross-Domain Learning

Cross-domain learning presents distinct challenges and opportunities for future research, particularly in enhancing the adaptability and robustness of machine learning models across varied environments. A primary challenge lies in managing domain shifts and data scarcity, which can adversely impact model performance. Addressing these issues necessitates the development of advanced domain adaptation techniques adept at handling variability in data distributions across different domains.

Future research should emphasize refining methods for navigating open set scenarios and unknown classes, crucial for enhancing the robustness of cross-domain learning models. Techniques such as open set recognition and novelty detection warrant further exploration to improve model adaptability to new and unseen classes, ensuring consistent performance across diverse domains.

Incorporating domain-specific information into cross-domain learning frameworks represents another promising area for exploration. By leveraging unique domain characteristics and expert knowledge, models can better manage the complexities of real-world data, thereby improving their generalization capabilities.

Moreover, scalability and efficiency in federated learning present significant opportunities for advancing cross-domain learning. By optimizing communication and computation processes, federated learning can facilitate collaborative model training across multiple domains, enhancing knowledge transfer and improving model robustness.

Addressing these challenges requires a holistic approach that integrates theoretical insights with practical innovations. By focusing on enhancing model adaptability, robustness, and scalability, researchers can develop resilient and effective cross-domain learning strategies capable of thriving in dynamic and unpredictable environments.

References

- [1] Adrienn Dineva, Amir Mosavi, Mate Gyimesi, and Istvan Vajda. Multi-label classification for fault diagnosis of rotating electrical machines, 2019.
- [2] Angela Meyer. Vibration fault diagnosis in wind turbines based on automated feature learning, 2022.
- [3] Xingyue Wang, Hanrong Zhang, Xinlong Qiao, Ke Ma, Shuting Tao, Peng Peng, and Hongwei Wang. Generalized out-of-distribution fault diagnosis (goofd) via internal contrastive learning, 2024.
- [4] Vikas Singh and Nishchal K. Verma. Intelligent condition based monitoring techniques for bearing fault diagnosis, 2020.
- [5] Hamzah A. A. M. Qaid, Bo Zhang, Dan Li, See-Kiong Ng, and Wei Li. Fd-llm: Large language model for fault diagnosis of machines, 2024.
- [6] Jinze Wang, Jiong Jin, Tiehua Zhang, Boon Xian Chai, Adriano Di Pietro, and Dimitrios Georgakopoulos. Leveraging auxiliary task relevance for enhanced bearing fault diagnosis through curriculum meta-learning, 2024.
- [7] Matthew Russell and Peng Wang. Maximizing model generalization for machine condition monitoring with self-supervised learning and federated learning, 2023.
- [8] Karl Löwenmark, Cees Taal, Stephan Schnabel, Marcus Liwicki, and Fredrik Sandin. Technical language supervision for intelligent fault diagnosis in process industry, 2022.
- [9] Jiancheng Zhao, Jiaqi Yue, Liangjun Feng, Chunhui Zhao, and Jinliang Ding. Addressing domain shift via knowledge space sharing for generalized zero-shot industrial fault diagnosis, 2023.
- [10] Qing Tian, Yanan Zhu, Chuang Ma, and Meng Cao. Unsupervised domain adaptation through transferring both the source-knowledge and target-relatedness simultaneously, 2021.
- [11] Mohammadreza Ghorvei, Mohammadreza Kavianpour, Mohammad TH Beheshti, and Amin Ramezani. Spatial graph convolutional neural network via structured subdomain adaptation and domain adversarial learning for bearing fault diagnosis, 2021.
- [12] Eduardo Fernandes Montesuma, Fred Ngolè Mboula, and Antoine Souloumiac. Lighter, better, faster multi-source domain adaptation with gaussian mixture models and optimal transport, 2024.
- [13] Anass Aghbalou and Guillaume Staerman. Hypothesis transfer learning with surrogate classification losses: Generalization bounds through algorithmic stability, 2023.
- [14] Yuchen Zhang, Tianle Liu, Mingsheng Long, and Michael Jordan. Bridging theory and algorithm for domain adaptation. In *International conference on machine learning*, pages 7404–7413. PMLR, 2019.
- [15] Bo Li, Yezhen Wang, Tong Che, Shanghang Zhang, Sicheng Zhao, Pengfei Xu, Wei Zhou, Yoshua Bengio, and Kurt Keutzer. Rethinking distributional matching based domain adaptation, 2020.
- [16] Jing Dong, Shiji Zhou, Baoxiang Wang, and Han Zhao. Algorithms and theory for supervised gradual domain adaptation, 2022.
- [17] Hoang Tran Vu and Ching-Chun Huang. Domain adaptation meets disentangled representation learning and style transfer, 2018.
- [18] Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, and Mario Marchand. Domain-adversarial neural networks, 2015.
- [19] Cheng Cheng, Beitong Zhou, Guijun Ma, Dongrui Wu, and Ye Yuan. Wasserstein distance based deep adversarial transfer learning for intelligent fault diagnosis, 2019.

