A Comprehensive Survey of Deep Transfer Learning for Anomaly Detection in Industrial Time Series: Methods, Applications, and Directions

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Abstract

Automating the monitoring of industrial processes has the potential to enhance efficiency and optimize quality by promptly detecting abnormal events and thus facilitating timely interventions. Deep learning, with its capacity to discern non-trivial patterns within large datasets, plays a pivotal role in this process. Standard deep learning methods are suitable to solve a specific task given a specific type of data. During training, the algorithms demand large volumes of labeled training data. However, due to the dynamic nature of processes and the environment, it is impractical to acquire the needed data for standard deep learning training for every slightly different case anew. Deep transfer learning offers a solution to this problem. By leveraging knowledge from related tasks and accounting for variations in data distributions, this learning framework solves new tasks even with little or no additional labeled data. The approach bypasses the need to retrain a model from scratch for every new setup and dramatically reduces the labeled data requirement. This survey provides an in-depth review of deep transfer learning, examining the problem settings of transfer learning and classifying the prevailing deep transfer learning methods. Moreover, we delve into applying deep transfer learning in the context of a broad spectrum of time series anomaly detection tasks prevalent in primary industrial domains, e.g., manufacturing process monitoring, predictive maintenance, energy management, and infrastructure facility monitoring. We conclude this survey by underlining the challenges and limitations of deep transfer learning in industrial contexts. We also provide practical directions for solution design and implementation for these tasks, leading to specific, actionable suggestions.

Keywords deep transfer learning · time series analysis · anomaly detection · manufacturing process monitoring · predictive maintenance

1 Introduction

The fourth industrial revolution — Industry 4.0 (Kagermann et al., 2011), that is characterized by increasing efficiency through the digitization of production, automation, and horizontal integration across companies (Roblek et al., 2016), and the advent of connected cyber-physical systems – referred to as internet of things (Wang et al. 2015; Jeschke et al. 2017; Dalenogare et al. 2018), increases the need for autonomous and intelligent process monitoring. This can be exemplified by the use case of a smart factory in which industrial processes are transformed to be more flexible, intelligent, and dynamic (Kagermann, 2017), or the use case of decentralized energy production with wind and solar (Abir et al., 2021). In these examples, AI-powered anomaly detection integrates the analysis of time series data to detect unusual patterns in the recorded data. By identifying parameters that fall outside a window of normal operation, operators can trigger interventions and adjustments to ensure high product quality and safe operations. To achieve this, physical properties such as pressure or temperature are monitored and analyzed in real-time. Changes in these variables capture drifting and abrupt faults caused by process failures or malfunctions (Park et al., 2020). The production process must adapt quickly to changes in production and the environment to meet the requirements for flexibility and dynamics. Further use cases exist in such diverse areas as manufacturing monitoring including automatic quality control, predictive maintenance of goods and services, infrastructure monitoring of e.g. building energy systems or power plants, digital agriculture, petrochemical process optimization, computer network intrusion detection, or aircraft flight monitoring, to name a few.

Artificial Intelligence, in particular deep learning, provides competent frameworks to automate intelligent monitoring in order to provide valuable assistance to operators and high-level control systems. Leveraging the power of deep learning, formative features of the data – technically referred to as *representations* (Bengio et al., 2013) – can be captured in a machine-learned model and thereby enable a detailed understanding of variations in standard operations.

However, in non-trivial and non-stationary conditions, the task or the underlying data may change. For example, the monitoring system of a milling machine may in one instance be tasked to detect a blunt tool based on the vibration and in another instance – using the same vibration measurements – to detect insufficient cooling lubricant. Knowledge acquired to solve one task in one setting with a given tool, machined part, and type of machine may be transferred to solve the same or similar task in a setting with a different tool, machined part, or type of machine. Slowly changing conditions (drifts), abrupt mode changes (for instance due to tool change), and new tasks (such as the detection of another failure mode) may require adjustments to the machine-learned model. In these cases, it is desirable to adjust the analysis model without retraining from scratch, as it is costly or impractical to acquire sufficient training data to learn the full manifold (Maschler et al., 2022).

