Review

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A Review of the Application of Transfer Learning in Fault Diagnosis and its Potential in Aerospace Condition Based Maintenance

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A Review of the Application of Transfer Learning in Fault Diagnosis and its Potential in Aerospace Condition Based Maintenance

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Abstract: Condition based maintenance (CBM), maintenance that is triggered by knowledge of component degradation, relies heavily on fault diagnosis to pinpoint the component or system that requires maintenance. While there have been many advances in applying machine learning in fault diagnosis in recent years, there remains a problem of insufficient data with which to train machine learning algorithms. One approach to this problem is to reuse lessons learnt on one system on another system by transfer learning (TL). Previous reviews about the application of TL in fault diagnosis have concluded that TL is effective to cross-domain fault diagnosis problems through leveraging data from other working conditions or similar machines, and they systematically covered how various types of TL methods apply to different fault diagnosis problems. However, they did not consider what TL algorithms have never been applied to fault diagnosis that can benefit fault diagnosis research. Therefore, there is the necessity to comprehensively study TL in general and identify, from the whole scope of TL, any novel methods that may further facilitate fault diagnosis and aerospace CBM. By investigating into the history of TL, one such novel TL method found is high-level TL methods that enables knowledge transfer between both dissimilar source and target domains. Developing high-level transfer learning solutions in fault diagnosis would improve the current lack of diversity in the specific applications and domains of transfer in this field. Regarding the potential in aerospace CBM, high-level transfer learning is expected to significantly improve the efficiency of data usage.

Keywords: condition based maintenance; fault diagnosis; machine learning; maintenance; transfer learning

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1. Introduction

In aerospace, Maintenance, Repair and Overhaul (MRO) is a crucial sector for ensuring the safety and reliability of aircraft, and significant costs have been associated with this sector. It has been estimated that the overall cost of carrying out MRO accounts for 10-15% of an airline carrier's budget [1]. The global commercial MRO demand is forecasted to be $ 78.5 billion for 2022 and is expected to grow to $ 121.2 billion by 2032 [2]. Condition based maintenance (CBM) is a technique that helps to reduce the cost of MRO. Using run-time data to determine the health state of aircraft, CBM enables operators to conduct inspection and maintenance based on evidence of need rather than routine time-based inspections, thereby reducing the cost of performing routine maintenance [3].

1.1. OSA-CBM

A general architecture to deliver CBM service is depicted by the Open Standard Architecture for Condition Based Maintenance (OSA-CBM), which is shown in Figure 1 [4]. OSA-CBM defines a typical CBM workflow containing data acquisition, data manipulation, state detection, health assessment, prognosis assessment, and finally, an advisory generation stage. Fault diagnosis

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concerns the 'Health Assessment' stage in the OSA-CBM framework, which produces the health state or degradation level of monitored systems, subsystems, or components [5]. Fault diagnosis is one of the most crucial stages in the OSA-CBM framework, because it converts aircraft data into health information. Hence, having an accurate prediction method from aircraft data to the health state of the aircraft is essential to the reliability of CBM.

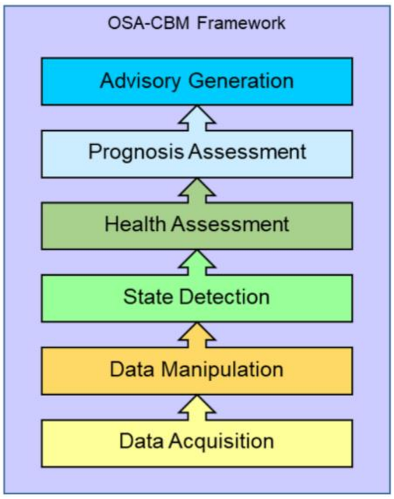

Figure 1. The architecture of Open Standard Architecture for Condition Based Maintenance (OSA-CBM) [4].

1.2. Transfer Learning for OSA-CBM

Traditionally, machine fault diagnosis refers to the process of determining the health state of a machine from the symptoms observed through the experience and knowledge of engineers [6]. In recent years, with advances in machine learning (ML) theories, ML-based fault diagnosis, the modern-day equivalent to the traditional fault diagnosis process, has received increasing attention from both academic and industrial researchers [7,8]. Compared with traditional methods that rely on human experts, ML-based fault diagnosis is believed to provide automation in various diagnostic stages and improve diagnostic accuracy [9], removing people from the loop. In addition, as systems become more complex and integrated, machines produce larger and richer datasets, which allow ML-based fault diagnosis to demonstrate its much greater diagnostic capacity than traditional methods [10].

Although machine learning empowers fault diagnosis with greater diagnostic capacity than traditional methods, machine learning models are prone to error if not applied carefully, especially when they are applied to scenarios different from the training scenarios, hence the need to transfer the models from one scenario to another [11]. Aiming to achieve such transfer of knowledge, transfer learning (TL) has been widely applied in fields such as image classification, natural language processing, recommendation systems, and human activity classification [12,13].

In fault diagnosis, TL has received increasing attention in recent years. Currently, TL has been successfully applied to bridge the gap between fault diagnosis in academic research and its application in practical scenarios [14]. The root cause for such a gap can be summarised by four aspects: 1) sample sizes are small for new machines, 2) labels are missing due to the labour-intensive nature of labelling or technical difficulties in labelling, 3) datasets are usually unbalanced with too few faulty case data, since machines generally operate under healthy conditions, and: 4) training data can display a distributional discrepancy from the testing data, for machines operate under various conditions [15]. Furthermore, the ability of TL to transfer diagnostic models between different fault severities has also demonstrated its strength in capturing incipient faults [16,17], which will contribute to achieving the desire for prognosis in the future [18].

Since TL has demonstrated its ability to generate accurate diagnostic results under challenges from real-scenario data and improve the reliability of fault diagnosis, this work aims to review the application of TL in fault diagnosis and discover its fullest potential in aerospace CBM.

1.3. Analysis of Existing Reviews in the Related Field

Several review papers exist for the application of TL in fault diagnosis, which are summarised in Table 1. The common elements among the existing reviews include the description of various TL approaches and examples of applying TL in fault diagnosis gathered from relevant research. Meanwhile, each review focused on different perspectives among the related fields.

Focusing on the most general perspective, [9,14] are the early works that reviewed different categories of TL with examples in fault diagnosis. [14] analysed relevant literatures in terms of their motivations, problem settings, specific approaches, and specific applications. [9] pointed out that TL could be the most high-potential technique for developing fault diagnosis solutions. General discussion of TL and fault diagnosis was also found in a more recent review, [19], which surveyed a much richer collection of relevant literature and systematically categorised them based on multiple criteria from their problem settings, solutions, and applications.

More recently, reviews in this field concentrated their focus on deep transfer learning (DTL) methods. [20] provided a comprehensive introduction to various DTL methods, detailing the major algorithms in each of the four main categories of DTL: instance-based, feature-based, parameter-based, and adversarial-based DTL. It raised examples of the application of these methods in fault diagnosis and suggested weakness in the methods and future progress. Similarly, [21] also discussed the application of DTL in fault diagnosis but respectively analysed it for feature extraction and fault classification. Evaluating DTL algorithms by their performance in specific datasets, [22] obtained conclusions about the choice of DTL algorithms for specific fault diagnosis problems. Other reviews on DTL took several different specific focuses. Focusing on specific category of DTL, [23] comprehensively investigated adversarial-based DTL and detailed how various adversarial-based DTL could be applied to different transfer settings. Focusing on different tasks and problem settings, [24] summarised different DTL methods applied to unlabelled target domains. [8] discussed the application of various DTL methods to common industrial scenarios and suggested DTL algorithms for several industrial use cases. Including both fault diagnosis and fault prognosis in its discussion, [25] reviewed how DTL facilitates fault diagnosis and remaining useful life.

Table 1. Summary of published reviews in the similar field.

Reference	Year of publication	Type of TL method discussed	Main contribution
Zheng et al.[14]	2019	Non-DTL DTL	This is an early review of the application of TL in fault diagnosis. It explained the basics of various TL methods, including instance-based, feature-based, deep learning-based, and adversarial-based TL. Based on literature about the application of TL in fault diagnosis, it produced a summary of motivations, problem settings, specific approaches, and specific applications of relevant research and suggested future directions.
Lei et al. [9]	2020	Non-DTL DTL	This paper reviewed the general application of machine learning to fault diagnosis. It illustrated a development roadmap of fault diagnosis solutions, where traditional machine learning methods is “the past”, deep learning is “the present”, and transfer learning may be “the future”. In the TL section, it provided top-level description to instance-based, feature-based, parameter-based, and adversarial-based TL algorithm with fault diagnosis examples.
Li et al. [21]	2020	DTL	This paper outlined the principle of common DTL methods for fault diagnosis, and it reviewed the application of DTL in fault diagnosis respectively for feature extraction and fault classification.
Zhao et al. [24]	2021	Unsupervised DTL	This paper focused on unsupervised DTL (i.e., DTL with unlabelled target domain), outlined how various unsupervised DTL algorithms apply to label-consistent, label-inconsistent, multi-domain transfer problems, and tested on bearings and gears datasets.

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Li et al. [8]	2022	DTL	This paper discussed three main categories of DTL (i.e., instance-based, feature-based, parameter-based) applied to four industrial scenarios for fault diagnosis: general performance improvement, partial domain fault diagnosis, emerging fault diagnosis, and compound fault decoupling, and it suggested DTL solution for various industrial needs.
Qian et al. [20]	2022	DTL	This paper comprehensively reviewed the application of DTL in fault diagnosis by explaining the principle of four major DTL categories: instance-based, feature-based, parameter-based, and adversarial-based DTL.
Yao et al. [25]	2022	Non-DTL DTL	This paper explained general categories of TL methods (feature-based, parameter-based, and adversarial-based) in both sallow and deep networks, and their application in fault diagnosis and fault prognosis (i.e., remaining useful life prediction).
Yang et al. [22]	2023	DTL	This review analysed various DTL algorithms as applied to specific datasets and provided evaluation from the fault diagnosis perspective.
Guo et al. [23]	2023	Adversarial DTL	This paper provided an in-depth review into the application of adversarial DTL (i.e., DTL with adversarial training) in fault diagnosis, and it detailed how non-generative adversarial DTL and generative adversarial DTL applies in different transfer settings.
Azari et al. [19]	2023	Non-DTL DTL	This paper reviewed the application of TL in predictive maintenance, and it systematically categorised relevant research by multiple criteria from problem settings, solutions, and applications.

Despite that the existing reviews have presented a comprehensive overview of various TL methods and how they have been applied to various fault diagnosis problems, there is a common limitation, which is they have only considered the TL algorithms that have been already applied to fault diagnosis problems without considering whole scope of TL, irrespective of its applications, and covering all the possible ways that TL may facilitate fault diagnosis. Hence, there is the necessity to comprehensively study TL in general and identify any TL methods, from the whole scope of TL, that may benefit fault diagnosis solutions, so that the potential of TL in fault diagnosis applications can be fully explored. This review has chosen aerospace CBM as the topic of concern and aims to explore how the application of TL in fault diagnosis, in ways that exist or not, could facilitate aerospace CBM.

With the aim to understand the general topic of TL irrespective of its applications, Section 2 of this review will investigate the history of TL to identify the whole scope of TL, and then by comparing TL with some common aerospace fault diagnosis algorithms, try to draw inspiration about high-potential TL methods in the fields of concern. Section 3 focuses on the existing application of TL in fault diagnosis. It evaluates the various types of TL applied to fault diagnosis and studies the specific applications and transfer scenarios in the existing literature. Section 4 focuses on the application of TL specifically in aerospace fault diagnosis, which is directly related to how TL has contributed to aerospace CBM. Then in the beginning of Section 5, research gaps and limitation in the existing literature from Section 3 and 4 are raised. Combining all the information above, future progress in applying TL in fault diagnosis and its benefit and potential in aerospace CBM will be suggested in Section 5. Finally, Section 6 summarises the main contribution of this review and provides a conclusion.

2. Transfer Learning

To understand the entire scope of TL and explore its potential to the greatest extent possible, this section discusses TL from several different perspectives. To start with, Section 2.1 looks into TL from a historical perspective, revealing how TL originates and what the entire scope of TL covers. Then, in Section 2.2, the most up-to-date definition and general structure of TL is introduced. Section 2.3 takes a more holistic perspective by not limiting the discussion to TL and compares TL with other methods using the idea of reusing previous solutions for new problems, which aims to find possible inspiration for further developing TL. Finally, Section 2.4 introduces a method called transfer learning by structural analogy, which is believed to have high potential in fault diagnosis.

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2.1. History of Transfer Learning

This section presents a detailed overview of the history of TL. By doing so, the scope of TL can be clarified and implications from a historical perspective can be drawn.

It is commonly believed that TL originates from transfer of learning, a method capturing how "people often apply the knowledge gained from previous learning tasks to help learn a new task" [11]. While most researchers marked the similarity between knowledge transfer in human learning activities and machine learning, no discussion has been found that explicitly described how transfer of learning progressed to TL.

Figure 2 summarises how TL evolved from transfer of learning, based on the literature gathered by this work. In the top half of Figure 2, key theories of transfer of learning in the field of human learning are listed against time. In the bottom half of Figure 2, key developments in TL as a machine learning method are shown. Starting from the top half of Figure 2, transfer of learning is commonly studied in two fields: motor learning and education theory. Transfer of learning in motor learning inspired the mainstream TL methods, which are explained in Section 2.1.1. Transfer of learning in education theory inspired the high-level transfer methods, which are explained in Section 2.1.2.

2.1.1. Inspiration from Motor Learning

The branch of transfer of learning in motor learning motivated the early works on TL that developed to the mainstream TL method today. The green path in Figure 2 highlights this historical development.

Transfer of learning in motor learning activities is also referred to as bilateral transfer or cross-education, which describes the behaviour that "practice of one part of the body in performing a skilled act increases the ability of the bilaterally symmetrical part in the same act" [26]. For instance, training the left hand on a certain action could result in an improvement in the right hand when performing the same action. The experiment by Bray was one of the early works attempting to comprehensively validate this phenomenon. In his experiment, the transfer of skills was not only tested between symmetrical limbs, such as between the left hand and the right hand, but also between asymmetrical limbs, such as between the right hand and the right foot [26]. Pretraining other limbs on a drawing task seemed to improve the testing limb on the same task. After interviewing the subjects, Bray concluded that the reasons for the behaviour were: i) the transfer of method, i.e., the subjects applied the method learnt during the pretraining phase to the new tasks rather than the limbs transferring the motor learning, and: ii) a reduction in nervousness after the pretraining phase. Finally, Bray designed an alternative experiment aimed at eliminating the influence of these two factors, but he was unable to prove whether there were other factors explaining the transfer, since it was extremely difficult to completely eliminate all influences from the experimental design. Research into transfer of learning on motor learning activities still remains an active branch of research today. However, with advances in neuroscience during the last century, researchers are now proposing explanations for the transfer of learning by biological brain activities. For example, Boroujeni and Shahbazi [27] observed bilateral transfer of badminton short service skills between the dominant and non-dominant hands, suggesting the reason as an overflow of motor impulses from the pretrained part of the body. Similarly, Kumar and Mandal [28] observed bilateral transfer of mirror-drawing skills and explained the transfer mechanism as interhemispheric transfer.

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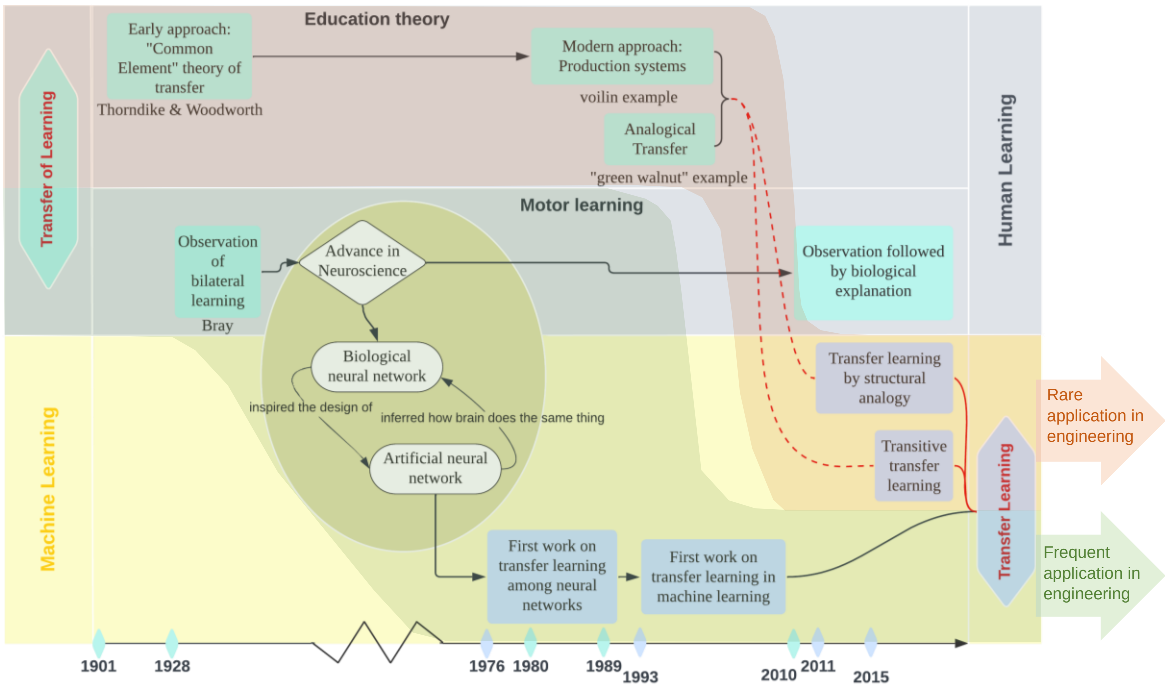

Figure 2. The history of transfer learning from transfer of learning in human learning domain (top half of Figure 2) to transfer learning in machine learning domain (bottom half of Figure 2).