-
- [20] Pei Cao, Shengli Zhang, and Jiong Tang. Pre-processing-free gear fault diagnosis using small datasets with deep convolutional neural network-based transfer learning, 2017.
- [21] Lucas Fernando Alvarenga e Silva, Daniel Carlos Guimarães Pedronette, Fábio Augusto Faria, João Paulo Papa, and Jurandy Almeida. Improving transferability of domain adaptation networks through domain alignment layers, 2022.
- [22] Arun K. Sharma and Nishchal K. Verma. Quick learning mechanism with cross-domain adaptation for intelligent fault diagnosis, 2021.
- [23] Trung Phung, Trung Le, Long Vuong, Toan Tran, Anh Tran, Hung Bui, and Dinh Phung. On learning domain-invariant representations for transfer learning with multiple sources, 2021.
- [24] Qin Wang, Gabriel Michau, and Olga Fink. Domain adaptive transfer learning for fault diagnosis, 2019.
- [25] Ziyang Wang, Mohamed Ragab, Wenmian Yang, Min Wu, Sinno Jialin Pan, Jie Zhang, and Zhenghua Chen. Overcoming negative transfer by online selection: Distant domain adaptation for fault diagnosis, 2024.
- [26] Abolfazl Farahani, Sahar Voghoei, Khaled Rasheed, and Hamid R Arabnia. A brief review of domain adaptation. *Advances in data science and information engineering: proceedings from ICDATA 2020 and IKE 2020*, pages 877–894, 2021.
- [27] Abolfazl Farahani, Sahar Voghoei, Khaled Rasheed, and Hamid R. Arabnia. A brief review of domain adaptation, 2020.
- [28] Yanzhi Wang, Chu Wang, Jinhong Wu, Ziyang Yu, and Qi Zhou. Domain adaptation-based edge computing for cross-conditions fault diagnosis, 2024.
- [29] Te Han, Chao Liu, Wenguang Yang, and Dongxiang Jiang. Deep transfer network with joint distribution adaptation: A new intelligent fault diagnosis framework for industry application, 2018.
- [30] Yishay Mansour, Mehryar Mohri, and Afshin Rostamizadeh. Domain adaptation: Learning bounds and algorithms, 2023.
- [31] Wenxuan Ma, Jinming Zhang, Shuang Li, Chi Harold Liu, Yulin Wang, and Wei Li. Making the best of both worlds: A domain-oriented transformer for unsupervised domain adaptation, 2022.
- [32] Artem Bituitkii. Unsupervised domain adaptation with deep neural-network, 2023.
- [33] Yen-Chang Hsu, Zhaoyang Lv, and Zsolt Kira. Learning to cluster in order to transfer across domains and tasks, 2018.
- [34] Anant Raj, Vinay P. Namboodiri, and Tinne Tuytelaars. Mind the gap: Subspace based hierarchical domain adaptation, 2015.
- [35] Mahardhika Pratama, Marcus de Carvalho, Renchunzi Xie, Edwin Lughofer, and Jie Lu. Atl: Autonomous knowledge transfer from many streaming processes, 2019.
- [36] Edward, Mohamed Ragab, Yuecong Xu, Min Wu, Yuecong Xu, Zhenghua Chen, Abdulla Alseieri, and Xiaoli Li. Everadapt: Continuous adaptation for dynamic machine fault diagnosis environments, 2024.
- [37] Chao Yuan and Chang-E Ren. Domain adaptation broad learning system based on locally linear embedding, 2021.
- [38] Zixuan Wang, Haoran Tang, Haibo Wang, Bo Qin, Mark D. Butala, Weiming Shen, and Hongwei Wang. Weighted joint maximum mean discrepancy enabled multi-source-multi-target unsupervised domain adaptation fault diagnosis, 2023.
- [39] Bo Zhang, Wei Li, Zhe Tong, and Meng Zhang. Bearing fault diagnosis under varying working condition based on domain adaptation, 2017.