Transfer learning is a machine learning framework to achieve this (Maschler and Weyrich, 2021; Zhuang et al., 2021; Pan and Yang, 2010; Tan et al., 2018; Yosinski et al., 2014). As depicted in Figure 1, data and algorithms from a related task may be leveraged in a new one. By accounting for changes in data distributions and tasks, or leveraging existing models, knowledge learned from related tasks can be used to improve performance on new tasks instead of retraining a model for each individual application from scratch. This transfer-learning-boosted modeling forms the basis for identifying anomalies that deviate from established patterns in a non-trivial manner without full re-training.

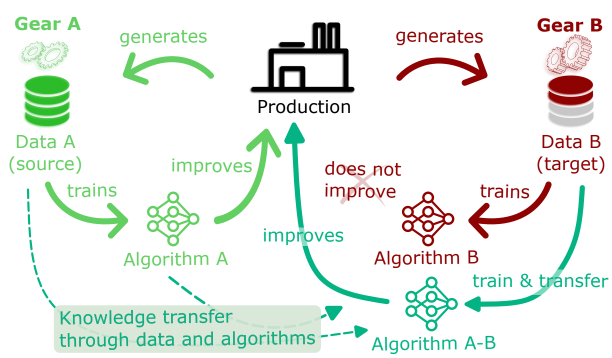

Figure 1: Transfer learning is useful when changes in production take place and sufficient data for full retraining is not available as shown here for a hypothetical production of two types of gears. In the production of gear A, a lot of data is available to train a deep learning model that helps improve production. In the production of gear B, data availability is more limited, and the traditionally trained deep learning model fails to improve production. With suitable methods, however, data and algorithms acquired during production of gear A can be leveraged to support improving the production of gear B, because the data and tasks in the production of both gears are related.

Deep transfer learning (Tan et al., 2018; Yu et al., 2022) extends the transfer learning paradigm by leveraging deep learning models. In industrial contexts, it ensures optimal production even as production conditions shift. This dynamic adaptability is key in maintaining the effectiveness of anomaly detection systems in the dynamic environment that characterizes industrial applications including the broad categories of manufacturing process monitoring, predictive maintenance, energy management, and infrastructure facility monitoring as detailed in Section 4.

In this survey, we review the foundations of deep transfer learning to equip the reader with working knowledge of the main principles and intuition for ideas. Further, we provide a comprehensive overview of the current state of the art of deep transfer learning approaches for time series anomaly detection for industrial applications. Our main contribution is a systematic review of research work on real-world industrial applications. For these, we discuss potential, challenges, and limitations and give directions for future work and potential. The paper is organized as follows: First, we introduce a taxonomy of transfer learning problem settings and further categorization of deep transfer learning approaches (Section 2). Then, we describe the task of anomaly detection in time series (Section 3) in selected industrial applications (Section 4). To conclude, we discuss current challenges, limitations, and future research directions (Sections 5–6) in the field.

2 Deep transfer learning

Transfer learning in a deep learning setting aims to increase the efficiency, performance, and generalization of deep learning models by transferring knowledge from one data set and task to a new one. This eliminates the need to train a deep learning model from scratch, which in turn reduces the amount of necessary data and compute required to solve a new task or new data domain. In either case, knowledge is transferred from a source to a target domain, as defined below. The transfer learning problem settings can be categorized as inductive or transductive transfer depending on the data and task conditions, while we categorize deep learning-based transfer learning approaches into instance transfer, parameter transfer, mapping transfer and domain-adversarial transfer. We illustrate them by using two intuitive examples in Figure 2, with more details being elaborated in the following sections.