How transfer of learning in motor learning motivated the mainstream TL has not been formally documented. This work believes that advances in the understanding of how the human brain conducts knowledge transfer shows a strong relation to TL, especially by neural networks. The understanding of biological neural networks inspired the design of artificial neural networks (ANNs), and the design of ANNs helped infer how the brain executes the same action [29]. Based on an ANN, the first mathematical modelling of TL among neural networks was developed in 1976, and the first work on TL in machine learning appeared in 1993 [30].

2.1.2. Inspiration from Education Theory

The branch of transfer of learning in education theory motivated TL methods focusing on high-level transfer, which considered the scenario where the source domain and the target domain do not share low-level similarities such as identical physical parameters and data structures. The red path in Figure 2 highlights this historical development.

Education theory explains transfer of learning on the conceptual level rather than the biological level of human learning. In education theory, "there is little agreement in the scholarly community about the nature of transfer, the extent to which it occurs, and the nature of its underlying mechanisms" [31]. Therefore, two of the most popular theories explaining the knowledge transfer are introduced here. The first mechanism is called the "common element" theory of transfer. As early as 1901, Thorndike and Woodworth proposed this theory to explain the knowledge transfer behaviour by stimulus-response associations and suggested that transfer increased for larger overlapping of common elements between the learning and testing tasks[32]. Taking playing the violin as an example, the early approach of the "common element" theory could explain why violin players can play the same melody in different pitches, as they contain the same motor sequence as the common element [32]. However, the observation of transfer exists not only for the same melody, but also among different sonatas, such as between a violin sonata by Händel and a Mozart sonata [32]. Hence, a modern approach of understanding the "common element" has taken the transferred common element as the production, i.e., "the procedural knowledge comprising of specific conditions followed by actions" [32]. Repeated practice accumulates productions consisting of sets of notes and the corresponding sets of finger movements, and when the same conditions (sets of notes) are met in new pieces, the player could transfer the productions and respond with the sets of finger movements [32]. The second mechanism is analogical transfer, which is a systematic framework capturing how humans rely on analogy to learn new tasks. Steiner [32] explained this framework using an example in which a young girl applied analogical transfer to identify a previously unknown object, a green walnut. The key step of the process is to retrieve known objects bearing analogies to the unknown object of the green walnut and to determine whether the green walnut shares certain properties with the analogical objects [32]. The integration of learning several properties would lead to the final identification of the unknown object as a green walnut. Figure 3 illustrates the first cycle of the process of recognising the green walnut. The cycle starts by finding that a small apple can be analogous to the green walnut, since they are both small green objects. Because apples are biteable, the same property can be tested on the green walnut, and a biting test results in the conclusion that the green walnut is not biteable, which leads to the knowledge that the skin of the unknown object, the green walnut, should be peeled [32].

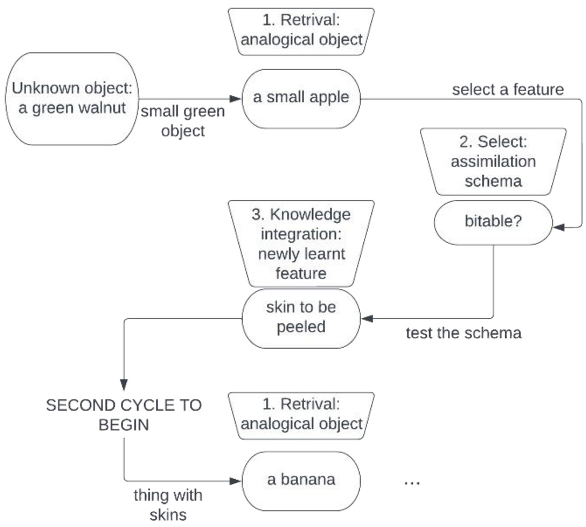

Figure 3. The illustration of a typical cycle in analogical transfer, using the 'green walnut' example.

Two TL methods are motivated by this branch of transfer of learning. The first method is Transitive Transfer Learning (TTL). Inspired by how humans make indirect inferences and learn by connecting many intermediate concepts to transfer knowledge between two seemingly unrelated fields, TTL adopts an intermediate domain to transfer knowledge between a source domain and a target domain with a very large gap [11]. The second method is transfer learning by structural analogy, which is inspired by how humans use analogy to connect seemingly unrelated ideas [33]. In transfer learning by structural analogy, analogical pairs are assigned between entities in two distant domains based on their structural relation, and the transfer of knowledge is applied by treating the entities in each analogical pair as equivalents [33].

2.1.3. Implication from the History of Transfer Learning

Although history shows that TL received inspiration from biological understanding and conceptual understanding of how knowledge transfer occurs in human learning activities, the TL methods motivated by the two branches have not received equal attention in engineering scenarios. Inspired by the biological understanding of knowledge transfer in human learning, the mainstream TL methods have seen abundant applications in engineering problems such as fault diagnosis. By contrast, TTL and transfer learning by structural analogy, inspired by the conceptual understanding of knowledge transfer in human learning, have never been applied to engineering problems.

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However, it is important to explore these methods, since they consider high-level transfer scenarios where low-level similarities no longer exist between the source and target domain. As one of the most important findings from investigating the history of TL, understanding how to implement high-level transfer to solve fault diagnosis problems should be conducted to complete the research on TL in fault diagnosis.

2.2. Definition and General Structure of Transfer Learning

This work defines TL as "the machine learning paradigm in which an algorithm extracts knowledge from one or more application scenarios to help boost the learning performance in a target scenario" [11]. The general structure of TL is shown in Figure 4. The term source domain is used to indicate where knowledge is borrowed from, and the term target domain is used to denote where the borrowed knowledge is applied. A traditional machine learning process is shown on the left of Figure 4. Borrowing knowledge from data, model or task description from the source domain to solve a new task in the target domain describes a TL-based approach, which is shown on the right of Figure 4. It should be pointed out that while most TL research defines the source and target domain as being "different but related", the definition followed by this work removes this constraint, since Section 2.1 has concluded that the whole scope of TL includes both low-level TL methods and high-level TL methods, i.e., the TL methods between seemingly unrelated source and target domains.

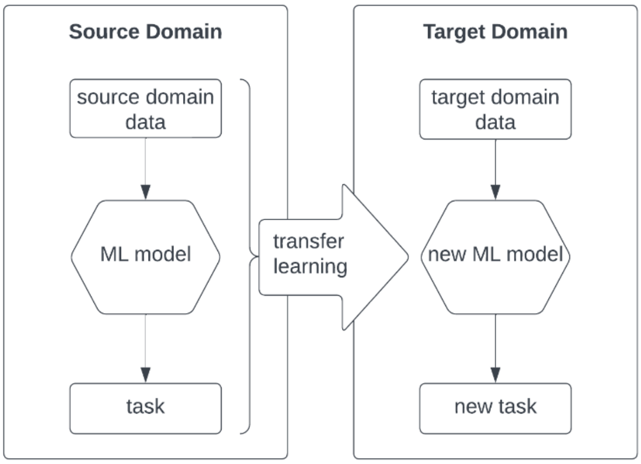

Figure 4. The general structure of transfer learning, illustrating that TL leverages knowledge from the source domain and applies it to the target domain.

2.3. Transfer Learning Compared to Other Methods Involving the Element of Knowledge Transfer

To understand TL in a broader context, it should be mentioned that the idea of leveraging previous knowledge is not unique to TL. Three methods that function by reusing previous knowledge for new tasks are compared with TL to provide new insights: case-based reasoning (CBR), procedural reasoning system (PRS), and analogical transfer. CBR and PRS are common algorithms in aerospace fault diagnosis, hence the comparison with TL is believed to be particularly meaningful for inspiring how TL can further facilitate aerospace fault diagnosis. The key features of these methods are summarised in Table 2 and compared with TL. Since this section aims to provide a general overview to compare and contrast the methods on a conceptual level, the technical details of each method will not be discussed.

Table 2. Four methods involving the idea of leveraging previous knowledge.

Method	Case-based Reasoning	Procedural Reasoning System	Analogical Transfer	Transfer Learning

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<table>
<tr><td rowspan="2">Domains between which transfer happens</td><td>from:</td><td>Historical cases</td><td>Knowledge Areas (KA) library</td><td>Learnt knowledge</td><td colspan="3">Source domain</td></tr>
<tr><td>to:</td><td>New cases</td><td>Newly established goals</td><td>Unlearnt knowledge</td><td colspan="3">Target domain</td></tr>
<tr><td colspan="2">Domain relation</td><td>Same field</td><td>Same field</td><td>As long as source analogues are found</td><td colspan="3">Label space:
Target ≤ Source</td></tr>
<tr><td colspan="2">Knowledge transferred</td><td>Solutions for cases</td><td>KAs: Sequences of actions toward achieving a goal</td><td>Source analogues; Assimilation schemas</td><td>Instances</td><td>Features</td><td>Models</td></tr>
<tr><td rowspan="4">Cycle stage corresponding to actions:</td><td>Retrieve</td><td>The most similar case(s)</td><td>Chosen KAs</td><td>Source analogue from known object; Assimilation schema</td><td>Auxiliary instances</td><td>Source domain features</td><td>Pretrained classifier</td></tr>
<tr><td>Reuse</td><td>Attempt to solve the problem</td><td>Execute KAs in the intention system</td><td>Apply assimilation schema to target</td><td>Training classifier for the target domain</td><td>Training domain-invariant classifier</td><td>Applied to the target task</td></tr>
<tr><td>Revise</td><td>Adapting solutions to the differences between cases</td><td>New subgoals</td><td>New conceptual similarity</td><td>Adjust instance weighting</td><td>Minimise feature distance</td><td>Parameter tuning</td></tr>
<tr><td>Retain</td><td>Solved new case enters case base</td><td>N/A</td><td>Knowledge integration</td><td colspan="3">New classifier</td></tr>
</table>

Starting with CBR, as a method that “solves new problems by adapting solutions that were used to solve old problems” [34], the properties and procedure of CBR inspired the framework of analysing all the methods in Table 2. Three key properties of each method are extracted: the domains between which transfer of knowledge occurs, how the domains should be related, and what knowledge is transferred. For CBR, knowledge is transferred from previous cases to new cases, given that they are similar cases in the same field, and the knowledge being transferred is the previous solution of the matched historical cases [35]. The main procedure of CBR, “Retrieve – Reuse – Revise – Retain”, is taken as a cycle of stages to leverage previous knowledge. In the “retrieve” stage, one or more cases are retrieved from the case base to match the new problem, and then a solution is suggested from the

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matched cases and tested on the new case in the "reuse" stage [35]. If the retrieved case is not a close match, adaptation of the solution from the retrieved case will be necessary in the "revise" stage, which produces a new case to be retained in the case base [35]. This four-stage description of the CBR process is not only terminology for CBR but can also be viewed as a framework for leveraging previous knowledge in general. The "retrieve", "reuse" and "revise" stages can be generalised as three logically inevitable stages of any knowledge reuse method, where previous knowledge is first retrieved and then re-applied to the new problem with modification if necessary. The "retain" stage can be used to describe the extension of existing knowledge following newly solved problems.

PRS can also be understood in light of the aforementioned framework. In PRS, previous knowledge is extracted from a library of knowledge areas (KAs) and applied when a new goal appears. The knowledge transferred to the new task is previously stored KAs, which are "sequences of actions and tests that may be performed to achieve given goals or to react to certain situations" [36]. Containing specific actions to take under certain conditions, KAs can only be transferred between similar problems with similar prescribed conditions. Hence, the knowledge transfer can only be considered for problems in the same field. The main stages of a PRS cycle are: 1) for the "retrieve" stage, various KAs are triggered following a new goal or an altered system belief, 2) for the "reuse" stage, one or more KAs are selected and executed within the intention structure of PRS, which leads to a new subgoal or a new belief, 3) this new subgoal or new belief then starts another PRS cycle, which resembles a "revise" stage [37]. The "retain" stage is not obvious for PRS.

In human learning theories, analogical transfer is a method for leveraging previous knowledge. It is a method that facilitates the understanding of unlearnt knowledge from previously learnt knowledge. Working by discovering true analogies in problems sharing "a similar deep structure but not necessarily specific content", no fixed relations are imposed on the domains of the knowledge transfer process [32]. Specifically, the knowledge transferred includes source analogues and assimilation schemas from the source analogues. A detailed example of an analogical transfer cycle is provided in Section 2.1.2, the "green walnut" example. For the "retrieve" stage, the source analogue of a small apple is retrieved, and the assimilation schema is identified as being biteable. The biting schema is then tested in the "reuse" stage, which leads to the knowledge integration that the green walnut is not biteable and therefore should be peeled in the "retain" stage. Having determined that the green walnut should be peeled, another source analogue is found to be a banana, since they both have skins [32]. Then, another analogical transfer cycle begins, which works as the "revise" stage.

The properties and procedures of TL were also extracted to compare TL with other knowledge transfer methods. Starting with the properties of TL, knowledge is transferred from the source domain to the target domain. The relation between the two domains is commonly defined as "different but related", and "the label space of the source domain should overlap that of the target domain" [9]. The knowledge transferred in TL depends on the specific category of the TL method. For instance-based TL, the knowledge transferred is borne in the source domain data instances. The main stages are as follows: 1) the auxiliary data instances are retrieved from the source domain, 2) the auxiliary instances are used to train a target domain classifier, 3) the weighting of the auxiliary instances and target domain instances is optimised for target task classification accuracy, and 4) a new classifier is obtained for the target domain task. In feature-based TL, the knowledge transferred is borne in the source domain features. The main stages are as follows: 1) selected data features are retrieved from the source domain, 2) the source domain features and target domain features are unified in the feature space and are used together to train a domain-invariant classifier, 3) the distribution distance between the source and target domain features is minimised so that the domain-invariant classifier performs well in the target task, and 4) a new classifier is obtained for the target domain task. In model-based TL, the knowledge transferred is borne in the model parameters or architectures. The main stages are: 1) a model pretrained in the source domain is retrieved, 2) the pretrained model is adapted to the target task by freezing, fine-tuning, or retraining with target domain data, 3) the transfer strategy and parameter tuning can be changed to suit each specific target application, and 4) a new classifier is obtained for the target domain task.

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From the above discussion, it is clear that TL actually shares similarities in its properties and procedures with other methods of leveraging previous knowledge. Sharing a similar goal, the other methods described in this section could inspire improvements in TL. One such inspiration from Table 2 is that, while all other methods transfer knowledge between similar domains, analogical transfer does not require low-level similarity to function. This shows that analogy could be a useful tool for leveraging previous knowledge from seemingly unrelated domains, which opens up wider opportunities for TL. The following section describes a TL method based on analogy.

2.4. Transfer Learning by Structural Analogy: A High-Potential Method in Fault Diagnosis

As Section 2.1 pointed out, the TL methods inspired by the conceptual level understanding of human knowledge transfer are able to address high-level transfer problems between two seemingly unrelated domains. Since high-level transfer has not been seriously considered in engineering scenarios, it is considered a high-potential direction for future TL studies. Section 2.3 concludes that applying analogies could be a way to expand the boundaries of TL methods. Combing these thoughts, one method aimed at high-level transfer problems that shows potential in fault diagnosis is TL by structural analogy. This method, proposed by Wang et al. [33], achieved knowledge transfer by finding analogical pairs of entities from two domains of interest and extracting the relational similarity between the two domains. The analogical pairs are found by simultaneously minimising the distance between entities from the two domains and the distance between the selected entities to the labels in their respective domain, so that the analogy made is also meaningful for label prediction [33]. To demonstrate the validity, Wang et al. [33] applied the algorithm to find analogical pairs of words in diagnosis documents for cardiovascular and respiratory tract diseases. The results are shown in Table 3. By treating the words in every analogical pair as equivalents, the classifier trained on source domain documents achieved 80.5% accuracy when applied to target domain documents, which was significantly higher than the 50% accuracy when the classifier was transferred without the information from structural analogy [33]. It should be noted that the words in the analogical pairs in Table 3 have no literal overlap, so this proves that the algorithm can make an analogy between seemingly unrelated entities and, based on the analogy made, enables positive knowledge transfer between two seemingly different domains.

Table 3. Analogical pairs from medical dataset on different diseases found using transfer learning by structural analogy [33].

Cardiovascular Diseases	Respiratory Tract Diseases
“endocard”	“infect”
“infect”	“pneumonia”
“heart”	“pulmonari”
“valv”	“repiratori”
“cell”	“lung”
“complic”	“cultur”
“cardiac”	“bacteri”
“aortic”	“tract”
“studi”	“case”
“effect”	“increas”

Although the example is not in an engineering scenario, the task of diagnosing a disease from a symptom document is very similar to a fault diagnosis task in which the machine health state is diagnosed from the observed symptom vector. Hence, applying transfer learning by structural analogy could be a promising method for fault diagnosis scenarios. Upon successful implementation, it would expand the boundary of TL in fault diagnosis from being between similar machines to being between seemingly unrelated machines as well.

3. Transfer Learning in Fault Diagnosis

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The following subsections focus on the application of TL in fault diagnosis. Section 3.1 introduces the different categories of TL methods used for fault diagnosis and briefly evaluates each category. Sections 3.2 to 3.3 present a literature survey conducted on the existing research on TL in fault diagnosis by gathering literature from the search of “transfer learning” and “machine fault diagnosis” in the article title, abstract, and keywords on Scopus. The search returned 718 entries in January 2023.

Two major aspects are discussed based on these entries, namely the specific applications and the relationship between the source and target domains in these works, which are presented in sections 3.2 and 3.3, respectively. For these two sections, the first 200 most relevant entries out of the 718 entries were selected as representative entries, because a generally repeating pattern of the research trends was identified for the first 100 entries and the second 100 entries. All figures in these sections are obtained from the analysis of representative entries. For transparency in data analysis, details of the representative entries are reported in Appendix A.

3.1. Classification of Existing Transfer Learning Methods in Fault Diagnosis

To understand how TL methods have been applied to fault diagnosis problems in detail, this section describes the popular categories of TL methods in fault diagnosis, and a summary of their pros and cons is listed in Table 4. Based on the nature of the knowledge being transferred, TL methods commonly applied to fault diagnosis can be divided into instance-based TL, feature-based TL, and parameter-based TL.