-
- [40] Huan He, Owen Queen, Teddy Koker, Consuelo Cuevas, Theodoros Tsiligkaridis, and Marinka Zitnik. Domain adaptation for time series under feature and label shifts, 2023.
 - [41] Hamza Riaz and Alan F. Smeaton. Vision based machine learning algorithms for out-of-distribution generalisation, 2023.
 - [42] Akshay Mehra, Bhavya Kailkhura, Pin-Yu Chen, and Jihun Hamm. Understanding the limits of unsupervised domain adaptation via data poisoning, 2021.
 - [43] Yaguo Lei, Bin Yang, Xinwei Jiang, Feng Jia, Naipeng Li, and Asoke K Nandi. Applications of machine learning to machine fault diagnosis: A review and roadmap. *Mechanical systems and signal processing*, 138:106587, 2020.
 - [44] Jitin Krishnan, Hemant Purohit, and Huzefa Rangwala. Diversity-based generalization for unsupervised text classification under domain shift, 2020.
 - [45] Kaiyang Zhou, Ziwei Liu, Yu Qiao, Tao Xiang, and Chen Change Loy. Domain generalization: A survey, 2022.
 - [46] Guangfu Gao, Peng Wu, and Hussain Dawood. Disk failure prediction based on multi-layer domain adaptive learning, 2023.
 - [47] Qin Wang, Cees Taal, and Olga Fink. Integrating expert knowledge with domain adaptation for unsupervised fault diagnosis, 2021.
 - [48] Justin Chen, Edward Gan, Kexin Rong, Sahaana Suri, and Peter Bailis. Crosstrainer: Practical domain adaptation with loss reweighting, 2019.
 - [49] Boshen Shi, Yongqing Wang, Fangda Guo, Bingbing Xu, Huawei Shen, and Xueqi Cheng. Graph domain adaptation: Challenges, progress and prospects, 2024.
 - [50] Guiran Liu and Binrong Zhu. A review of intelligent device fault diagnosis technologies based on machine vision, 2024.
 - [51] Qiang Liu, Jiade Zhang, Jingna Liu, and Zhi Yang. Feature extraction and classification algorithm, which one is more essential? an experimental study on a specific task of vibration signal diagnosis, 2021.
 - [52] Lucas Costa Brito, Gian Antonio Susto, Jorge Nei Brito, and Marcus Antonio Viana Duarte. Fault diagnosis using explainable ai: a transfer learning-based approach for rotating machinery exploiting augmented synthetic data, 2022.
 - [53] Qian Chen, Xingjian Dong, and Zhike Peng. Interpreting what typical fault signals look like via prototype-matching, 2024.
 - [54] Hao Guan and Mingxia Liu. Domain adaptation for medical image analysis: a survey. *IEEE Transactions on Biomedical Engineering*, 69(3):1173–1185, 2021.
 - [55] Yanzuo Lu, Meng Shen, Andy J Ma, Xiaohua Xie, and Jian-Huang Lai. Mlnet: Mutual learning network with neighborhood invariance for universal domain adaptation, 2024.
 - [56] Helen Zhou, Sivaraman Balakrishnan, and Zachary C. Lipton. Domain adaptation under missingness shift, 2023.
 - [57] Sarah Matta, Mathieu Lamard, Philippe Zhang, Alexandre Le Guilcher, Laurent Borderie, Béatrice Cochener, and Gwenolé Quéllec. A systematic review of generalization research in medical image classification, 2024.
 - [58] Laifa Tao, Haifei Liu, Guoao Ning, Wenyan Cao, Bohao Huang, and Chen Lu. Llm-based framework for bearing fault diagnosis, 2024.
 - [59] Peng Peng, Hanrong Zhang, Mengxuan Li, Gongzhuang Peng, Hongwei Wang, and Weiming Shen. Sclifd: supervised contrastive knowledge distillation for incremental fault diagnosis under limited fault data, 2023.