2.1 Transfer learning problem definition

Domain $\mathcal{D}$ includes the domain feature space $\mathcal{X}$ and marginal data distribution $P(X)$ as $\mathcal{D} = \{\mathcal{X}, P(X)\}$, where X is the domain data, $X = \{x_1, \ldots, x_n\} \in \mathcal{X}$. Similarly, a learning task is defined as $\mathcal{T} = \{\mathcal{Y}, f_{\mathcal{T}}(\cdot)\}$, where $\mathcal{Y}$ denotes the task space and usually represents class label. For anomaly detection tasks, $\mathcal{Y}$ is the set of the two classes "normal" and "abnormal". The function $f_{\mathcal{T}}(\cdot)$ can be used to predict the corresponding label of a new instance x_i. The objective predictive function $f_{\mathcal{T}}(\cdot)$ can be learned from domain data and can be interpreted as a form of conditional probability. Thus, the learning task can be rewritten as $\mathcal{T} = \{\mathcal{Y}, P(Y|X)\}$, where $P(Y|X)$ is used as a likelihood measure to determine how well a given data set X fits with a corresponding class label set Y.

We largely follow the definition of transfer learning by Pan and Yang (2010) and Zhuang et al. (2021). Given a source domain $\mathcal{D}_S$ and learning task $\mathcal{T}_S$, as well as a target domain $\mathcal{D}_T$ and learning task $\mathcal{T}_T$, transfer learning aims to improve the performance of the predictive function $f_{\mathcal{T}}(\cdot)$ in $\mathcal{D}_T$ by transferring knowledge from $\mathcal{D}_S$ and $\mathcal{T}_S$, where $\mathcal{D}_S \neq \mathcal{D}_T$ and/or $\mathcal{T}_S \neq \mathcal{T}_T$. Usually, the size of source dataset is much smaller than target dataset.

This definition of transfer learning can be broadened, i.e., the target task can profit from multiple source domains. Transfer learning is thus the idea of making the best use of related source domains to solve new tasks. In contrast, traditional machine learning (ML) methods learn each task separately from scratch, and each respective model can only be applied to the corresponding task.

We define a taxonomy of transfer learning problems settings as shown in Figure 2 mainly depending on the label availability in the two domains to be easily applicable to the requirements of a case at hand (compare different definitions for other purposes in the literature Pan and Yang (2010); Tan et al. (2018); Zhuang et al. (2021)).

We differentiate it into inductive and transductive transfer learning (Pan and Yang, 2010)[1]. Inductive transfer learning is applied when the target task is different from the source task, i.e., $\mathcal{T}_S \neq \mathcal{T}_T$ (meaning that $\{\mathcal{Y}_{\mathcal{S}} \neq \mathcal{Y}_{\mathcal{T}}\}$ or $\{P(Y_S|X_S) \neq P(Y_T|X_T)\}$). The conditional probability distribution is induced with labeled training data in the target domain (Torrey and Shavlik, 2009). A corresponding example is illustrated as Scenario A in Figure 2, where the learning tasks are different and the goal of transfer learning is to recognize point anomaly from the collective anomaly task. Related areas of inductive transfer learning are multi-task learning (Caruana, 1997; Ruder, 2017) and sequential learning, depending on whether tasks are learned simultaneously or sequentially.

[1]In this survey, we do not consider unsupervised learning scenarios since either source labels or target labels are provided for most industrial applications.