The differences between the instance-based TL, feature-based TL, and parameter-based TL are shown in Figure 5. The architecture of each category of the TL method is marked along with a typical fault diagnosis process, which takes raw data as the input and transforms raw data into features using feature extraction, before a classifier acts on the features to produce a predicted health state for the machine.

3.1.1. Instance-Based Transfer Learning

For instance-based TL, knowledge transfer is essentially achieved by reusing labelled source domain data as auxiliary data to train a target domain classifier [11]. As shown at the top of Figure 5, knowledge transfer occurred in the domain of the raw data. TrAdaboost is a common instance-based TL method, which applies differential instance weighting mechanisms for the source and target domains, where weights are reduced for misclassification samples in the source training set to exclude unrelated samples but strengthened in the target training set to enhance the training [38]. Using k-nearest neighbours (kNN) as the classifier, Yang et al. [38] extracted fault information from a group of electricity distribution transformers to train a model to diagnose a target transformer with little data. Combining TrAdaboost with support vector machine (SVM) as the fault classifier, Qiu et al. [39] used data from an old model of a fuel pump as the auxiliary training data in the diagnosis task of a new model of the fuel pump with scarce data. Compared with the SVM trained with only target domain data or a combination of target and auxiliary data, implementing TrAdaBoost when training the SVM significantly improved the diagnostic accuracy [39]. This example shows that instance-based TL methods are particularly useful for small target data problems if abundant auxiliary data exist. Working with raw data, it is a highly interpretable approach and can be combined with various classifiers to suit specific applications.

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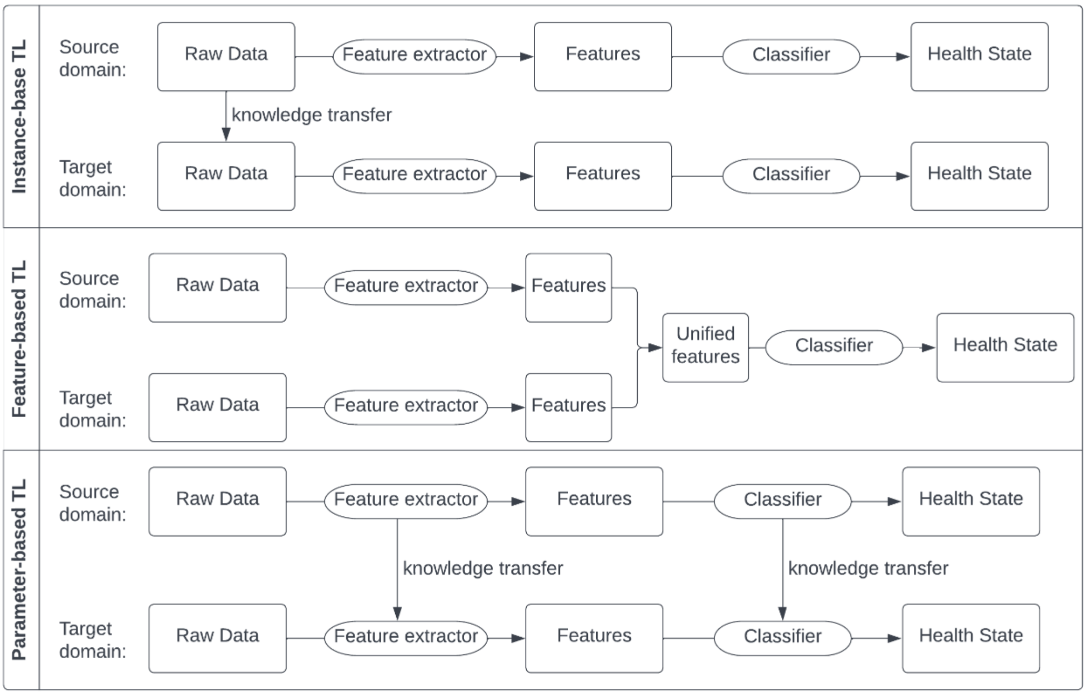

Figure 5. Illustration of the general architecture of different categories of transfer learning in a typical fault diagnosis process: instance-based method (top); feature-based method (middle); parameter-based method (bottom).

Table 4. Evaluation of different types of transfer learning methods applied to fault diagnosis.

Category	Example algorithm	Pros	Cons
Instance-based TL	TrAdaboost	• Particularly effective for small target task data • Working directly with the data • Can combine with a range of classifiers	• May compromise the output accuracy if abundant target training data is available • Susceptible to data distribution discrepancy
Feature-based TL	transfer component analysis (TCA)	• Aligns marginal distribution • Can combine with a range of classifiers • Easy to implement, allowing updated target training data to boost performance	• Conditional distribution discrepancy not addressed • Working with abstracted features rather than the raw data is less intuitive
	joint distribution adaptation (JDA)	• Aligns marginal distribution • Conditional distribution directly addressed, making a more working condition-robust method	• More complex procedure, more terms to optimise • Noticeably more computation time compared to other feature-based methods and some deep network-based methods • Less intuitive method
	DTL through representation adaptation	• An end-to-end solution to fault diagnosis	• Lack of interpretability

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Parameter (model)-based TL	CNN-based TL	• An end-to-end solution to fault diagnosis • Higher potential to generalise on a higher level	• Lack of interpretability

However, this method has two major limitations. Firstly, if there is abundant target domain data, applying TrAdaboost could compromise the prediction accuracy, compared to directly training with target domain data [39]. Secondly, it is suitable only if the source domain data is very similar to the target domain data. If auxiliary data with significant distribution discrepancy is to be borrowed, additional processing is usually required. For instance, Du et al. [40] combined transfer component analysis (TCA) with TrAdaBoost to achieve knowledge transfer in the diagnosis of bearings under different conditions. Three fault modes were studied: an inner race fault, an outer race fault, and a roller fault. TCA is first applied to extract low-dimensional features from both the source and target domains with similar distributions, before TrAdaBoost is applied when using the source domain auxiliary training data to obtain the ultimate strong classifier based on Decision Tree [40].

3.1.2. Feature-Based Transfer Learning

Feature-based TL methods operate in an abstracted feature space rather than the raw data space [11]. The general process is shown in the middle of Figure 5. The source and target domain data are transformed into features in an abstracted feature space, where their distribution discrepancy is reduced to allow a classifier to act on the unified features.

Distribution discrepancy is classified into two categories. The first type is marginal distribution, which refers to the marginal probability distribution of cases regardless of their labels. The second type is conditional distribution, which is often approximated in fault diagnosis applications by the probability distribution of cases under each label.

The most fundamental algorithm is TCA, which addresses the marginal distribution discrepancy. In this method, a distance measure is required. For example, Xu et al. [41] characterised the distribution distance using the maximum mean discrepancy (MMD), and the distance between the transformed source and target domain features was minimised in a high-dimensional space. After TCA, a classifier (kNN) trained with transformed features from the source domain is transferred to predict target domain faults, and high diagnostic accuracy is demonstrated by applying the method on Case Western Reserve University (CWRU) bearing dataset data at different rotational speeds [41]. TCA has the advantage that it can also be combined with a range of classifiers, and it allows the inclusion of updated target training data to enhance its performance. However, conditional distribution discrepancy is not considered in TCA.

To consider both marginal distribution and conditional distribution simultaneously, joint distribution adaptation (JDA) is a commonly used method [42]. Qian et al. [43] took source and target domain data at different rotational speeds and loads and used JDA to process the data and SoftMax as the classifier. Their feature-based TL method resulted in 99.9% and 100% diagnostic accuracy over all fault types studied for the bearing and gearbox datasets, respectively. Hence, including the conditional distribution alignment, JDA is capable of providing high diagnostic accuracy, but it requires more computational time than other TL methods [43].

A common shortcoming of all feature-based methods is that since the classifier acts on abstract features transformed from the raw data, methods such as TCA and JDA are less intuitive than instance-based methods. Recent developments have focused on more advanced processing of distribution discrepancy to further improve the accuracy and reliability of feature-based TL methods. For instance, extending beyond aligning marginal and conditional distributions, manifold embedded distribution alignment (MEDA) also evaluates the relative importance of marginal and conditional distributions [44]. Partial domain adaptation (PDA), which deals with target domain with label space as a subset of that in the source domain, and open-set domain adaptation, where target domain

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contains unknown labels that do not belong to the source domain, both fall under the category of feature-based TL [45,46].

Combining feature-based TL methods with deep neural networks, feature-based deep transfer learning (DTL), also known as DTL through representation adaptation, is a popular solution for fault diagnosis. It refers to DTL methods with the fundamental aim of eliminating the distance between features from the source and target domains. Feature-based DTL can either align the features in the top layers of a deep model or in multiple layers. Using top layer adaptation, Xiang et al. [47] minimised the feature distance by calculating the MMD distance in the two fully connected layers of a CNN model when transferring it between different operating conditions of bearing datasets. Aligning all intermediate features using the multiple layer adaptation method, Xiao et al. [48] calculated the MMD distance for the intermediate features in the convolutional layers and the fully connected layers to transfer the CNN model between various working conditions of an induction motor. Compared to other feature-based TL, feature-based DTL provides an end-to-end automated fault diagnosis solution, but the lack of interpretability remains a drawback of this method.

3.1.3. Parameter-Based Transfer Learning

Parameter-based TL, also known as model-based TL, is different to the previously mentioned categories in that the transferred knowledge is encoded in "model parameters, priors or model architectures" [11]. This type of TL is most common in a DTL setting, which describes TL methods using deep neural networks as the prediction function [49].

In parameter-based TL, knowledge transfer occurs by reusing the parameters of the deep network trained by the source domain data to solve target problems. In Figure 5, this is represented by the bottom approach, where the source feature extraction and classifier are transferred to the target task. Several different strategies exist for implementing parameter-based DTL. In short, the parameters in each layer of a deep network can either be: 1) frozen, i.e., source domain parameters are used in the target problem directly; 2) fine-tuned, i.e., source domain parameters are fine-tuned by the target data before being applied to the target problem; or 3) retrained, i.e., source domain parameters are disregarded and new parameters trained from random values by the target data [50]. The best strategy for parameter transfer depends on the specific applications, and research suggests that the factors to consider could include the size of the target data and its similarity to the source data [14]. For instance, Dong et al. [50] concluded that fine-tuned feature extraction layers with frozen classification layers are more effective than fine-tuning all layers when transferring diagnostic knowledge from a dynamic bearing model to the experimental data of the same bearing.

Parameter-based DTL has the advantage of providing an end-to-end solution to fault diagnosis problems. Because deep networks combine feature extraction with a classifier, they can use machine data as the input and output the predicted health state, which is a highly automated approach [9]. Furthermore, since knowledge transferred concerns the model rather than any specific dataset, parameter-based TL shows higher potential to generalise on a higher level. However, deep networks being a "black box" solution means these methods generally have poor interpretability [20].

3.2. Application of Transfer learning-Based Fault Diagnosis

The specific applications of TL in fault diagnosis, determined from what experiment data is used in each research work, is a topic of concern. As shown in Figure 6, bearings and gearboxes dominate the specific applications, and they account for nearly three-quarters of all applications. The remaining applications contain various items such as transformers, pumps, and motors, with the corresponding numbers of publications shown in Figure 6.

This trend in TL applications was also reported by Zheng et al. [14] who wrote a review paper on cross-domain fault diagnosis using knowledge transfer strategy, in which they identified bearings and gearboxes as "the two most widely (used) research and validation objects of current cross-domain diagnosis literature" and that they outnumbered other application objects by large margins.

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They speculated that this was because it was easier to find open-source datasets for these two objects [14].

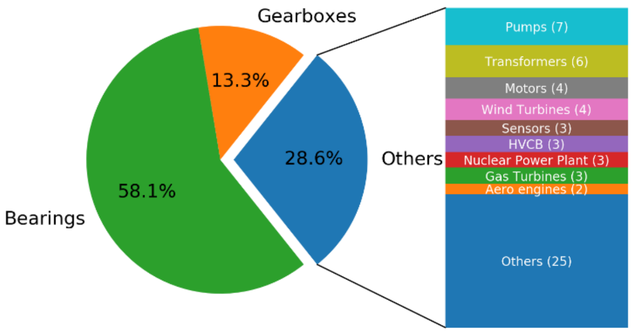

Figure 6. Specific applications of the TL-based fault diagnosis research studied by this work.

3.3. Domains of Transfer

Another important feature is the relationship between the source and target domains in existing studies, as shown in Figure 7.

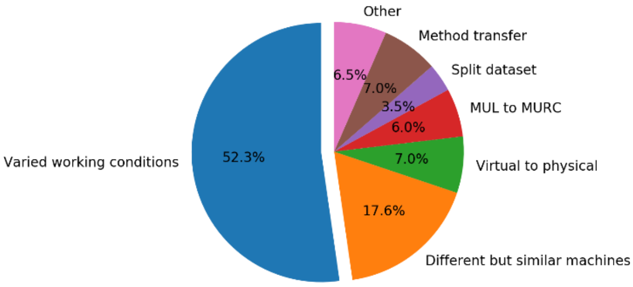

Figure 7. The relationship between the source and target domain of the TL-based fault diagnosis research studied by this work.

The most notable finding was that more than half of the analysed studies considered the transfer scenario of varied working conditions of the same machine. Three variations of working conditions are found in these studies, either individually or in combination: 1) varied loadings and rotational speeds, 2) various fault types during operation, and: 3) various degradation levels of the components. For instance, Zhu et al. [51] transferred the diagnostic model between four groups of CWRU bearing data taken at different loads, 0 HP, 1 HP, 2 HP, and 3 HP, while the rotational speeds remained almost the same. Dong et al. [52] explored the transfer of diagnostic models for ball bearing experimental data taken at three different rotational speeds (1000, 1500, and 2500 rpm) while maintaining a constant 5 kg radial load to the bearing. For the transfer scenario between different fault types, Xie et al. [53] designed a method based on generative adversarial networks to transfer diagnostic knowledge between three groups of CWRU data with no fault, inner ring fault, and outer ring fault. Regarding the transfer between various degradation levels, Chen et al. [16] transferred a deep neural network trained on data with a large-diameter fault (0.012 mm) to data with a small-diameter fault (0.007 mm).

The second most popular choice of transfer domains is between different representations of similar machines, which accounts for nearly a quarter of all domain choices studied. Different representations were found on three levels, including the transfer between different but similar machines, the transfer between virtual and physical assets, and the transfer between machines used in the laboratory (MUL) and machines used in real case (MURC). An example of transfer between

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different but similar machines is that Li et al. [54] considered a group of 15 wind turbines of the same type, and transfer is applied from 14 wind turbines to a similar wind turbine with small data. Bearing research by Dong et al. [50] provides an example of transfer between virtual and physical assets. Dynamic models were first constructed for bearings from two different laboratories, and using simulation data from the dynamic models as the auxiliary source domain data, diagnostic knowledge was transferred to real bearing experiment data [50]. Regarding the transfer between MUL and MURC, Yang et al. [55] used the data from SKF6205 bearing with a 52 mm outrace diameter and 3 HP load as the source domain data and transferred the diagnostic model to data from a locomotive bearing with a 160 mm outrace diameter and 9800 N vertical load [56].

Less common choices of the transfer domain are summarised as "split dataset" and "method transfer". The "split dataset" refers to the scenarios where source and target domains are randomly split from the original dataset of the same machine under the same working condition. For example, Cao et al. [57] designed a gearbox experiment and generated 104 samples for each health condition. Under each health condition, the 104 samples were randomly selected as the source domain data and target domain data with the source domain data size varying between 2% and 80% of the 104 samples, and the effect on the diagnostic accuracy of the transferred model was discussed. The "method transfer" refers to the research where TL applies on the method level, such as transferring image classification deep networks to fault classification. For example, Zhang and Zhou [58] used the CNN model trained by the ImageNet dataset in the source domain, and by converting time-series signals to two-dimensional grayscale images, the CNN trained by image classification was adopted for fault classification of CWRU bearing data in the target domain.

The remaining transfer domains are collected by the "other" term in Figure 7. This includes various ideas, and three examples are detailed below. Since it is difficult to de-noise the data generated by seawater hydraulic pumps operating under harsh conditions, Miao et al. [59] used oil pump data as the auxiliary data, and by transferring diagnostic knowledge to a seawater hydraulic pump as the target data, the accuracy was improved by 30.5% compared with conventional machine learning methods. Also demonstrating the capacity of TL in dealing with noise, Fan et al. [60] pretrained a CNN on normal CWRU bearing data and fine-tuned the CNN on the same dataset with the addition of Gaussian white noise. A 96.67% diagnostic accuracy was achieved under strong noise at 10 dB signal to noise ratio [60]. The third example was research by Chen et al. [61], who applied TL to deal with missing data due to multi-rate sampling. Although sensors at different sampling rates produce only a few structurally incomplete samples, there are abundant data that are structurally incomplete. To make use of the abundant data that are structurally incomplete, Chen et al. [61] pretrained deep neural networks (DNNs) on the structurally incomplete data and transferred the parameters to boost the diagnostic accuracy of the final DNN trained with sparse structurally complete data.

4. Transfer Learning Research in Aerospace Fault Diagnosis

A thorough review of all existing literature concerning the application of TL to fault diagnosis in the aerospace sector was carried out. The key outcomes are summarised in Table 5.

4.1. Aero-Engines

For research on aero-engines, four studies focusing on engine gas path diagnosis from different transfer problem settings were identified. Zhao and Chen [62] considered the transfer between nominal state data (source dataset) and degraded state data (target dataset), and their work aimed to design an accurate diagnostic model based on very little target domain training data. By developing a turbofan engine simulation based on mathematical models, and using it to generate gas path data, they tested two extreme learning machine (ELM) based TL methods, which yielded better prediction accuracy than ELMs without TL under all noise levels [62]. Aimed at the transfer between various flight conditions, Li et al. [63] tested a unilateral alignment transfer neural network between simulated turbofan data at different operating points, and concluded that their method outperformed

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other feature-based TL algorithms. In contrast to other studies that mainly used simulation data, Liu [64] validated his TL-based gas path fault diagnostic algorithm against experimental data from China Eastern Airlines, and the diagnostic accuracy reached 95.6% when transferring from four engines, which were used as source data. Furthermore, transfer was also implemented between different aero-engine variants. As Zhou et al. [65] demonstrated, using a Residual-Back Propagation Neural Network (Res-BPNN) as the feature extractor, a deep domain-adaptation module, and a regression module, the model achieved diagnostic knowledge transfer between CFM56-5B2 and CFM56-7B26 datasets.