-
- [60] Zhenrui Yue, Huimin Zeng, Ziyi Kou, Lanyu Shang, and Dong Wang. Contrastive domain adaptation for early misinformation detection: A case study on covid-19, 2022.
- [61] Wenxuan Ma, Jinming Zhang, Shuang Li, Chi Harold Liu, Yulin Wang, and Wei Li. Exploiting both domain-specific and invariant knowledge via a win-win transformer for unsupervised domain adaptation, 2021.
- [62] Hai H. Tran, Sumyeong Ahn, Taeyoung Lee, and Yung Yi. Enlarging discriminative power by adding an extra class in unsupervised domain adaptation, 2020.
- [63] Zhongliang Chen, Zhuofei Huang, and Wenxiong Kang. A novel transfer learning method utilizing acoustic and vibration signals for rotating machinery fault diagnosis, 2023.
- [64] Fatemeh Mohammadi Shakiba, Milad Shojaee, S. Mohsen Azizi, and Mengchu Zhou. Transfer learning for fault diagnosis of transmission lines, 2022.
- [65] Han Zhao, Shanghang Zhang, Guanhong Wu, José MF Moura, Joao P Costeira, and Geoffrey J Gordon. Adversarial multiple source domain adaptation. *Advances in neural information processing systems*, 31, 2018.
- [66] Payam Karisani. Multiple-source domain adaptation via coordinated domain encoders and paired classifiers, 2022.
- [67] Saif S. S. Al-Wahaibi and Qiugang Lu. Improving convolutional neural networks for fault diagnosis by assimilating global features, 2022.
- [68] Hongxiang Qiu, Eric Tchetgen Tchetgen, and Edgar Dobriban. Efficient and multiply robust risk estimation under general forms of dataset shift, 2024.
- [69] Lixin Duan, Dong Xu, and Ivor Tsang. Learning with augmented features for heterogeneous domain adaptation, 2012.
- [70] Zelin Zang, Lei Shang, Senqiao Yang, Fei Wang, Baigui Sun, Xuansong Xie, and Stan Z. Li. Boosting novel category discovery over domains with soft contrastive learning and all-in-one classifier, 2023.
- [71] Kuniaki Saito, Kohei Watanabe, Yoshitaka Ushiku, and Tatsuya Harada. Maximum classifier discrepancy for unsupervised domain adaptation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3723–3732, 2018.
- [72] Yiju Yang, Tianxiao Zhang, Guanyu Li, Taejoon Kim, and Guanghui Wang. An unsupervised domain adaptation model based on dual-module adversarial training, 2021.
- [73] Geng-Xin Xu, Chen Liu, Jun Liu, Zhongxiang Ding, Feng Shi, Man Guo, Wei Zhao, Xiaoming Li, Ying Wei, Yaozong Gao, Chuan-Xian Ren, and Dinggang Shen. Cross-site severity assessment of covid-19 from ct images via domain adaptation, 2021.
- [74] Pau Panareda Busto and Juergen Gall. Open set domain adaptation. In *Proceedings of the IEEE international conference on computer vision*, pages 754–763, 2017.
- [75] Corinna Cortes, Mehryar Mohri, and Andres Muñoz Medina. Adaptation algorithm and theory based on generalized discrepancy, 2015.
- [76] Ohad Amosy and Gal Chechik. Teacher-student consistency for multi-source domain adaptation, 2020.
- [77] Jogendra Nath Kundu, Suvaansh Bhambri, Akshay Kulkarni, Hiran Sarkar, Varun Jampani, and R. Venkatesh Babu. Subsidiary prototype alignment for universal domain adaptation, 2022.
- [78] Tong Xu, Lin Wang, Wu Ning, Chunyan Lyu, Kejun Wang, and Chenhui Wang. Joint attention-driven domain fusion and noise-tolerant learning for multi-source domain adaptation, 2022.
- [79] Konstantinos Bousmalis, George Trigeorgis, Nathan Silberman, Dilip Krishnan, and Dumitru Erhan. Domain separation networks, 2016.