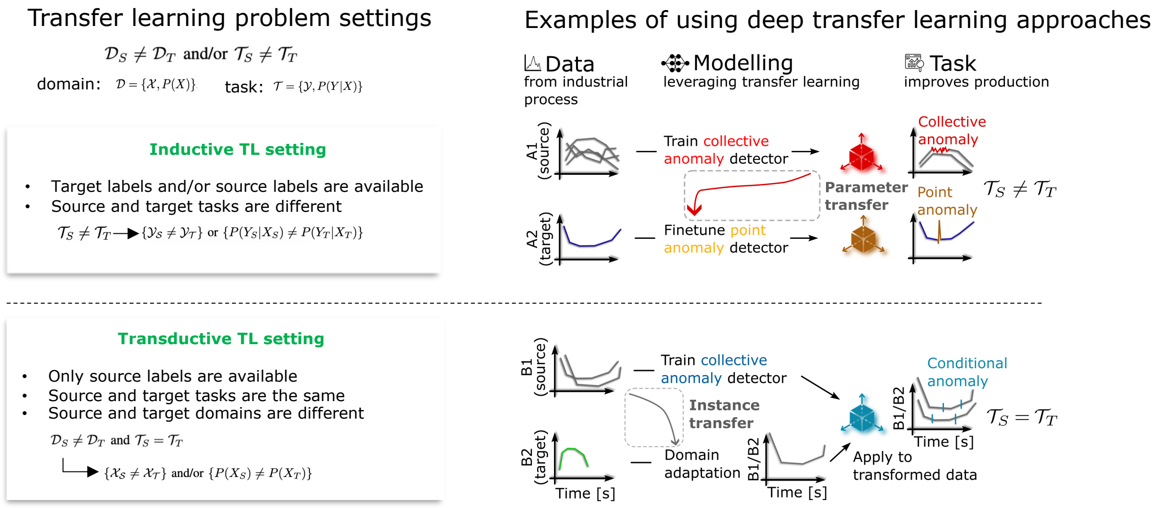

Figure 2: Taxonomy of transfer learning problem settings (left; see Section 2.1 for the definition of terms) and corresponding examples using deep transfer learning approaches (right). On the left, we classify transfer learning problems as inductive or transductive transfer settings, mainly depending on the label availability and task similarities. Correspondingly, we provide two examples using deep transfer learning methods: In the inductive transfer setting, we collect time series data from screw production and wrench production. Labeled screw data (A1) is used to detect collective anomalies (a set of data points behaving differently compared to the entire time series (Choi et al., 2021; Chalapathy and Chawla, 2019), further explained in Section 3). Then, parameter transfer (Section 2.2.2) is applied to transfer knowledge by fine-tuning the pre-trained model from labeled screw data to detect point anomalies (further explained in Section 3) on labeled wrench data (A2). For the transductive transfer setting in the lower panel, we present a different situation for contextual anomaly detection (further explained in Section 3). In this case, we have two datasets, B1 and B2, analyzed using the same model. However, the data in B2 significantly differs in appearance from the data in B1. To address this issue, instance transfer (further explained in Section 2.2.1) is used. Through this learning process, the data in B2 is transformed in a way that makes it compatible with the model which has been trained exclusively on data from B1. Transfer learning, in this case, is thus achieved by adapting the data to fit the model through domain adaptation rather than adjusting the model to fit new data.

Transductive transfer learning is applied when the source and target tasks are the same, while the source and target domain are different, i.e., $\mathcal{T}_S = \mathcal{T}_T$ and $\mathcal{D}_S \neq \mathcal{D}_T$ (meaning that $\{\mathcal{X}_S \neq \mathcal{X}_T\}$ or $\{P(X_S) \neq P(X_T)\}$. A subcategory is domain adaptation (Kouw and Loog, 2019) when the feature space of source and target data are the same but the corresponding marginal distributions are different (i.e., $\{\mathcal{X}_S = \mathcal{X}_T\}$ and $\{P(X_S) \neq P(X_T)\}$). Scenario B in Figure 2 is an example of transductive transfer learning where the learning tasks are identical, and the goal of transfer learning is to recognize contextual anomalies in an unlabelled data set.

Other learning paradigms closely related to transfer learning are listed below:

Multi-task learning is a machine learning technique where a single model is trained on multiple tasks simultaneously. The idea is to improve the performance of the model by learning a shared representation that captures the features between all tasks.

Continuous learning (Parisi et al., 2019) is a learning process where the model continuously learns new tasks from previous tasks over time without forgetting how to solve previous tasks. To some extent, continuous learning can be seen as a sequential transfer learning process, with the constraint to preserve the performance on the previous tasks which leads to an accumulation of knowledge over time.

Few-shot learning (Wang et al., 2020) is a type of machine learning where a model can learn and perform well on a new task with only a limited number of labeled samples. In extreme cases, the model can learn with one label (Fei-Fei et al., 2006) and without any label (Lampert et al., 2009). While transfer learning usually involves reusing the model from relevant tasks and continuing training on the target dataset.