Table 5. Summary of transfer learning application in aerospace fault diagnosis.

Application - type	**Application - subtype**	**Domains of transfer**	**Relationship between the domains**	**Reference**
Aero-engines	Turbofan engine gas path	Between nominal state and degraded state data from aero-engine simulation under each working condition	Varied working conditions	[62]
		Between data taken at different working conditions of aero-engine simulation	Varied working conditions	[63]
		Between engines in an airline fleet	Different but similar machines	[64]
		Between CFM56-5B2 and CFM56-7B26	Different but similar machines	[65]
Gas turbines	Gas turbine gas path	Between data-rich gas turbines to data-poor gas turbines of the same type. Between GE9FA to Siemens V64.3 gas turbine	Different but similar machines	[66]
	Gas turbine combustion chamber	Between data-rich Taurus 70 gas turbine to data-poor Titan 130 gas turbine	Different but similar machines	[67]
	Gas turbine rotor	Under different working conditions. Between different gas turbines of the same type	Varied working conditions	[68]
Sensors	UAV inertial sensors	Between offline samples to online samples of UAV inertial sensors	Varied working conditions	[69]
	Spacecraft attitude determination & control system (ADCS)	Between digital simulation and semi-physical simulation of a ground micro triaxial air bearing table	Virtual to physical	[70]
		Between ADCS simulation and LightSail 2 solar satellite mission data	Virtual to physical	[71]
Actuators	Electro-mechanical actuators (EMAs)	Between EMAs with varying sensor position profiles, load profiles, and sensor output directions	Other	[72]
Structural components	Aeronautics composite material (ACM)	Between welding database and X-ray imaging of ACM	Other	[73]

	Wing damage	Between pre-repair wing to post-repair wing	Other	[74]
		Between Gnat aircraft wing and Piper Tomahawk aircraft wing	Different but similar machines	[75]
	Tailplane damage	Between tailplanes from “Arrow” variant and “Cherokee” variant of PA-28 aircraft	Different but similar machines	[76]
Other aerospace topics	Aircraft fuel pump	Between old and new centrifugal aircraft fuel pump	Varied working conditions	[39]
	Quadrotor	Between two quadrotor UAVs of different model and propeller diameter	Different but similar machines	[77]
	Commercial aircraft flight data	Between ground taxiing data and stable flight data	Varied working conditions	[78]

4.2. Gas Turbines

Owing to their similarity to aero-engines, gas turbines used for power generation are also an application field of interest. This sector has received attention from researchers interested in implementing TL to improve diagnostic accuracy. For instance, Yang et al. [66] transferred a CNN model trained on gas turbines with abundant labelled data to gas turbines with little labelled data and used the little labelled data to fine-tune the pretrained CNN model, and a final version of the CNN was obtained for the data-poor gas turbine. When the data-rich turbine generated 100% labelled data and the data-poor turbine generated 20% labelled data, the proposed method produced 98.37% and 98.92% diagnostic accuracy for GE9FA and Siemens V64.3 gas turbines, respectively [66]. The transfer scenario between different types of gas turbines was also discussed, and a 98.68% prediction accuracy was observed when the model was transferred from the GE9FA gas turbine with 100% labelled data to the Siemens V64.3 gas turbine with 20% labelled data [66]. In addition, following a similar process for transferring diagnostic knowledge from data-rich gas turbines to data-poor gas turbines, Bai et al. [67] investigated how this transfer approach benefitted gas turbine combustion chamber fault detection. The data-rich and data-poor gas turbines were set to be of different types, with the Taurus 70 gas turbine as the source domain, containing abundant faulty cases, and the Titan 130 gas turbine as the target domain, with few faulty cases [67]. The proposed CNN-based TL method produced a higher diagnostic accuracy (95.02%) for the data-poor gas turbine compared to directly mixing the data from data-rich and data-poor gas turbines for training and not conducting the transfer, which gave 91.19% accuracy by the best performing option among all algorithms tested [67]. Another aspect of gas turbines studied was gas turbine rotors. Liu et al. [68] installed vibration sensors on several commercial gas turbines and developed a TL-based rotor fault diagnostic algorithm to classify the rotors as in “normal state”, “air flow excited state”, “imbalance state” and “misalignment state”. The diagnostic accuracy reached 96.45% when diagnostic knowledge was transferred between data under different working conditions, and 95.13% when diagnostic knowledge was transferred between different gas turbines of the same type.

4.3. Sensors

The fault diagnosis of aerospace-related sensors has also received considerable attention. Gao et al. [69] employed a deep transfer learning algorithm based on representation adaptation to transfer a CNN model trained on offline samples to online samples of micro-electromechanical systems (MEMS) inertial sensors on unmanned aerial vehicles (UAVs). For spacecraft attitude determination and control systems (ADCS), He et al. [70] attempted to address the problem of the lack of faulty spacecraft samples. Selecting data generated from a digital simulation platform as the source dataset and data from a semi-physical experiment of a triaxial air bearing table as the target dataset, their TL

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method demonstrated a higher overall diagnostic efficiency than non-transfer methods. Experimenting on real mission-scale equipment, Mansell and Spencer [71] trained a diagnostic model consisting of a long short-term memory (LSTM) neural network on ADCS fault simulation data and transferred the model to the LightSail 2 mission data. As a major achievement, their TL approach discovered magnetometer glitches that were "completely unknown to the flight team before their discovery and diagnosis by the LSTM network" [71]. Moreover, the transfer scenario between different position profiles and the output directions of the sensors is discussed. Electro-Mechanical Actuators (EMAs) face a major challenge in their condition monitoring owing to their sensors [72]. Specifically, Siahpour et al. [72] expressed concerns that existing algorithms could not identify changes in the sensor location, directions, or characteristics when the actuator fails or in case of a sensor replacement. To mitigate the risk of degrading EMA diagnosis accuracy, Siahpour et al. [72] developed a deep transfer learning method to transfer diagnostic knowledge between data with three sensor position profiles (trapezoidal, triangular, and sine sweep) and three output directions (direction of actuator motion, vertical, and horizontal). Their cross-sensor fault diagnostic problems achieved over 95% overall diagnostic accuracy.

4.4. Structural Components

Another aerospace topic where TL helps in fault diagnosis is with structural components, such as fuselage damage identification and localisation. In this area, TL mainly helps by facilitating image recognition tasks. For inclusion defect detection of aeronautic composite material (ACM), since obtaining sufficient X-ray images showing inclusion defects of this high-quality product is difficult and expensive, Gong et al. [73] leveraged the abundant labelled samples from a welding database. Specifically, having observed a similar appearance of the inclusion defect by group "welds" and the inclusion defects in ACM imaging, Gong et al. [73] trained a deep network on 2300 samples from the GDXray database and transferred it to the non-destructive testing (NDT) X-ray imaging of ACM containing 40 training samples. The transferred deep network had 96.8% prediction accuracy. For the damage localisation of aircraft wings, since post-repair data is usually unlabelled, Gardner et al. [74] considered the need for TL from labelled pre-repair data to unlabelled post-repair data. By implementing domain adaptation by JDA, their final method produced a 96.4% prediction accuracy for the target domain test data [74]. The authors then conducted further TL research on aircraft wings, and in the work by Gardner et al. [75], the transfer scenario between two aircraft wings of different structures was studied – from the labelled Gnat aircraft wing to the unlabelled Piper Tomahawk aircraft wing dataset. In detail, an abstract graphical representation (attributed graph) was constructed for each wing in the beginning, and then by identifying the largest common substructure from the attributed graphs, "the most appropriate subset of label combinations from Gnat that can be mapped into the Piper Tomahawk and produce positive transfer" [75]. A 100% damage localisation accuracy was reported for the target domain wing following a domain adaptation TL method [75]. Furthermore, TL was also applied to transfer damage detection knowledge between different tailplanes. Bull et al. [76] applied a feature-based TL method, Transfer Component Analysis (TCA), to match the normal condition data from three tailplanes of different variants of the Piper PA-28 aircraft, which increased the true positive rate from 13% from the conventional method to 100% from the TCA method.

4.5. Other Aerospace Topics

Other TL studies include those on aircraft fuel pumps, quadrotors, and commercial aircraft flight data. For centrifugal aircraft fuel pumps, Qiu et al. [39] collected data from an old model and a new model of similar pumps on a test bench and showed that the instance-based TL method, TrAdaboost, significantly outperformed other methods when only sparse target domain data of the new pump was available. In a quadrotor unmanned aerial vehicle (UAV) study, Liu et al. [77] focused on detecting UAV propeller failures based on audio data and used CNN-based TL to transfer diagnostic knowledge between two UAV quadrotors of different models and propeller diameters. The CNN-

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based TL method produced a 91.82% prediction accuracy compared to a 55.00% accuracy using a non-TL method [77]. Regarding the flight data of commercial aircraft, Xiong et al. [78] used deep transfer learning with a recurrent neural network to transfer between ground taxiing data and stable flight data, focusing on the task of predicting the x-axis vibration acceleration at the next moment in time as an abnormality detection basis. A 30% prediction improvement was reported after applying the TL approach [78].

5. Limitation in Existing Research and Future Progress

The application of TL in fault diagnosis is a burgeoning field of research. However, through this literature review, existing research lacks diversity in the specific application and the domains of transfer. Future progress in applying TL to fault diagnosis and how it can facilitate CBM are suggested in this section.

5.1. The Research Gap in Application and Domains of Transfer

Section 3.2 concludes that bearings and gearboxes dominate the application choices, which is largely due to the existence of high-quality open-access datasets. This study supplements the similar comments made in 2019 by Zheng et al. [14], in a way suggesting that the lack of open-access data in other engineering applications might have impeded the wider application of TL. To explore an opportunity to widen the application in aerospace fields, Section 4 examines all TL research in the aerospace sector and discovered examples in aero-engines, gas turbines, sensors, actuators, structural components, fuel pumps, UAVs, and flight data. Structural components and flight data were considered as examples in structural health monitoring and motion tracing, and the rest were considered as examples of component-level fault diagnosis, but there was no application in system-level research. Compared to component-level research, the major difference is the component interactions in system-level analysis, and it requires research attention to understand how TL may help transfer knowledge of system-level fault diagnosis under the influence of component interactions. Future work by the authors will be based on the first research gap in applying TL to system- or subsystem-level fault diagnosis in aerospace systems.

The second research gap was inspired by the findings on the transfer domain choice. Section 3.3 reported that over three-quarters of the research work analysed focused on diagnostic knowledge transfer between the same machine under different working conditions or similar machines under different representations. While almost all existing TL research on fault diagnosis requires the existence of low-level similarities in similar data structures and physical parameters, future opportunities exist by finding ways to expand TL research to more dissimilar source and target domains and, ultimately, to address high-level transfer problems unbounded by the requirement of low-level similarities.

The lack of diversity in the specific application and domains of transfer in the existing literature is a good indication of the potential of developing high-level TL for fault diagnosis. With high-level TL solutions in fault diagnosis, the application of relevant research could see wider diversity, because the open-access dataset could be leveraged to design fault diagnosis solutions for other applications as well.

5.2. Future Progress

Section 2 revealed, through the history of TL, that the entire scope of TL should include both low-level transfer and high-level transfer solutions. Because high-level transfer has not been extensively researched in fault diagnosis, successful implementation of the idea would greatly expand the capability of TL. In fact, a few studies have demonstrated similar ideas and justified the feasibility of implementing TL between more dissimilar domains and seemingly unsimilar domains.

Regarding early attempts to expand TL research in fault diagnosis to more dissimilar source and target domains, two studies have been identified. Li et al. [79] considered the incorporation of new

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faults in the target domain that are unseen in the source domain. The problem was tackled by adding a classifier specialised in distinguishing new faults in the target domain from known faults in the source domain. Taking this thinking further, Deng et al. [80] explored how TL can be implemented in partial transfer scenarios in which the labels in the source and target domains are not identical, considering that "the partial transfer scenario is more common for industrial applications" [80]. A double-layer attention based generative adversarial network (DA-GAN) was built to address the partial transfer problem by guiding the model to identify which part of the data should be processed or ignored before domain adaptation, thereby promoting positive transfer while alleviating negative transfer [80]. The proposed model demonstrated the ability to handle transfer on different machines (TDM) and partial transfers with different faults. The model can bear five differences simultaneously: 1) different bearing types, e.g., ball bearing vs. rolling bearing, 2) different fault characteristics, e.g., artificial damage vs. early-stage degradation, 3) different damage modes, e.g., plastic deformation vs. inner race fault, 4) different machines, e.g., bearing datasets from different labs, and 5) different working conditions, e.g., 1500 rpm vs. 2400 rpm [80]. In these transfer scenarios, the proposed method resulted in 89.4% overall prediction accuracy, which is higher than that of other GAN-based methods (71.4% and 79.4%), and significantly higher than that of a feature-based method (39.6%) because of negative transfer.

Regarding high-level transfer problems, only one work on TL for fault diagnosis has been found, which is the research done by Liu et al. [81]. In their work, the target domain data was taken from an oil-gas treatment station, which contained very few samples in each fault state, and the source domain data was taken from a Tennessee Eastman (TE) process, which contained abundant samples in each fault state. Their work illustrated a high-level transfer problem, because the oil-gas treatment process in the target domain did not share any identical components or variables with the TE process in the source domain, and the components of each system did not share the same configuration. The adopted TL approach was to first pretrain a Residual Neural Network (ResNet) model on the source domain TE process data and then fine-tune the ResNet hyperparameters using the target domain oil-gas treatment station data. This method generated a diagnostic accuracy of 97.00% compared with 90.67% without the TL process, which demonstrates the possibility of improving the diagnostic accuracy in the target domain with a small amount of data by exposing the model to more training data in a dissimilar source domain via TL. To account for this result, Liu et al. [81] applied an explainable AI technique to visualise the attention regions of the ResNet network, i.e., what the network focuses on in terms of variables and time domains, with and without TL. They concluded that the improvement in the diagnostic accuracy after TL was due to the effect of TL on concentrating the attention regions of the ResNet network in the target domain. Furthermore, the concentrated attention regions in the target domain also share the highest similarity with the attention regions in the source domain. Hence, the reason for the improvement in diagnostic accuracy by TL can be described as the TL process selecting the most similar regions of the source and target domains and concentrating the focus of the diagnostic network on the selected region in the target domain. However, despite Liu et al. [81] demonstrating the successful implementation of TL on a high-level transfer problem, other high-level transfer examples are absent in fault diagnosis, revealing a research gap.

As a reflection of the work by Liu et al. [81], firstly, one crucial condition for achieving the knowledge transfer between the two dissimilar systems is that the diagnostic model used, ResNet, is capable of extracting features from datasets of different complexity. In their study, the ResNet model was pretrained on source domain data with 52 × 10 dimensions and fine-tuned on target domain data with 36 × 10 dimensions. This serves to inspire future work on the high-level transfer problem along the lines that the model used should be capable of handling input data with different complexities, which is inevitably associated with dissimilar source and target domains.

Secondly, after discovering that TL concentrated the attention region on the part of the target domain data with the highest similarity to that in the source domain, no physical explanation was found to accompany this finding. Had such explanations been provided, for example, by pointing

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out how the seemingly unrelated components in the two systems have similar effects on the systems or interact with the rest of the systems in a similar way, the clarity of the method and explainability of the results would have been further improved. Unlike low-level transfer scenarios where identical components are expected in the source domain and target domain systems, high-level transfer problems rely on the similarity between seemingly unrelated components of different systems, hence providing a physical explanation of why the seemingly unrelated components should be considered similar could be crucial when validating the result. From another perspective, finding similarities between seemingly unrelated components in different systems based on physical insight may also be the key to implementing TL in such scenarios. The method mentioned in Section 2.4, transfer learning by structural analogy, could be adapted to fault diagnosis applications as a high-level TL method following this approach and could provide ideas for future research.

From the above, two major directions for developing future solutions for high-level transfer problems are: 1) developing TL models that can handle source and target domain data with different complexities, and 2) establishing similarity between seemingly unrelated components in source and target domain systems with the help of physical insight. The authors of this work believe that a combination of the two approaches would result in an accurate and credible solution to high-level transfer problems.

5.3. Benefit and Potential for Aerospace Condition Based Maintenance

Currently, TL has demonstrated its ability to improve the diagnostic accuracy of fault diagnosis models when dealing with imperfect data in the target domain, such as scarce data, lack of labels, lack of faulty cases, or different distributions from the source domain. Hence, applying TL to the diagnostic model in aerospace CBM would improve its robustness and accuracy when encountering similar problems with real-case data. This advantage of TL would not only improve the diagnosis model, but would also help alleviate the challenges faced by CBM.

The first common challenge for aerospace CBM that TL can help alleviate is scarce failure data [82]. It can be dealt with using TL methods that leverage knowledge from a source domain where abundant failure data exists, for example, for a similar machine or under test conditions. This is particularly useful for aerospace CBM. Because aerospace vehicles are usually expensive and reliable, generating failure data for the safety-critical components that very rarely fail could only be practically and economically done by lab experiment [83]. The second challenge is, as CBM in aerospace faces strict legislation challenges before implementation, the improved accuracy and robustness against real-scenario problems brought about by applying TL would contribute to satisfying the strict legislative requirements. Currently, aviation legislators have restricted CBM applications to non-critical component, which means although CBM is a well-established concept in academic research, its application in aviation industry is still premature and unable to relieve the burdens brought by most of the interval-based tasks [83]. For aerospace CBM to relieve such burden and bring cost benefit by its real-world application, the CBM models must be reliable enough to be certified, hence the enhanced reliability brought by incorporating TL to fault diagnosis models could be critical to the implementation of aerospace CBM.