-
- [80] Somshubra Majumdar, Shantanu Acharya, Vitaly Lavrukhin, and Boris Ginsburg. Damage control during domain adaptation for transducer based automatic speech recognition, 2022.
 - [81] Yuntao Du, Yinghao Chen, Fengli Cui, Xiaowen Zhang, and Chongjun Wang. Cross-domain error minimization for unsupervised domain adaptation, 2021.
 - [82] Roberto Vega and Russell Greiner. Domain-shift adaptation via linear transformations, 2022.
 - [83] Jing Wang, Jiahong Chen, Jianzhe Lin, Leonid Sigal, and Clarence W. de Silva. Discriminative feature alignment: Improving transferability of unsupervised domain adaptation by gaussian-guided latent alignment, 2020.
 - [84] Jun Wen, Risheng Liu, Nenggan Zheng, Qian Zheng, Zhefeng Gong, and Junsong Yuan. Exploiting local feature patterns for unsupervised domain adaptation, 2018.
 - [85] Chaohui Yu, Jindong Wang, Chang Liu, Tao Qin, Renjun Xu, Wenjie Feng, Yiqiang Chen, and Tie-Yan Liu. Learning to match distributions for domain adaptation, 2020.
 - [86] Han Zhao, Shanghang Zhang, Guanhang Wu, João P. Costeira, José M. F. Moura, and Geoffrey J. Gordon. Multiple source domain adaptation with adversarial training of neural networks, 2017.
 - [87] Yueqing Liang, Canyu Chen, Tian Tian, and Kai Shu. Fair classification via domain adaptation: A dual adversarial learning approach, 2023.
 - [88] Zhangjie Cao, Kaichao You, Mingsheng Long, Jianmin Wang, and Qiang Yang. Learning to transfer examples for partial domain adaptation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 2985–2994, 2019.
 - [89] Ximei Wang, Liang Li, Weirui Ye, Mingsheng Long, and Jianmin Wang. Transferable attention for domain adaptation. In *Proceedings of the AAAI conference on artificial intelligence*, volume 33, pages 5345–5352, 2019.
 - [90] Kurt Willis and Luis Oala. Post-hoc domain adaptation via guided data homogenization, 2021.
 - [91] Massimiliano Mancini, Samuel Rota Bulò, Barbara Caputo, and Elisa Ricci. Best sources forward: domain generalization through source-specific nets, 2018.
 - [92] Taotao Jing, Ming Shao, and Zhengming Ding. Discriminative cross-domain feature learning for partial domain adaptation, 2020.
 - [93] Ying Li, Xingwei Wang, Rongfei Zeng, Praveen Kumar Donta, Ilir Murturi, Min Huang, and Schahram Dustdar. Federated domain generalization: A survey, 2024.
 - [94] Yang Yuxiang, Zeng Xinyi, Zeng Pinxian, Zu Chen, Yan Binyu, Zhou Jiliu, and Wang Yan. Adaptive hardness-driven augmentation and alignment strategies for multi-source domain adaptations, 2025.
 - [95] Zhongying Deng, Da Li, Yi-Zhe Song, and Tao Xiang. Robust target training for multi-source domain adaptation, 2022.
 - [96] Bo Li, Yezhen Wang, Shanghang Zhang, Dongsheng Li, Trevor Darrell, Kurt Keutzer, and Han Zhao. Learning invariant representations and risks for semi-supervised domain adaptation, 2021.
 - [97] Zeya Wang, Baoyu Jing, Yang Ni, Nanqing Dong, Pengtao Xie, and Eric P. Xing. Adversarial domain adaptation being aware of class relationships, 2020.
 - [98] Hanbing Liu, Jingge Wang, Xuan Zhang, Ye Guo, and Yang Li. Enhancing continuous domain adaptation with multi-path transfer curriculum, 2024.
 - [99] Cross-domain graph anomaly detection via anomaly-aware contrastive alignment.
 - [100] Sitong Mao, Keli Zhang, and Fu lai Chung. Mixed set domain adaptation, 2020.

-
- [101] Minghao Xu, Hang Wang, and Bingbing Ni. Graphical modeling for multi-source domain adaptation, 2022.
- [102] Ziyang Zong, Jun He, Lei Zhang, and Hai Huan. Domain gap estimation for source free unsupervised domain adaptation with many classifiers, 2022.
- [103] Jian Liang, Dapeng Hu, Yunbo Wang, Ran He, and Jiashi Feng. Source data-absent unsupervised domain adaptation through hypothesis transfer and labeling transfer, 2021.
- [104] Dan Iter and David Grangier. On the complementarity of data selection and fine tuning for domain adaptation, 2021.
- [105] Yang Chen, Yingwei Pan, Yu Wang, Ting Yao, Xinmei Tian, and Tao Mei. Transferrable contrastive learning for visual domain adaptation, 2021.
- [106] Jinyang Jiao, Ming Zhao, Jing Lin, and Kaixuan Liang. A comprehensive review on convolutional neural network in machine fault diagnosis. *Neurocomputing*, 417:36–63, 2020.
- [107] Oliver Scheel, Loren Schwarz, Nassir Navab, and Federico Tombari. Explicit domain adaptation with loosely coupled samples, 2020.
- [108] Shanshan Wang, Lei Zhang, and JingRu Fu. Adversarial transfer learning for cross-domain visual recognition, 2019.
- [109] Jogendra Nath Kundu, Rahul Mysore Venkatesh, Naveen Venkat, Ambareesh Revanur, and R. Venkatesh Babu. Class-incremental domain adaptation, 2020.
- [110] Behrang Mehrparvar and Ricardo Vilalta. Conceptual domain adaptation using deep learning, 2018.
- [111] Fan Zhou, Changjian Shui, Bincheng Huang, Boyu Wang, and Brahim Chaib-draa. Discriminative active learning for domain adaptation, 2020.
- [112] Zhaozhong Yang, Liangjie Gou, Chao Min, Duo Yi, Xiaogang Li, and Guoquan Wen. Domain adaption and physical constraints transfer learning for shale gas production, 2023.
- [113] Jack Breen, Kieran Zucker, Nicolas M. Orsi, and Nishant Ravikumar. Assessing domain adaptation techniques for mitosis detection in multi-scanner breast cancer histopathology images, 2022.
- [114] Tomer Galanti and Lior Wolf. A theory of output-side unsupervised domain adaptation, 2017.
- [115] Li Zhong, Zhen Fang, Feng Liu, Bo Yuan, Guangquan Zhang, and Jie Lu. Bridging the theoretical bound and deep algorithms for open set domain adaptation, 2020.
- [116] Tuhin Das, Robert-Jan Bruintjes, Attila Lengyel, Jan van Gemert, and Sara Beery. Domain adaptation for rare classes augmented with synthetic samples, 2021.
- [117] Huanjie Wang, Jie Tan, Xiwei Bai, and Jiechao Yang. Deep prototypical networks based domain adaptation for fault diagnosis, 2019.
- [118] Qing Yu, Atsushi Hashimoto, and Yoshitaka Ushiku. Divergence optimization for noisy universal domain adaptation, 2021.
- [119] Li Zhong, Zhen Fang, Feng Liu, Jie Lu, Bo Yuan, and Guangquan Zhang. How does the combined risk affect the performance of unsupervised domain adaptation approaches?, 2020.
- [120] Artem Rozantsev, Mathieu Salzmann, and Pascal Fua. Beyond sharing weights for deep domain adaptation. *IEEE transactions on pattern analysis and machine intelligence*, 41(4):801–814, 2018.

Disclaimer:

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.

www.SurveyX.cn