In the future, if the application of high-level TL in fault diagnosis is successfully developed, further benefits can be achieved, which should be considered as the potential of TL for aerospace CBM. The potential is the ability of high-level TL to reduce the costs associated with data generation. Although TL is designed to handle imperfect data in the target domain, a source domain with an adequate quantity of labelled data and proportion of failure data is still required. The collection of such high-quality datasets is expensive in most industries, including the aerospace industry. With high-level TL, knowledge may be leveraged from dissimilar domains, such as those with available high-quality datasets in another industry (e.g., leveraging bearing datasets to diagnose faults in automobile timing belts) or from a different machine in the same industry (e.g., leveraging a hydraulic system dataset for pneumatic system fault diagnosis). This would greatly improve the efficiency of using available high-quality datasets and potentially reduce the effort and expenses of

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generating high-quality datasets for new applications. As a result, it potentially encourages further research on aerospace CBM.

6. Summary and Conclusion

Aiming to explore the greatest extend of how TL facilitates fault diagnosis and aerospace CBM, this literature review studied beyond the existing TL methods applied to fault diagnosis. The investigation led to two major findings:

1. The whole scope of TL has been explored by studying the history of TL and comparing TL with similar methods, revealing:

   i) Learning from the history of TL, the scope of TL should include both low- and high-level transfer scenarios. TL algorithms exist for both scenarios, although high-level transfer scenarios have received little attention in their application to fault diagnosis.

   ii) By comparing TL with other methods that leverage previous knowledge, analogy has been identified as a powerful tool to leverage previous knowledge from seemingly unrelated domains, thus pointing to a way to develop TL algorithms for high-level transfer scenarios.
2. Research gaps have been identified by reviewing the existing research. These include:

   i) The paucity of applications beyond bearings and gearboxes. In aerospace fault diagnosis, little is known about how TL contributes to system- or subsystem-level fault diagnosis.

   ii) The lack of TL research between dissimilar source and target domains.

In conclusion, this paper explores TL and its application to fault diagnosis and its potential in aerospace CBM. The history of TL reveals that its scope exceeds low-level transfer scenarios, which corrects the common belief that TL relies only on low-level similarity and highlights the potential for developing TL between dissimilar domains. The research gap found in applying TL to dissimilar source and target domains also suggests that developing high-level TL methods for fault diagnosis would expand the boundary of research interest. A general approach for high-level problems, such as the one proposed, is to combine a model that handles data with different complexities and physical insight to account for the similarity between seemingly unrelated components. Upon successful implementation, high-level TL has the potential to greatly improve the efficiency of leveraging high-quality data from diverse fields for training fault diagnosis models and encouraging more research effort in aerospace CBM.

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Abbreviations

The following abbreviations are used in this manuscript:

CBM	Condition based maintenance
CNN	Convolutional neural network
CWRU	Case Western Reserve University
DNN	Deep neural network
DTL	Deep transfer learning
JDA	Joint distribution alignment
ML	Machine learning
MMD	Maximum mean discrepancy
TCA	Transfer component analysis
TL	Transfer learning

Appendix A

Table A1 lists the 200 papers that applies transfer learning to fault diagnosis, which are studied in this work. Information includes their specific application, the relationship between their source and target domains, publication years with reference associated with each paper.

Table A1. Summary of the 200 papers that applies transfer learning to fault diagnosis, as the source of the literature survey.

Paper number	Specific application	Transfer domains	Year	Reference
1	bearings	varied working conditions	2016	Shen, F., Chen, C., Yan, R., & Gao, R. X. (2016). Bearing fault diagnosis based on SVD feature extraction and transfer learning classification. *Proceedings of 2015 Prognostics and System Health Management Conference, PHM 2015*. https://doi.org/10.1109/PHM.2015.7380088
2	bearings	varied working conditions	2017	Zhang, R., Tao, H., Wu, L., & Guan, Y. (2017). Transfer Learning with Neural Networks for Bearing Fault Diagnosis in Changing Working Conditions. *IEEE Access*, *5*, 14347–14357. https://doi.org/10.1109/ACCESS.2017.2720965
3	bearings	varied working conditions	2017	Chen, C., Shen, F., & Yan, R. (2017). Enhanced least squares support vector machine-based transfer learning strategy for bearing fault diagnosis. *Yi Qi Yi Biao Xue Bao/Chinese Journal of Scientific Instrument*, *38*(1), 33–40.
4	bearings	varied working conditions	2018	Chen, D., Yang, S., & Zhou, F. (2018). Incipient Fault Diagnosis Based on DNN with Transfer Learning. *ICCAIS 2018 - 7th International Conference on Control, Automation and Information Sciences*, 303–308. https://doi.org/10.1109/ICCAIS.2018.8570702
5	bearings and gears	varied working conditions	2018	Qian, W., Li, S., & Wang, J. (2018). A New Transfer Learning Method and its Application on Rotating Machine Fault Diagnosis Under Variant Working Conditions. *IEEE Access*, *6*, 69907–69917. https://doi.org/10.1109/ACCESS.2018.2880770
6	bearings	varied working conditions	2018	Tong, Z., & Li, W. (2018). Bearing fault diagnosis based on transfer learning under various working conditions. *25th International Congress on Sound and Vibration 2018, ICSV 2018: Hiroshima Calling*, *5*, 2708–2715.
7	gearbox	split dataset	2018	Cao, P., Zhang, S., & Tang, J. (2018). Preprocessing-Free Gear Fault Diagnosis Using Small Datasets with Deep Convolutional Neural Network-Based Transfer Learning. *IEEE Access*, *6*, 26241–26253. https://doi.org/10.1109/ACCESS.2018.2837621
8	bearings	varied working conditions	2018	Tong, Z., Li, W., Zhang, B., Jiang, F., & Zhou, G. (2018). Bearing Fault Diagnosis under Variable Working Conditions Based on Domain Adaptation Using Feature Transfer Learning. *IEEE Access*, *6*, 76187–76197. https://doi.org/10.1109/ACCESS.2018.2883078
9	bearings	varied speed	2018	Hasan, M. J., & Kim, J. M. (2018). Bearing Fault Diagnosis under Variable Rotational Speeds Using Stockwell Transform-Based Vibration Imaging and Transfer Learning. *Applied Sciences 2018, Vol. 8, Page 2357*, *8*(12), 2357. https://doi.org/10.3390/APP8122357
10	HVCB	simulation to experiment	2019	Pan, Y., Mei, F., Miao, H., Zheng, J., Zhu, K., & Sha, H. (2019). An Approach for HVCB Mechanical Fault Diagnosis Based on a Deep Belief Network and a Transfer Learning Strategy. *Journal of Electrical Engineering and Technology*, *14*(1), 407–419. https://doi.org/10.1007/S42835-018-00048-Y/FIGURES/13
11	bearings	method: ImageNet and fault diagnosis	2019	Wen, L., Gao, L., Dong, Y., Zhu, Z., Wen, L., Gao, L., Dong, Y., & Zhu, Z. (2019). A negative correlation ensemble transfer learning method for fault diagnosis based on convolutional neural network. *Mathematical Biosciences and Engineering 2019 5:3311*, *16*(5), 3311–3330. https://doi.org/10.3934/MBE.2019165
12	production line	virtual to physical	2019	Xu, Y., Sun, Y., Liu, X., & Zheng, Y. (2019). A Digital-Twin-Assisted Fault Diagnosis Using Deep Transfer Learning. *IEEE Access*, *7*, 19990–19999. https://doi.org/10.1109/ACCESS.2018.2890566
13	gearboxes	different sampling rate	2019	Chen, D., Yang, S., & Zhou, F. (2019). Transfer learning based fault diagnosis with missing data due to multi-rate sampling. *Sensors (Switzerland)*, *19*(8). https://doi.org/10.3390/S19081826
14	bearings	varied working conditions	2019	Zhang, Z., Li, X., Wen, L., Gao, L., & Gao, Y. (2019). Fault diagnosis using unsupervised transfer learning based on adversarial network. *IEEE International Conference on Automation Science and Engineering*, *2019-August*, 305–310. https://doi.org/10.1109/COASE.2019.8842881
15	bearings	method: image classification to feature extraction	2019	Hoang, D. T., & Kang, H. J. (2019). A Bearing Fault Diagnosis Method using Transfer Learning and Dempster-Shafer Evidence Theory. *ACM International Conference Proceeding Series*, 33–38. https://doi.org/10.1145/3388218.3388220
16	induction motor	varied working conditions	2019	Xiao, D., Huang, Y., Qin, C., Liu, Z., Li, Y., & Liu, C. (2019). Transfer learning with convolutional neural networks for small sample size problem in machinery fault diagnosis. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, *233*(14), 5131–5143. https://doi.org/10.1177/0954406219840381
17	bearings	varied working conditions	2019	Chunfeng, W., Zheng, L., Jun, Z., & Wei, W. (2019). Heterogeneous Transfer Learning Based on Stack Sparse Auto-Encoders for Fault Diagnosis. *Proceedings 2018 Chinese Automation Congress, CAC 2018*, 4277–4281. https://doi.org/10.1109/CAC.2018.8623158
18	gas turbine	between datasets & machines	2019	Zhong, S. sheng, Fu, S., & Lin, L. (2019). A novel gas turbine fault diagnosis method based on transfer learning with CNN. *Measurement: Journal of the International Measurement Confederation*, *137*, 435–453. https://doi.org/10.1016/J.MEASUREMENT.2019.01.022
19	bearings	varied working conditions	2019	Wang, Q., Michau, G., & Fink, O. (2019). Domain Adaptive Transfer Learning for Fault Diagnosis. *Proceedings - 2019 Prognostics and System Health Management Conference, PHM-Paris 2019*, 279–285. https://doi.org/10.1109/PHM-PARIS.2019.00054
20	bearings	different types of bearings, varied working conditions	2019	Guo, L., Lei, Y., Xing, S., Yan, T., & Li, N. (2019). Deep Convolutional Transfer Learning Network: A New Method for Intelligent Fault Diagnosis of Machines with Unlabeled Data. *IEEE Transactions on Industrial Electronics*, *66*(9), 7316–7325. https://doi.org/10.1109/TIE.2018.2877090
21	bearings	varied working conditions	2019	Sun, M., Wang, H., Liu, P., Huang, S., & Fan, P. (2019). A sparse stacked denoising autoencoder with optimized transfer learning applied to the fault diagnosis of rolling bearings. *Measurement: Journal of the International Measurement Confederation*, *146*, 305–314. https://doi.org/10.1016/J.MEASUREMENT.2019.06.029
22	bearings	MUL to MURC	2019	Yang, B., Lei, Y., Jia, F., & Xing, S. (2019). A Transfer Learning Method for Intelligent Fault Diagnosis from Laboratory Machines to Real-Case Machines. *Proceedings - 2018 International Conference on Sensing, Diagnostics, Prognostics, and Control, SDPC 2018*, 35–40. https://doi.org/10.1109/SDPC.2018.8664814
23	bearings	varied working conditions	2019	Hasan, M. J., Sohaib, M., & Kim, J. M. (2019). 1D CNN-based transfer learning model for bearing fault diagnosis under variable working conditions. *Advances in Intelligent Systems and Computing*, *888*, 13–23. https://doi.org/10.1007/978-3-030-03302-6_2
24	N/A	N/A	2019	Zhang, Z., Liu, J., Huang, L., & Zhang, X. (2019). A bearing fault diagnosis method based on semi-supervised and transfer learning. *Beijing Hangkong Hangtian Daxue Xuebao/Journal of Beijing University of Aeronautics and Astronautics*, *45*(11), 2291–2300. https://doi.org/10.13700/J.BH.1001-5965.2019.0082
25	bearings	artificial to real damages	2019	Jiang, G., Xu, Z., & Guan, S. (2019). An intelligent bearing fault diagnosis method with transfer learning from artificial damage to real damage. *Proceedings - 2019 International Conference on Intelligent Computing, Automation and Systems, ICICAS 2019*, 464–469. https://doi.org/10.1109/ICICAS48597.2019.00103
26	N/A (survey paper on broad topics)	N/A (survey paper on broad topics)	2019	Zhao, Z., Zhang, Q., Yu, X., Sun, C., Wang, S., Yan, R., & Chen, X. (2021). Applications of Unsupervised Deep Transfer Learning to Intelligent Fault Diagnosis: A Survey and Comparative Study. *IEEE Transactions on Instrumentation and Measurement*, *70*. https://doi.org/10.1109/TIM.2021.3116309

27	bearing	varied working conditions	2019	Che, C., Wang, H., Fu, Q., & Ni, X. (2019). Deep transfer learning for rolling bearing fault diagnosis under variable operating conditions. *Advances in Mechanical Engineering*, *11*(12). https://doi.org/10.1177/1687814019897212
28	bearing	varied working conditions	2019	Xie, Y., & Zhang, T. (2019). A Transfer Learning Strategy for Rotation Machinery Fault Diagnosis based on Cycle-Consistent Generative Adversarial Networks. *Proceedings 2018 Chinese Automation Congress, CAC 2018*, 1309–1313. https://doi.org/10.1109/CAC.2018.8623346
29	bearing	varied working conditions	2019	Wen, L., Gao, L., & Li, X. (2019). A new deep transfer learning based on sparse auto-encoder for fault diagnosis. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *49*(1), 136–144. https://doi.org/10.1109/TSMC.2017.2754287
30	bearing	variable speed	2019	Hasan, M. J., Islam, M. M. M., & Kim, J. M. (2019). Acoustic spectral imaging and transfer learning for reliable bearing fault diagnosis under variable speed conditions. *Measurement: Journal of the International Measurement Confederation*, *138*, 620–631. https://doi.org/10.1016/J.MEASUREMENT.2019.02.075
31	bearings	method: image classification to fault classification	2019	Ma, P., Zhang, H., Fan, W., Wang, C., Wen, G., & Zhang, X. (2019). A novel bearing fault diagnosis method based on 2D image representation and transfer learning-convolutional neural network. *Measurement Science and Technology*, *30*(5), 055402. https://doi.org/10.1088/1361-6501/AB0793
32	bearings and gears	varied working conditions	2019	Qian, W., Li, S., Yi, P., & Zhang, K. (2019). A novel transfer learning method for robust fault diagnosis of rotating machines under variable working conditions. *Measurement: Journal of the International Measurement Confederation*, *138*, 514–525. https://doi.org/10.1016/J.MEASUREMENT.2019.02.073
33	bearings	varied working conditions	2019	Du, Z., Yang, B., Lei, Y., Li, X., & Li, N. (2019). A Hybrid Transfer Learning Method for Fault Diagnosis of Machinery under Variable Operating Conditions. *2019 Prognostics and System Health Management Conference, PHM-Qingdao 2019*. https://doi.org/10.1109/PHM-QINGDAO46334.2019.8942974
34	induction motor, bearings, gearbox	method: image classification to fault classification	2019	Shao, S., McAleer, S., Yan, R., & Baldi, P. (2019). Highly Accurate Machine Fault Diagnosis Using Deep Transfer Learning. *IEEE Transactions on Industrial Informatics*, *15*(4), 2446–2455. https://doi.org/10.1109/TII.2018.2864759
35	bearings, gearbox	varied working conditions	2019	Qian, W., Li, S., Wang, J., Xin, Y., & Ma, H. (2019). A New Deep Transfer Learning Network for Fault Diagnosis of Rotating Machine under Variable Working Conditions. *Proceedings - 2018 Prognostics and System Health Management Conference, PHM-Chongqing 2018*, 1010–1016. https://doi.org/10.1109/PHM-CHONGQING.2018.00180
36	bearings	lab to locomotive	2019	Yang, B., Lei, Y., Jia, F., & Xing, S. (2019). An intelligent fault diagnosis approach based on transfer learning from laboratory bearings to locomotive bearings. *Mechanical Systems and Signal Processing*, *122*, 692–706. https://doi.org/10.1016/J.YMSSP.2018.12.051
37	motor	real to invariant working condition	2019	Xiao, D., Huang, Y., Zhao, L., Qin, C., Shi, H., & Liu, C. (2019). Domain Adaptive Motor Fault Diagnosis Using Deep Transfer Learning. *IEEE Access*, *7*, 80937–80949. https://doi.org/10.1109/ACCESS.2019.2921480
38	bearings	method: image classification to fault classification	2019	Wen, L., Li, X., Li, X., & Gao, L. (2019). A new transfer learning based on VGG-19 network for fault diagnosis. *Proceedings of the 2019 IEEE 23rd International Conference on Computer Supported Cooperative Work in Design, CSCWD 2019*, 205–209. https://doi.org/10.1109/CSCWD.2019.8791884
39	transformer	similar machines	2019	Yang, Z., Zhou, R., Shen, Y., Yang, F., Lei, Y., & Yan, F. (2019). On-line Fault Identify and Diagnosis Model of Distribution Transformer Based on Parallel Big Data Stream and Transfer Learning. *Gaodianya Jishu/High Voltage Engineering*, *45*(6), 1697–1706. https://doi.org/10.13336/J.1003-6520.HVE.20190604003
40	fog radio access networks	dataset to dataset	2020	Wu, W., Peng, M., Chen, W., & Yan, S. (2020). Unsupervised Deep Transfer Learning for Fault Diagnosis in Fog Radio Access Networks. *IEEE Internet of Things Journal*, *7*(9), 8956–8966. https://doi.org/10.1109/JIOT.2020.2997187
41	diesel generator	simulation to machines	2020	Lei, X., & Lu, N. (2021). *A DEEP TRANSFER LEARNING BASE FAULT DIAGNOSIS METHOD FOR DIESEL GENERATOR*. 21–26. https://doi.org/10.1049/ICP.2021.1424
42	bearings	dataset to dataset	2020	Li, Z., Cao, Z., Luo, K., & Fu, H. (2020). A Novel Method for Fault Diagnosis of Rolling Bearings Based on Domain-Adversarial Partial Transfer Learning. *Proceedings - 11th International Conference on Prognostics and System Health Management, PHM-Jinan 2020*, 414–419. https://doi.org/10.1109/PHM-JINAN48558.2020.00080
43	N/A (review paper on broad topics)	N/A (review paper on broad topics)	2020	Li, C., Zhang, S., Qin, Y., & Estupinan, E. (2020). A systematic review of deep transfer learning for machinery fault diagnosis. *Neurocomputing*, *407*, 121–135. https://doi.org/10.1016/J.NEUCOM.2020.04.045
44	bearings	varied working conditions	2020	Xu, W., Wan, Y., Zuo, T. Y., & Sha, X. M. (2020). Transfer Learning Based Data Feature Transfer for Fault Diagnosis. *IEEE Access*, *8*, 76120–76129. https://doi.org/10.1109/ACCESS.2020.2989510
45	bearings	different sensor positions	2020	Shao, J., Huang, Z., & Zhu, J. (2020). Transfer Learning Method Based on Adversarial Domain Adaption for Bearing Fault Diagnosis. *IEEE Access*, *8*, 119421–119430. https://doi.org/10.1109/ACCESS.2020.3005243
46	bearings	variable load conditions	2020	Shi, J., Wu, X., Liu, X., & Liu, T. (2020). Mechanical fault diagnosis based on variational mode decomposition combined with deep transfer learning. *Nongye Gongcheng Xuebao/Transactions of the Chinese Society of Agricultural Engineering*, *36*(14), 129–137. https://doi.org/10.11975/J.ISSN.1002-6819.2020.14.016
47	bearings	varied working conditions	2020	Zhu, J., Chen, N., & Shen, C. (2020). A New Deep Transfer Learning Method for Bearing Fault Diagnosis under Different Working Conditions. *IEEE Sensors Journal*, *20*(15), 8394–8402. https://doi.org/10.1109/JSEN.2019.2936932
48	bearings, gears	varied working conditions	2020	Wu, J., Zhao, Z., Sun, C., Yan, R., & Chen, X. (2020). Few-shot transfer learning for intelligent fault diagnosis of machine. *Measurement: Journal of the International Measurement Confederation*, *166*. https://doi.org/10.1016/J.MEASUREMENT.2020.108202
49	spacecraft attitude system	split dataset	2020	Tang, Y., Dou, L., Zhang, R., Zhang, X., & Liu, W. (2020). Deep Transfer Learning-based Fault Diagnosis of Spacecraft Attitude System. *Chinese Control Conference, CCC*, *2020-July*, 4072–4077. https://doi.org/10.23919/CCC50068.2020.9188710
50	gearboxes	varied working conditions	2020	Wan, Z., Yang, R., & Huang, M. (2020). Deep Transfer Learning-Based Fault Diagnosis for Gearbox under Complex Working Conditions. *Shock and Vibration*, *2020*. https://doi.org/10.1155/2020/8884179
51	bearings	varied working conditions	2020	Wang, X., Shen, C., Xia, M., Wang, D., Zhu, J., & Zhu, Z. (2020). Multi-scale deep intra-class transfer learning for bearing fault diagnosis. *Reliability Engineering and System Safety*, *202*. https://doi.org/10.1016/J.RESS.2020.107050
52	bearings	varied working conditions	2020	Dong, S., He, K., & Tang, B. (2020). The fault diagnosis method of rolling bearing under variable working conditions based on deep transfer learning. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *42*(11). https://doi.org/10.1007/S40430-020-02661-3
53	diesel engines, bearings	method: image classification to fault classification	2020	Wu, D., Ren, G., Fan, H., & Li, X. (2020). Mechanical Fault Diagnosis based on Dual-tree Complex Wavelet Packet Time-frequency Distribution and Residual Network Transfer Learning. *2020 IEEE 5th International Conference on Signal and Image Processing, ICSIP 2020*, 877–882. https://doi.org/10.1109/ICSIP49896.2020.9339288
54	bearings	variable load conditions	2020	Wang, Y., Wang, C., Kang, S., Xie, J., Wang, Q., & Mikulovich, V. I. (2020). Network-combined broad learning and transfer learning: A new intelligent fault diagnosis method for rolling bearings. *Measurement Science and Technology*, *31*(11). https://doi.org/10.1088/1361-6501/AB8FEE
55	bearings	variable load conditions	2020	Xiang, G., Chen, W., Peng, Y., Wang, Y., & Qu, C. (2020). Deep Transfer Learning Based on Convolutional Neural Networks for Intelligent Fault Diagnosis of Spacecraft. *Proceedings - 2020 Chinese Automation Congress, CAC 2020*, 5522–5526. https://doi.org/10.1109/CAC51589.2020.9327214
56	bearing	varied working conditions	2020	Zhang, G. B., Li, H., Ran, Y., & Li, Q. J. (2020). A transfer learning model for bearing fault diagnosis. *Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)*, *50*(5), 1617–1626. https://doi.org/10.13229/J.CNKI.JDXBGXB20190493
57	CSTR, pulp mill	simulation to physical	2020	Li, W., Gu, S., Zhang, X., & Chen, T. (2020). Transfer learning for process fault diagnosis: Knowledge transfer from simulation to physical processes. *Computers and Chemical Engineering*, *139*. https://doi.org/10.1016/J.COMPCHEMENG.2020.106904

58	bearings and gears	varied working conditions	2020	Zhou, J., Yang, X., Zhang, L., Shao, S., & Bian, G. (2020). Multisignal VGG19 Network with Transposed Convolution for Rotating Machinery Fault Diagnosis Based on Deep Transfer Learning. *Shock and Vibration*, *2020*. https://doi.org/10.1155/2020/8863388
59	bearings	varied working conditions	2020	Cheng, C., Zhou, B., Ma, G., Wu, D., & Yuan, Y. (2020). Wasserstein distance based deep adversarial transfer learning for intelligent fault diagnosis with unlabeled or insufficient labeled data. *Neurocomputing*, *409*, 35–45. https://doi.org/10.1016/J.NEUCOM.2020.05.040
60	bearings	varied working conditions	2020	Jia, S., Wang, J., Han, B., Zhang, G., Wang, X., & He, J. (2020). A novel transfer learning method for fault diagnosis using maximum classifier discrepancy with marginal probability distribution adaptation. *IEEE Access*, *8*, 71475–71485. https://doi.org/10.1109/ACCESS.2020.2987933
61	seawater hydraulic pump	different machines (sea to oil)	2020	Miao, Y., Jiang, Y., Huang, J., Zhang, X., & Han, L. (2020). Application of Fault Diagnosis of Seawater Hydraulic Pump Based on Transfer Learning. *Shock and Vibration*, *2020*. https://doi.org/10.1155/2020/9630986
62	distribution transformer	similar machines	2020	Yang, Z., Shen, Y., Zhou, R., Yang, F., Wan, Z., & Zhou, Z. (2020). A transfer learning fault diagnosis model of distribution transformer considering multi-factor situation evolution. *IEEJ Transactions on Electrical and Electronic Engineering*, *15*(1), 30–39. https://doi.org/10.1002/TEE.23024
63	distribution transformer	similar machines	2020	Yang, Z., Shen, Y., Yang, F., Cai, W., & Liang, L. (2019). A Transfer Learning Fault Diagnosis Model of Distribution Transformer Considering Multi-Factor Situation Evolution. *Diangong Jishu Xuebao/Transactions of China Electrotechnical Society*, *34*(7), 1505–1515. https://doi.org/10.19595/J.CNKI.1000-6753.TCES.L80183
64	bearings	varied working conditions	2020	Li, J., Huang, R., & Li, W. (2020). Intelligent Fault Diagnosis for Bearing Dataset Using Adversarial Transfer Learning based on Stacked Auto-Encoder. *Procedia Manufacturing*, *49*, 75–80. https://doi.org/10.1016/J.PROMFG.2020.06.014
65	train bearings	varied working conditions	2020	Shen, C. Q., Wang, X., Wang, D., Que, H. B., Shi, J. J., & Zhu, Z. K. (2020). Multi-scale convolution intra-class transfer learning for train bearing fault diagnosis. *Jiaotong Yunshu Gongcheng Xuebao/Journal of Traffic and Transportation Engineering*, *20*(5), 151–164. https://doi.org/10.19818/J.CNKI.1671-1637.2020.05.012
66	gearbox	varied working conditions	2020	Chen, C., Shen, F., Fan, Z., Gao, R. X., & Yan, R. (2020). A KLIEP-based Transfer Learning Model for Gear Fault Diagnosis under Varying Working Conditions. *International Conference on Sensing, Measurement and Data Analytics in the Era of Artificial Intelligence, ICSMD 2020 - Proceedings*, 188–193. https://doi.org/10.1109/ICSMD50554.2020.9261691
67	bearings	varied working conditions	2020	Zhao, B., Zhang, X., Zhan, Z., & Pang, S. (2020). Deep multi-scale convolutional transfer learning network: A novel method for intelligent fault diagnosis of rolling bearings under variable working conditions and domains. *Neurocomputing*, *407*, 24–38. https://doi.org/10.1016/J.NEUCOM.2020.04.073
68	wind turbine gearbox	varied load	2020	Guo, J., Wu, J., Zhang, S., Long, J., Chen, W., Cabrera, D., & Li, C. (2020). Generative transfer learning for intelligent fault diagnosis of the wind turbine gearbox. *Sensors (Switzerland)*, *20*(5). https://doi.org/10.3390/S20051361
69	linear motion guide	high to low speed	2020	Cho, S. H., Kim, S., & Choi, J. H. (2020). Transfer learning-based fault diagnosis under data deficiency. *Applied Sciences (Switzerland)*, *10*(21), 1–11. https://doi.org/10.3390/APP10217768
70	bearings and gearbox	varied working conditions	2020	Li, J., Huang, R., He, G., Wang, S., Li, G., & Li, W. (2020). A Deep Adversarial Transfer Learning Network for Machinery Emerging Fault Detection. *IEEE Sensors Journal*, *20*(15), 8413–8422. https://doi.org/10.1109/JSEN.2020.2975286
71	bearings	lab to locomotive	2020	Zhao, K., Jiang, H., Wu, Z., & Lu, T. (2022). A novel transfer learning fault diagnosis method based on Manifold Embedded Distribution Alignment with a little labeled data. *Journal of Intelligent Manufacturing*, *33*(1), 151–165. https://doi.org/10.1007/S10845-020-01657-Z
72	gearbox	varied working conditions	2020	Li, J., Li, X., He, D., & Qu, Y. (2020). A domain adaptation model for early gear pitting fault diagnosis based on deep transfer learning network. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, *234*(1), 168–182. https://doi.org/10.1177/1748006X19867776
73	gearbox	lab to locomotive	2020	Yang, B., Lei, Y., Jia, F., Li, N., & Du, Z. (2020). A Polynomial Kernel Induced Distance Metric to Improve Deep Transfer Learning for Fault Diagnosis of Machines. *IEEE Transactions on Industrial Electronics*, *67*(11), 9747–9757. https://doi.org/10.1109/TIE.2019.2953010
74	N/A	N/A	2020	Jin, C., Ragab, M., & Aung, K. M. M. (2020). Secure Transfer Learning for Machine Fault Diagnosis Under Different Operating Conditions. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *12505 LNCS*, 278–297. https://doi.org/10.1007/978-3-030-62576-4_14
75	bearings	varied working conditions	2020	Li, X., Zhang, W., Ma, H., Luo, Z., & Li, X. (2020). Partial transfer learning in machinery cross-domain fault diagnostics using class-weighted adversarial networks. *Neural Networks*, *129*, 313–322. https://doi.org/10.1016/J.NEUNET.2020.06.014
76	quadrotors	different machines	2020	Liu, W., Chen, Z., & Zheng, M. (2020). An Audio-Based Fault Diagnosis Method for Quadrotors Using Convolutional Neural Network and Transfer Learning. *Proceedings of the American Control Conference*, *2020-July*, 1367–1372. https://doi.org/10.23919/ACC45564.2020.9148044
77	bearings	variable load conditions	2021	Song, X., Zhu, D., Liang, P., & An, L. (2021). A new bearing fault diagnosis method using elastic net transfer learning and LSTM. *Journal of Intelligent and Fuzzy Systems*, *40*(6), 12361–12369. https://doi.org/10.3233/JIFS-210503
78	bearings	dataset to machines	2021	Peng, C., Li, L., Chen, Q., Tang, Z., Gui, W., & He, J. (2021). A Fault Diagnosis Method for Rolling Bearings Based on Parameter Transfer Learning under Imbalance Data Sets. *Energies 2021, Vol. 14, Page 944*, *14*(4), 944. https://doi.org/10.3390/EN14040944
79	nuclear power plants	variable load conditions	2021	Wang, Z., Xia, H., Zhang, J., Annor-Nyarko, M., Zhu, S., Jiang, Y., & Yin, W. (2022). A deep transfer learning method for system-level fault diagnosis of nuclear power plants under different power levels. *Annals of Nuclear Energy*, *166*, 108771. https://doi.org/10.1016/J.ANUCENE.2021.108771
80	bearings, ball screw	test rigs to real machines	2021	Zhu, Z., Wang, L., Peng, G., & Li, S. (2021). WDA: An Improved Wasserstein Distance-Based Transfer Learning Fault Diagnosis Method. *Sensors 2021, Vol. 21, Page 4394*, *21*(13), 4394. https://doi.org/10.3390/S21134394
81	transformer windings	simulation to machines	2021	Duan, J., He, Y., & Wu, X. (2021). Serial transfer learning (STL) theory for processing data insufficiency: Fault diagnosis of transformer windings. *International Journal of Electrical Power & Energy Systems*, *130*, 106965. https://doi.org/10.1016/J.IJEPES.2021.106965
82	gearboxes	variable load conditions	2021	Qian, Q., Qin, Y., Wang, Y., & Liu, F. (2021). A new deep transfer learning network based on convolutional auto-encoder for mechanical fault diagnosis. *Measurement*, *178*, 109352. https://doi.org/10.1016/J.MEASUREMENT.2021.109352
83	bearings	variable load conditions	2021	Zhu, D., Song, X., Yang, J., Cong, Y., & Wang, L. (2021). A bearing fault diagnosis method based on L1 regularization transfer learning and LSTM deep learning. *2021 IEEE International Conference on Information Communication and Software Engineering, ICICSE 2021*, 308–312. https://doi.org/10.1109/ICICSE52190.2021.9404081
84	equipments	varied working conditions	2021	Xue, T., Wu, D., & Wang, H. (2021). Research on Application of Transfer Learning in Equipment Fault Diagnosis. *Journal of Physics: Conference Series*, *1986*(1), 012099. https://doi.org/10.1088/1742-6596/1986/1/012099
85	N/A (survey paper on broad topics)	N/A (survey paper on broad topics)	2021	Li, W., Huang, R., Li, J., Liao, Y., Chen, Z., He, G., Yan, R., & Gryllias, K. (2022). A perspective survey on deep transfer learning for fault diagnosis in industrial scenarios: Theories, applications and challenges. *Mechanical Systems and Signal Processing*, *167*. https://doi.org/10.1016/J.YMSSP.2021.108487
86	building energy systems	varied working conditions	2021	Liu, J., Zhang, Q., Li, X., Li, G., Liu, Z., Xie, Y., Li, K., & Liu, B. (2021). Transfer learning-based strategies for fault diagnosis in building energy systems. *Energy and Buildings*, *250*. https://doi.org/10.1016/J.ENBUILD.2021.111256
87	bearings	varied working conditions	2021	Wang, T., Li, T., Jiang, P., Cheng, Y., & Tang, T. (2022). A fault diagnosis method for rolling bearings based on inter-class repulsive force discriminant transfer learning. *Measurement Science and Technology*, *33*(1). https://doi.org/10.1088/1361-6501/AC2B72

88	bearings	variable load conditions	2021	He, J., Li, X., Chen, Y., Chen, D., Guo, J., & Zhou, Y. (2021). Deep Transfer Learning Method Based on 1D-CNN for Bearing Fault Diagnosis. *Shock and Vibration*, *2021*. https://doi.org/10.1155/2021/6687331
89	pump	simulation to machines	2021	Xia, M., Shao, H., Williams, D., Lu, S., Shu, L., & de Silva, C. W. (2021). Intelligent fault diagnosis of machinery using digital twin-assisted deep transfer learning. *Reliability Engineering and System Safety*, *215*. https://doi.org/10.1016/J.RESS.2021.107938
90	distribution transformer	machine to machine	2021	Yang, Z., Yang, F., Shen, Y., Yang, L., Su, L., Hu, W., & Le, J. (2023). On-Line Fault Diagnosis Model of Distribution Transformer Based on Parallel Big Data Stream and Transfer Learning. *IEEJ Transactions on Electrical and Electronic Engineering*, *18*(3), 332–340. https://doi.org/10.1002/TEE.23307
91	bearings	varied working conditions	2021	Liu, Y. Z., Shi, K. M., Li, Z. X., Ding, G. F., & Zou, Y. S. (2021). Transfer learning method for bearing fault diagnosis based on fully convolutional conditional Wasserstein adversarial Networks. *Measurement: Journal of the International Measurement Confederation*, *180*. https://doi.org/10.1016/J.MEASUREMENT.2021.109553
92	bearings	varied working conditions	2021	Zhang, X., Yu, D., & Liu, S. (2021). Fault Diagnosis Method for Small Sample Bearing Based on Transfer Learning. *Hsi-An Chiao Tung Ta Hsueh/Journal of Xi'an Jiaotong University*, *55*(10), 30–37. https://doi.org/10.7652/XJTUXB202110004
93	bearings	varied working conditions	2021	Ge, Y., Qin, J., & Ding, J. (2021). A Method of Bearing Fault Diagnosis Based on Transfer Learning Without Parameter. *Lecture Notes in Electrical Engineering*, *737*, 73–81. https://doi.org/10.1007/978-981-33-6318-2_9
94	transformer rectifier unit	machine to machine	2021	Chen, S., Ge, H., Li, H., Sun, Y., & Qian, X. (2021). Hierarchical deep convolution neural networks based on transfer learning for transformer rectifier unit fault diagnosis. *Measurement: Journal of the International Measurement Confederation*, *167*. https://doi.org/10.1016/J.MEASUREMENT.2020.108257
95	bearings	varied working conditions	2021	Wang, Z., Liu, Q., Chen, H., & Chu, X. (2021). A deformable CNN-DLSTM based transfer learning method for fault diagnosis of rolling bearing under multiple working conditions. *International Journal of Production Research*, *59*(16), 4811–4825. https://doi.org/10.1080/00207543.2020.1808261
96	bearings	machine to machine	2021	Xiang, S., Zhang, J., Gao, H., Shi, D., & Chen, L. (2021). A Deep Transfer Learning Method for Bearing Fault Diagnosis Based on Domain Separation and Adversarial Learning. *Shock and Vibration*, *2021*. https://doi.org/10.1155/2021/5540084
97	bearings	different type of bearings	2021	Wang, Z., He, X., Yang, B., & Li, N. (2022). Subdomain Adaptation Transfer Learning Network for Fault Diagnosis of Roller Bearings. *IEEE Transactions on Industrial Electronics*, *69*(8), 8430–8439. https://doi.org/10.1109/TIE.2021.3108726
98	wind turbine	machine to machine	2021	Li, Y., Jiang, W., Zhang, G., & Shu, L. (2021). Wind turbine fault diagnosis based on transfer learning and convolutional autoencoder with small-scale data. *Renewable Energy*, *171*, 103–115. https://doi.org/10.1016/J.RENENE.2021.01.143
99	industrial robot	split dataset	2021	Lee, K., Han, S., Pham, V. H., Cho, S., Choi, H. J., Lee, J., Noh, I., & Lee, S. W. (2021). Multi-objective instance weighting-based deep transfer learning network for intelligent fault diagnosis. *Applied Sciences (Switzerland)*, *11*(5), 1–21. https://doi.org/10.3390/APP11052370
100	bearings	varied working conditions	2021	Zou, Y., Liu, Y., Deng, J., Jiang, Y., & Zhang, W. (2021). A novel transfer learning method for bearing fault diagnosis under different working conditions. *Measurement: Journal of the International Measurement Confederation*, *171*. https://doi.org/10.1016/J.MEASUREMENT.2020.108767
101	bearings, gearboxes	varied working conditions	2021	Pei, X., Zheng, X., & Wu, J. (2021). Rotating Machinery Fault Diagnosis through a Transformer Convolution Network Subjected to Transfer Learning. *IEEE Transactions on Instrumentation and Measurement*, *70*. https://doi.org/10.1109/TIM.2021.3119137
102	sensor	offline to online samples	2021	Gao, T., Sheng, W., Yin, Y., & Du, X. (2021). A Transfer Learning Based Unmanned Aerial Vehicle MEMS Inertial Sensors Fault Diagnosis Method. *Journal of Physics: Conference Series*, *1852*(4). https://doi.org/10.1088/1742-6596/1852/4/042084
103	N/A	N/A	2021	Lou, Y., & Xiang, J. (2021). A machinery fault diagnosis method based on dynamical simulation driving feature transfer learning. *"Advances in Acoustics, Noise and Vibration - 2021" Proceedings of the 27th International Congress on Sound and Vibration, ICSV 2021*.
104	bearings	varied working conditions	2021	Li, F., Tang, T., Tang, B., & He, Q. (2021). Deep convolution domain-adversarial transfer learning for fault diagnosis of rolling bearings. *Measurement*, *169*, 108339. https://doi.org/10.1016/J.MEASUREMENT.2020.108339
105	bevel-gear	varied working conditions	2021	Di, Z. Y., Shao, H. D., & Xiang, J. W. (2021). Ensemble deep transfer learning driven by multisensor signals for the fault diagnosis of bevel-gear cross-operation conditions. *Science China Technological Sciences*, *64*(3), 481–492. https://doi.org/10.1007/S11431-020-1679-X
106	bearings	varied working conditions	2021	Wang, C., Zhu, G., Liu, T., Xie, Y., & Zhang, D. (2023). A sub-domain adaptive transfer learning base on residual network for bearing fault diagnosis. *JVC/Journal of Vibration and Control*, *29*(1–2), 105–117. https://doi.org/10.1177/10775463211042976
107	bearings, wind turbines	diverse working conditions & machines	2021	Han, T., Liu, C., Wu, R., & Jiang, D. (2021). Deep transfer learning with limited data for machinery fault diagnosis. *Applied Soft Computing*, *103*. https://doi.org/10.1016/J.ASOC.2021.107150
108	sensor	normal to different environment	2021	Sun, Y., Liu, S., Zhao, T., Zou, Z., Shen, B., Yu, Y., Zhang, S., & Zhang, H. (2021). A New Hydrogen Sensor Fault Diagnosis Method Based on Transfer Learning With LeNet-5. *Frontiers in Neurorobotics*, *15*. https://doi.org/10.3389/FNBOT.2021.664135
109	bearings	machine to machine	2021	Sun, M., Wang, H., Liu, P., Huang, S., Wang, P., & Meng, J. (2022). Stack Autoencoder Transfer Learning Algorithm for Bearing Fault Diagnosis Based on Class Separation and Domain Fusion. *IEEE Transactions on Industrial Electronics*, *69*(3), 3047–3058. https://doi.org/10.1109/TIE.2021.3066933
110	bearings, gearboxes	varied working conditions	2021	Li, Y., Ren, Y., Zheng, H., Deng, Z., & Wang, S. (2021). A Novel Cross-Domain Intelligent Fault Diagnosis Method Based on Entropy Features and Transfer Learning. *IEEE Transactions on Instrumentation and Measurement*, *70*. https://doi.org/10.1109/TIM.2021.3122742
111	bearing	different but similar machines & conditions	2021	Yang, Z., Yang, R., & Huang, M. (2021). Rolling bearing incipient fault diagnosis method based on improved transfer learning with hybrid feature extraction. *Sensors*, *21*(23). https://doi.org/10.3390/S21237894
112	bearing	different but similar machines, varied working conditions	2021	Zheng, Z., Fu, J., Lu, C., & Zhu, Y. (2021). Research on rolling bearing fault diagnosis of small dataset based on a new optimal transfer learning network. *Measurement: Journal of the International Measurement Confederation*, *177*. https://doi.org/10.1016/J.MEASUREMENT.2021.109285
113	bearings	different but similar machines, varied working conditions	2021	Yang, Z., Wang, X., & Yang, R. (2021). Transfer Learning Based Rolling Bearing Fault Diagnosis. *Proceedings of 2021 IEEE 10th Data Driven Control and Learning Systems Conference, DDCLS 2021*, 354–359. https://doi.org/10.1109/DDCLS52934.2021.9455448
114	bearings and gears	varied working conditions	2021	Shao, J., Huang, Z., Zhu, Y., Zhu, J., & Fang, D. (2021). Rotating machinery fault diagnosis by deep adversarial transfer learning based on subdomain adaptation. *Advances in Mechanical Engineering*, *13*(8). https://doi.org/10.1177/16878140211040226
115	aircraft fuel pump	similar machines	2021	Qiu, Z., Miao, Y., Hong, W., Jiang, Y., Liu, Y., Pan, J., & Li, X. (2021). Fault diagnosis of aircraft fuel pump based on transfer learning. *2021 7th International Conference on Condition Monitoring of Machinery in Non-Stationary Operations, CMMNO 2021*, 171–175. https://doi.org/10.1109/CMMNO53328.2021.9467576
116	bearings	varied working conditions	2021	Chen, R., Zhu, Y., Hu, X., Zhao, S., & Zhang, X. (2021). Fault diagnosis of rolling bearing under different working conditions using adaptation regularization based transfer learning. *Yi Qi Yi Biao Xue Bao/Chinese Journal of Scientific Instrument*, *42*(8), 95–103. https://doi.org/10.19650/J.CNKI.CJSI.J2107721

117	reciprocating compressor valve	lab to real case	2021	Guo, F. Y., Zhang, Y. C., Wang, Y., Ren, P. J., & Wang, P. (2021). Fault Diagnosis of Reciprocating Compressor Valve Based on Transfer Learning Convolutional Neural Network. *Mathematical Problems in Engineering*, *2021*. https://doi.org/10.1155/2021/8891424
118	bearings	TIM and TDM	2021	Deng, Y., Huang, D., Du, S., Li, G., Zhao, C., & Lv, J. (2021). A double-layer attention based adversarial network for partial transfer learning in machinery fault diagnosis. *Computers in Industry*, *127*. https://doi.org/10.1016/J.COMPIND.2021.103399
119	gearbox	varied working conditions	2021	Zhang, X., Han, B., Wang, J., Zhang, Z., & Yan, Z. (2021). A novel transfer-learning method based on selective normalization for fault diagnosis with limited labeled data. *Measurement Science and Technology*, *32*(10). https://doi.org/10.1088/1361-6501/AC03E5
120	bearings, pump	method: image classification to fault classification	2021	Zhang, D., & Zhou, T. (2021). Deep Convolutional Neural Network Using Transfer Learning for Fault Diagnosis. *IEEE Access*, *9*, 43889–43897. https://doi.org/10.1109/ACCESS.2021.3061530
121	gearbox	varied working conditions	2021	Chen, R., Yang, X., Hu, X., Li, J., Chen, C., & Tang, L. (2021). Planetary gearbox fault diagnosis method based on deep belief network transfer learning. *Zhendong Yu Chongji/Journal of Vibration and Shock*, *40*(1). https://doi.org/10.13465/J.CNKI.JVS.2021.01.017
122	bearings	method: image classification to fault classification	2021	Ruhi, Z. M., Jahan, S., & Uddin, J. (2021). A novel hybrid signal decomposition technique for transfer learning based industrial fault diagnosis. *Annals of Emerging Technologies in Computing*, *5*(4), 37–53. https://doi.org/10.33166/AETIC.2021.04.004
123	A/C sensor	different but similar machines	2021	Li, X., & Kong, X. (2021). Aircraft sensor Fault Diagnosis Method Based on Residual Antagonism Transfer Learning. *2021 IEEE International Conference on Artificial Intelligence and Industrial Design, AIID 2021*, 469–472. https://doi.org/10.1109/AIID51893.2021.9456530
124	machining tool	split dataset	2021	Deebak, B. D., & Al-Turjman, F. (2022). Digital-twin assisted: Fault diagnosis using deep transfer learning for machining tool condition. *International Journal of Intelligent Systems*, *37*(12), 10289–10316. https://doi.org/10.1002/INT.22493
125	analog circuits	split dataset	2021	Yu, D., Zhang, A., & Mu, W. (2021). SCA-SVM Fault Diagnosis of Analog Circuits Based on Transfer Learning. *Proceedings of 2021 IEEE 10th Data Driven Control and Learning Systems Conference, DDCLS 2021*, 818–823. https://doi.org/10.1109/DDCLS52934.2021.9455518
126	rare earth extraction equipment	method: image classification to fault classification	2021	Li, A. H., Luo, Y., He, Y. H., Cheng, Z., Wang, T. F., & Peng, Y. H. (2021). Fault diagnosis method of rare earth extraction production line based on wavelet packet and alexnet transfer learning. *Journal of Physics: Conference Series*, *1820*(1). https://doi.org/10.1088/1742-6596/1820/1/012102
127	gears, bearings	varied working conditions	2021	Xiang, G., & Tian, K. (2021). Spacecraft Intelligent Fault Diagnosis under Variable Working Conditions via Wasserstein Distance-Based Deep Adversarial Transfer Learning. *International Journal of Aerospace Engineering*, *2021*. https://doi.org/10.1155/2021/6099818
128	bearings	simulation to physical	2021	Dong, Y., Li, Y., Zheng, H., Wang, R., & Xu, M. (2022). A new dynamic model and transfer learning based intelligent fault diagnosis framework for rolling element bearings race faults: Solving the small sample problem. *ISA Transactions*, *121*, 327–348. https://doi.org/10.1016/J.ISATRA.2021.03.042
129	bearings	lab to industrial	2021	Cao, X., Wang, Y., Chen, B., & Zeng, N. (2021). Domain-adaptive intelligence for fault diagnosis based on deep transfer learning from scientific test rigs to industrial applications. *Neural Computing and Applications*, *33*(9), 4483–4499. https://doi.org/10.1007/S00521-020-05275-X
130	motor	lab to real machine	2021	Fang, Y., Wang, M., & Wei, L. (2021). Deep Transfer Learning in Inter-turn Short Circuit Fault Diagnosis of PMSM. *2021 IEEE International Conference on Mechatronics and Automation, ICMA 2021*, 489–494. https://doi.org/10.1109/ICMA52036.2021.9512785
131	transformer	simulation to physical	2021	Liu, X., He, Y., & Wang, L. (2021). Adaptive transfer learning based on a two-stream densely connected residual shrinkage network for transformer fault diagnosis over vibration signals. *Electronics (Switzerland)*, *10*(17). https://doi.org/10.3390/ELECTRONICS10172130
132	bearings	original to noise sample	2021	Fan, H., Xue, C., Zhang, X., Cao, X., Gao, S., & Shao, S. (2021). Vibration Images-Driven Fault Diagnosis Based on CNN and Transfer Learning of Rolling Bearing under Strong Noise. *Shock and Vibration*, *2021*. https://doi.org/10.1155/2021/6616592
133	gas turbine	different types of machine	2021	Yang, X., Bai, M., Liu, J., Liu, J., & Yu, D. (2021). Gas path fault diagnosis for gas turbine group based on deep transfer learning. *Measurement: Journal of the International Measurement Confederation*, *181*. https://doi.org/10.1016/J.MEASUREMENT.2021.109631
134	bearings	varied working conditions	2021	Si, J., Shi, H., Chen, J., & Zheng, C. (2021). Unsupervised deep transfer learning with moment matching: A new intelligent fault diagnosis approach for bearings. *Measurement: Journal of the International Measurement Confederation*, *172*. https://doi.org/10.1016/J.MEASUREMENT.2020.108827
135	wind turbine, pump truck	varied operating or climate conditions	2021	Deng, Z., Wang, Z., Tang, Z., Huang, K., & Zhu, H. (2021). A deep transfer learning method based on stacked autoencoder for cross-domain fault diagnosis. *Applied Mathematics and Computation*, *408*, 126318. https://doi.org/10.1016/J.AMC.2021.126318
136	bearings	split dataset	2021	Zhang, N., Li, Y., Yang, X., & Zhang, J. (2021). Bearing Fault Diagnosis Based on BP Neural Network and Transfer Learning. *Journal of Physics: Conference Series*, *1881*(2). https://doi.org/10.1088/1742-6596/1881/2/022084
137	gearbox	varied working conditions	2021	Chen, C., Shen, F., Xu, J., & Yan, R. (2021). Domain Adaptation-Based Transfer Learning for Gear Fault Diagnosis under Varying Working Conditions. *IEEE Transactions on Instrumentation and Measurement*, *70*. https://doi.org/10.1109/TIM.2020.3011584
138	bearings	split dataset	2021	Zhang, W., & Li, X. (2022). Federated Transfer Learning for Intelligent Fault Diagnostics Using Deep Adversarial Networks with Data Privacy. *IEEE/ASME Transactions on Mechatronics*, *27*(1), 430–439. https://doi.org/10.1109/TMECH.2021.3065522
139	bearings	varied speed	2021	Schwendemann, S., Amjad, Z., & Sikora, A. (2021). Bearing fault diagnosis with intermediate domain based Layered Maximum Mean Discrepancy: A new transfer learning approach. *Engineering Applications of Artificial Intelligence*, *105*. https://doi.org/10.1016/J.ENGAPPAI.2021.104415
140	bearings	different machines	2022	Jia, S., Deng, Y., Lv, J., Du, S., & Xie, Z. (2022). Joint distribution adaptation with diverse feature aggregation: A new transfer learning framework for bearing diagnosis across different machines. *Measurement: Journal of the International Measurement Confederation*, *187*. https://doi.org/10.1016/J.MEASUREMENT.2021.110332
141	bearings	varied working conditions	2022	Kuang, J., Xu, G., Zhang, S., Tao, T., Wei, F., & Yu, Y. (2022). A deep partial adversarial transfer learning network for cross-domain fault diagnosis of machinery. *Proceedings - 2022 Prognostics and Health Management Conference, PHM-London 2022*, 507–512. https://doi.org/10.1109/PHM2022-LONDON52454.2022.00095
142	building energy system	varied working conditions	2022	Zhang, Q., Tian, Z., Niu, J., Zhu, J., & Lu, Y. (2022). A study on transfer learning in enhancing performance of building energy system fault diagnosis with extremely limited labeled data. *Building and Environment*, *225*, 109641. https://doi.org/10.1016/J.BUILDENV.2022.109641
143	bearings	lab to real	2022	Wang, R., Jiang, H., Wu, Z., Xu, J., & Zhang, J. (2022). A reinforcement transfer learning method based on a policy gradient for rolling bearing fault diagnosis. *Measurement Science and Technology*, *33*(6), 065020. https://doi.org/10.1088/1361-6501/AC50E7
144	HVCB (circuit breaker)	lab to real	2022	Wang, Y., Yan, J., Wang, J., & Geng, Y. (2022). A Novel Hybrid Transfer Learning Approach for Small-Sample High-Voltage Circuit Breaker Fault Diagnosis On-site. *Proceedings of 2022 IEEE 5th International Electrical and Energy Conference, CIEEC 2022*, 922–927. https://doi.org/10.1109/CIEEC54735.2022.9846507
145	bearings	varied working conditions	2022	Tong, J., Liu, C., Zheng, J., Pan, H., Wang, X., & Bao, J. (2022). 1D-DRSETL: a novel unsupervised transfer learning method for cross-condition fault diagnosis of rolling bearing. *Measurement Science and Technology*, *33*(8), 085110. https://doi.org/10.1088/1361-6501/AC6F46

146	aero engines	similar machines (different age)	2022	Zhao, Y. P., & Chen, Y. bin. (2022). Extreme learning machine based transfer learning for aero engine fault diagnosis. *Aerospace Science and Technology*, *121*, 107311. https://doi.org/10.1016/J.AST.2021.107311
147	HVCB (circuit breaker)	lab to real	2022	Wang, Y., Yan, J., Ye, X., Jing, Q., Wang, J., & Geng, Y. (2022). Few-Shot Transfer Learning With Attention Mechanism for High-Voltage Circuit Breaker Fault Diagnosis. *IEEE Transactions on Industry Applications*, *58*(3), 3353–3360. https://doi.org/10.1109/TIA.2022.3159617
148	bearings	different but similar machines	2022	Wang, T., Li, T., Jiang, P., Cheng, Y., & Tang, T. (2021). A fault diagnosis method for rolling bearings based on inter-class repulsive force discriminant transfer learning. *Measurement Science and Technology*, *33*(1), 015011. https://doi.org/10.1088/1361-6501/AC2B72
149	bearings	varied working conditions	2022	Li, Y., Wan, H., & Jiang, L. (2022). Alignment subdomain-based deep convolutional transfer learning for machinery fault diagnosis under different working conditions. *Measurement Science and Technology*, *33*(5), 055006. https://doi.org/10.1088/1361-6501/AC40A7
150	gas turbine	varied working conditions	2022	Liu, S., Wang, H., Tang, J., & Zhang, X. (2022). Research on fault diagnosis of gas turbine rotor based on adversarial discriminative domain adaption transfer learning. *Measurement*, *196*, 111174. https://doi.org/10.1016/J.MEASUREMENT.2022.111174
151	inverter	varied working conditions	2022	Sun, Q., Peng, F., & Li, H. (2022). Small Sample Fault Diagnosis Method of Three-phase Inverter Based on Transfer Learning. *2022 Global Reliability and Prognostics and Health Management Conference, PHM-Yantai 2022*. https://doi.org/10.1109/PHM-YANTAI55411.2022.9942185
152	bearings	different but similar machines	2022	Shi, H., & Shang, Y. (2022). Initial Fault Diagnosis of Rolling Bearing Based on Second-Order Cyclic Autocorrelation and DCAE Combined with Transfer Learning. *IEEE Transactions on Instrumentation and Measurement*, *71*. https://doi.org/10.1109/TIM.2021.3132065
153	nuclear power plant	varied working conditions	2022	Li, J., Lin, M., Li, Y., & Wang, X. (2022). Transfer learning with limited labeled data for fault diagnosis in nuclear power plants. *Nuclear Engineering and Design*, *390*, 111690. https://doi.org/10.1016/J.NUCENGDES.2022.111690
154	bearings	varied working conditions	2022	Hu, Q., Si, X., Qin, A., Lv, Y., & Liu, M. (2022). Balanced Adaptation Regularization Based Transfer Learning for Unsupervised Cross-Domain Fault Diagnosis. *IEEE Sensors Journal*, *22*(12), 12139–12151. https://doi.org/10.1109/JSEN.2022.3174396
155	gearbox	varied working conditions	2022	Du, Y., Cheng, X., Liu, Y., Dou, S., Tu, J., Liu, Y., & Su, X. (2023). Gearbox Fault Diagnosis Method Based on Improved MobileNetV3 and Transfer Learning. *Tehnički Vjesnik*, *30*(1), 198–206. https://doi.org/10.17559/TV-20221025165425
156	bearings	varied working conditions	2022	Kuang, J., Xu, G., Tao, T., & Wu, Q. (2022). Class-Imbalance Adversarial Transfer Learning Network for Cross-Domain Fault Diagnosis with Imbalanced Data. *IEEE Transactions on Instrumentation and Measurement*, *71*. https://doi.org/10.1109/TIM.2021.3136175
157	bearings	different but similar machines	2022	Sun, M., Wang, H., Liu, P., Huang, S., Wang, P., & Meng, J. (2022). Stack Autoencoder Transfer Learning Algorithm for Bearing Fault Diagnosis Based on Class Separation and Domain Fusion. *IEEE Transactions on Industrial Electronics*, *69*(3), 3047–3058. https://doi.org/10.1109/TIE.2021.3066933
158	bearings	varied working conditions	2022	Hou, Y., Yang, A., Guo, W., Zheng, E., Xiao, Q., Guo, Z., & Huang, Z. (2022). Bearing Fault Diagnosis Under Small Data Set Condition: A Bayesian Network Method With Transfer Learning for Parameter Estimation. *IEEE Access*, *10*, 35768–35783. https://doi.org/10.1109/ACCESS.2022.3151240
159	bearings	different but similar machines	2022	Wang, Z., He, X., Yang, B., & Li, N. (2022). Subdomain Adaptation Transfer Learning Network for Fault Diagnosis of Roller Bearings. *IEEE Transactions on Industrial Electronics*, *69*(8), 8430–8439. https://doi.org/10.1109/TIE.2021.3108726
160	rotor system	different but similar machines	2022	Wang, S., Wang, Q., Xiao, Y., Liu, W., & Shang, M. (2022). Research on rotor system fault diagnosis method based on vibration signal feature vector transfer learning. *Engineering Failure Analysis*, *139*, 106424. https://doi.org/10.1016/J.ENGFAILANAL.2022.106424
161	motor	simulation to real	2022	Huangfu, H., Zhou, Y., Zhang, J., Ma, S., Fang, Q., & Wang, Y. (2022). Research on Inter-Turn Short Circuit Fault Diagnosis of Electromechanical Actuator Based on Transfer Learning and VGG16. *Electronics 2022, Vol. 11, Page 1232*, *11*(8), 1232. https://doi.org/10.3390/ELECTRONICS11081232
162	bearings	varied working conditions	2022	Zhang, W., Zhang, P., He, X., & Zhang, D. (2022). Convolutional Neural Network Based Two-Layer Transfer Learning for Bearing Fault Diagnosis. *IEEE Access*, *10*, 109779–109794. https://doi.org/10.1109/ACCESS.2022.3213657
163	bearings	different but similar machines	2022	Zhang, Y., Liu, W., Gu, H., Alexisa, A., & Jiang, X. (2022). A novel wind turbine fault diagnosis based on deep transfer learning of improved residual network and multi-target data. *Measurement Science and Technology*, *33*(9), 095007. https://doi.org/10.1088/1361-6501/AC7036
164	bearings	varied working conditions	2022	Chen, J., Li, J., Huang, R., Yue, K., Chen, Z., & Li, W. (2022). Federated Transfer Learning for Bearing Fault Diagnosis With Discrepancy-Based Weighted Federated Averaging. *IEEE Transactions on Instrumentation and Measurement*, *71*. https://doi.org/10.1109/TIM.2022.3180417
165	gearbox	simulation to real	2022	Xiong, Z., Li, M., Tang, Y., Xiao, S., & Song, M. (2022). Research on fault diagnosis method of deep transfer learning driven by simulation data. *Vibroengineering Procedia*, *43*, 21–26. https://doi.org/10.21595/VP.2022.22674
166	bearings	varied working conditions	2022	Huo, C., Jiang, Q., Shen, Y., Qian, C., & Zhang, Q. (2022). New transfer learning fault diagnosis method of rolling bearing based on ADC-CNN and LATL under variable conditions. *Measurement*, *188*, 110587. https://doi.org/10.1016/J.MEASUREMENT.2021.110587
167	gearbox	method: image classification to fault classification	2022	Li, H., Lv, Y., Yuan, R., Dang, Z., Cai, Z., & An, B. (2022). Fault diagnosis of planetary gears based on intrinsic feature extraction and deep transfer learning. *Measurement Science and Technology*, *34*(1), 014009. https://doi.org/10.1088/1361-6501/AC9543
168	gearbox	different but similar machines	2022	Pacheco, F., Drimus, A., Duggen, L., Cerrada, M., Cabrera, Di., & Sanchez, R. V. (2022). Deep Ensemble-Based Classifier for Transfer Learning in Rotating Machinery Fault Diagnosis. *IEEE Access*, *10*, 29778–29787. https://doi.org/10.1109/ACCESS.2022.3158023
169	bearings	varied working conditions	2022	Wang, C., Zhu, G., Liu, T., Xie, Y., & Zhang, D. (2021). A sub-domain adaptive transfer learning base on residual network for bearing fault diagnosis. *Https://Doi.Org/10.1177/10775463211042976*, *29*(1–2), 105–117. https://doi.org/10.1177/10775463211042976
170	bearings	method: image classification to fault classification	2022	Wang, Z., Shangguan, W., Peng, C., & Cai, B. (2022). A fault diagnosis method based on data feature reconstruction and deep transfer learning. *2022 IEEE Asia-Pacific Conference on Image Processing, Electronics and Computers, IPEC 2022*, 1–5. https://doi.org/10.1109/IPEC54454.2022.9777526
171	bearings	method: image classification to fault classification	2022	Zhou, J., Yang, X., & Li, J. (2022). Deep Residual Network Combined with Transfer Learning Based Fault Diagnosis for Rolling Bearing. *Applied Sciences 2022, Vol. 12, Page 7810*, *12*(15), 7810. https://doi.org/10.3390/APP12157810
172	bearings	varied working conditions	2022	He, W., Chen, J., Zhou, Y., Liu, X., Chen, B., & Guo, B. (2022). An Intelligent Machinery Fault Diagnosis Method Based on GAN and Transfer Learning under Variable Working Conditions. *Sensors 2022, Vol. 22, Page 9175*, *22*(23), 9175. https://doi.org/10.3390/S22239175
173	bearings	varied working conditions	2022	Jiang, L., Zheng, C., & Li, Y. (2022). Rotating machinery fault diagnosis based on transfer learning and an improved convolutional neural network. *Measurement Science and Technology*, *33*(10), 105012. https://doi.org/10.1088/1361-6501/AC7D3D
174	bearings	varied working conditions	2022	Zhao, J., Yang, S., Li, Q., Liu, Y., & Wang, J. (2022). Reply to Comment on 'A novel transfer learning bearing fault diagnosis method based on multiple-source domain adaptation.' *Measurement Science and Technology*, *33*(9), 098001. https://doi.org/10.1088/1361-6501/AC6D48
175	bearings	different but similar machines	2022	Wang, Z., Cui, J., Cai, W., & Li, Y. (2022). Partial Transfer Learning of Multidiscriminator Deep Weighted Adversarial Network in Cross-Machine Fault Diagnosis. *IEEE Transactions on Instrumentation and Measurement*, *71*. https://doi.org/10.1109/TIM.2022.3166786

176	bearings	varied working conditions	2022	Rakitzis, A., Nguyen, K. T. P., Tran, K. P., Zhang, R., & Gu, Y. (2022). A Transfer Learning Framework with a One-Dimensional Deep Subdomain Adaptation Network for Bearing Fault Diagnosis under Different Working Conditions. *Sensors 2022, Vol. 22, Page 1624*, *22*(4), 1624. https://doi.org/10.3390/S22041624
177	bearings	different but similar machines	2022	Asutkar, S., Chalke, C., Shivgan, K., & Tallur, S. (2023). TinyML-enabled edge implementation of transfer learning framework for domain generalization in machine fault diagnosis. *Expert Systems with Applications*, *213*, 119016. https://doi.org/10.1016/J.ESWA.2022.119016
178	bearings	different but similar machines	2022	Liu, G., Shen, W., Gao, L., & Kusiak, A. (2023). Automated broad transfer learning for cross-domain fault diagnosis. *Journal of Manufacturing Systems*, *66*, 27–41. https://doi.org/10.1016/J.JMSY.2022.11.003
179	bearings	varied working conditions	2022	Chen, R., Zhu, Y., Yang, L., Hu, X., & Chen, G. (2022). Adaptation Regularization Based on Transfer Learning for Fault Diagnosis of Rotating Machinery Under Multiple Operating Conditions. *IEEE Sensors Journal*, *22*(11), 10655–10662. https://doi.org/10.1109/JSEN.2022.3165398
180	oil-gas treatment station	different machines	2022	Liu, J., Hou, L., Zhang, R., Sun, X., Yu, Q., Yang, K., & Zhang, X. (2023). Explainable fault diagnosis of oil-gas treatment station based on transfer learning. *Energy*, *262*, 125258. https://doi.org/10.1016/J.ENERGY.2022.125258
181	bearings	varied working conditions	2022	Ding, Y., Jia, M., Zhuang, J., Cao, Y., Zhao, X., & Lee, C. G. (2023). Deep imbalanced domain adaptation for transfer learning fault diagnosis of bearings under multiple working conditions. *Reliability Engineering & System Safety*, *230*, 108890. https://doi.org/10.1016/J.RESS.2022.108890
182	bearings	different but similar machines	2022	He, J., Ouyang, M., Chen, Z., Chen, D., & Liu, S. (2022). A Deep Transfer Learning Fault Diagnosis Method Based on WGAN and Minimum Singular Value for Non-Homologous Bearing. *IEEE Transactions on Instrumentation and Measurement*, *71*. https://doi.org/10.1109/TIM.2022.3160533
183	bearings	simulation to real	2022	Zhao, J., & Huang, W. (2021). Transfer learning method for rolling bearing fault diagnosis under different working conditions based on CycleGAN. *Measurement Science and Technology*, *33*(2), 025003. https://doi.org/10.1088/1361-6501/AC3942
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185	bearings	simulation to real	2022	Zhu, P., Dong, S., Pan, X., Hu, X., & Zhu, S. (2022). A simulation-data-driven subdomain adaptation adversarial transfer learning network for rolling element bearing fault diagnosis. *Measurement Science and Technology*, *33*(7), 075101. https://doi.org/10.1088/1361-6501/AC57EF
186	gearbox	varied working conditions	2022	Zhang, L., Zhang, J., Peng, Y., & Lin, J. (2022). Intra-Domain Transfer Learning for Fault Diagnosis with Small Samples. *Applied Sciences 2022, Vol. 12, Page 7032*, *12*(14), 7032. https://doi.org/10.3390/APP12147032
187	aero engines	different but similar machines	2022	Liu, J. (2022). Gas path fault diagnosis of aircraft engine using HELM and transfer learning. *Engineering Applications of Artificial Intelligence*, *114*, 105149. https://doi.org/10.1016/J.ENGAPPAI.2022.105149
188	insulator	method: image classification to fault classification	2022	Yang, L., Shen, J., Wu, M., & Liu, Y. (2022). Insulator Fault Diagnosis Based on Improved Transfer Learning from UAV Images. *Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics*, *2022-October*, 2093–2098. https://doi.org/10.1109/SMC53654.2022.9945251
189	ball screw	sensor positions	2022	Xie, Y., Liu, C., Huang, L., & Duan, H. (2022). Ball Screw Fault Diagnosis Based on Wavelet Convolution Transfer Learning. *Sensors 2022, Vol. 22, Page 6270*, *22*(16), 6270. https://doi.org/10.3390/S22166270
190	bearings	different but similar machines	2022	Zong, X., Yang, R., Wang, H., Du, M., You, P., Wang, S., & Su, H. (2022). Semi-Supervised Transfer Learning Method for Bearing Fault Diagnosis with Imbalanced Data. *Machines 2022, Vol. 10, Page 515*, *10*(7), 515. https://doi.org/10.3390/MACHINES10070515
191	bearings	sim to real	2022	Ruan, D., Chen, Y., Gühmann, C., Yan, J., & Li, Z. (2022). Dynamics Modeling of Bearing with Defect in Modelica and Application in Direct Transfer Learning from Simulation to Test Bench for Bearing Fault Diagnosis. *Electronics 2022, Vol. 11, Page 622*, *11*(4), 622. https://doi.org/10.3390/ELECTRONICS11040622
192	nuclear power plant	varied working conditions	2022	Li, J., Lin, M., Li, Y., & Wang, X. (2022). Transfer learning network for nuclear power plant fault diagnosis with unlabeled data under varying operating conditions. *Energy*, *254*, 124358. https://doi.org/10.1016/J.ENERGY.2022.124358
193	wind turbine	different but similar machines	2022	Yang, W., & Yu, G. (2022). Federated Multi-Model Transfer Learning-Based Fault Diagnosis with Peer-to-Peer Network for Wind Turbine Cluster. *Machines 2022, Vol. 10, Page 972*, *10*(11), 972. https://doi.org/10.3390/MACHINES10110972
194	pump	varied working conditions	2022	He, Y., Tang, H., Ren, Y., & Kumar, A. (2022). A deep multi-signal fusion adversarial model based transfer learning and residual network for axial piston pump fault diagnosis. *Measurement*, *192*, 110889. https://doi.org/10.1016/J.MEASUREMENT.2022.110889
195	bearings	varied working conditions	2022	Zeng, M., Li, S., Li, R., Li, J., Xu, K., & Li, X. (2022). A transfer-learning fault diagnosis method considering nearest neighbor feature constraints. *Measurement Science and Technology*, *34*(1), 015114. https://doi.org/10.1088/1361-6501/AC8DAE
196	bearings	simulation to real	2022	Dong, Y., Li, Y., Zheng, H., Wang, R., & Xu, M. (2022). A new dynamic model and transfer learning based intelligent fault diagnosis framework for rolling element bearings race faults: Solving the small sample problem. *ISA Transactions*, *121*, 327–348. https://doi.org/10.1016/J.ISATRA.2021.03.042
197	gearbox	bearings to gearbox	2022	Qian, G., & Liu, J. (2023). Fault diagnosis based on gated recurrent unit network with attention mechanism and transfer learning under few samples in nuclear power plants. *Progress in Nuclear Energy*, *155*, 104502. https://doi.org/10.1016/J.PNUCENE.2022.104502
198	bearings	varied working conditions	2022	Wang, B., Wang, B., & Ning, Y. (2022). A novel transfer learning fault diagnosis method for rolling bearing based on feature correlation matching. *Measurement Science and Technology*, *33*(12), 125006. https://doi.org/10.1088/1361-6501/AC8D20
199	bearings	different but similar machines	2022	Zhang, Y., Li, S., Zhang, A., Li, C., & Qiu, L. (2022). A Novel Bearing Fault Diagnosis Method Based on Few-Shot Transfer Learning across Different Datasets. *Entropy 2022, Vol. 24, Page 1295*, *24*(9), 1295. https://doi.org/10.3390/E24091295
200	pump	method: image classification to fault classification	2022	Wu, Y., Feng, Z., Liang, J., Liu, Q., & Sun, D. (2022). Fault Diagnosis Algorithm of Beam Pumping Unit Based on Transfer Learning and DenseNet Model. *Applied Sciences 2022, Vol. 12, Page 11091*, *12*(21), 11091. https://doi.org/10.3390/APP122111091

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