Table 1: Overview of deep transfer learning approaches with references.

Deep transfer learning approach	Short description	References
Instance transfer	Augmenting target data by transforming data instance from the source domain	He et al., 2022; Amirian et al., 2021; Wang et al., 2018
Parameter transfer	Transfer learned parameters of a pre-trained model from source domain and adapting the model for target domain	Bommasani et al., 2022; Devlin et al., 2019; Vaswani et al., 2017; Dou et al., 2022; Alexandr et al., 2021; Yosinski et al., 2014; Guo et al., 2019; Sager et al., 2022; Brown et al., 2020
Mapping transfer	Reducing feature discrepancies between source and target domains by minimizing the distance between mapped features in the latent space	Zhuang et al., 2021; Tzeng et al., 2014; Long et al., 2017, 2015; Zhang et al., 2015; Venkateswara et al., 2017
Domain-adversarial transfer	Extracting an indiscriminative feature representation between source and target domain through adversarial training	Tzeng et al., 2015; Ganin et al., 2017; Ajakan et al., 2015; Tzeng et al., 2017

Meta-learning (Finn et al., 2017; Hospedales et al., 2022) is a machine learning technique that focuses on the learning process. It is known as "learning to learn". For meta-learning, models are trained on a different set of tasks instead of a set of data in the traditional machine learning setting. In this sense, meta-learning can be seen as a form of transfer learning because it involves transferring knowledge from task to task.

Knowledge distillation (Gou et al., 2021) effectively learns a small model trained to mimic the behavior of a larger, more complex model. The knowledge learned by the larger model can be transferred to the smaller model, which can then be used for the target task, e.g., on a less powerful edge device.

Self-supervised learning (Liu et al., 2023; Bai et al., 2021) involves training a model to predict some aspect of the input data without any external supervision. The learned representations can be used for various downstream tasks, including those that involve transferring knowledge from one domain to another.

2.2 Deep transfer learning approaches

Since deep neural networks (DNNs) can learn useful feature representations from large amounts of data through back-propagation (Bengio et al., 2013), they have been widely adopted for tackling complex problems, which involve large-scale and high-dimensional data, also in practice (Schmidhuber, 2015; Lukic et al., 2016; Stadelmann et al., 2018; Schmidhuber, 2022). Deep transfer learning methods implement transfer learning principles within DNN and, among other things, enable deep learning based analysis pipelines to be applied to new datasets. On a high level, deep transfer learning approaches can be divided into data-driven and model-driven ones. Data-driven approaches focus on transferring knowledge by transforming and adjusting the data instances. Model-driven approaches leverage DNNs to develop domain-invariant features by reducing the feature discrepancy between source and target domain data and then transferring generalized knowledge to new tasks. Following the taxonomy of (Tan et al., 2018; Pan and Yang, 2010; Shi et al., 2022), we divide deep transfer learning approaches further into 4 categories: instance transfer, parameter transfer, mapping transfer, and domain-adversarial transfer, as illustrated in Table 1. Instance transfer and mapping transfer are data-driven approaches, parameter transfer is a model-driven approach, while domain-adversarial transfer is a combination of both.

2.2.1 Instance transfer

The intuition of instance transfer is that although source and target domains differ, it is still possible to transform and reuse source data together with a few labeled target samples. A typical approach is to re-create some labeled data from the source domain. He et al. (2022) propose an instance-based deep transfer learning model with attention mechanism to predict stock movement. They first create new samples from the source dataset that are similar to the target samples by using attention weights, and then train on the created samples and target training samples for prediction tasks. Amirian et al. (2021) introduce an innovative instance transfer method for domain adaptation. They propose an effective auto-encoder model with a pseudo-label classifier to reconstruct new data instances that obtain general features across different datasets for medical image analysis. Taking another avenue, Wang et al. (2018)

exclude the source data that have a bad impact on training target data. Specifically, they choose a pre-trained model from a source domain, estimate the impact of all training samples in the target domain, and remove samples that lower the performance of the model.

2.2.2 Parameter transfer

Parameter transfer adapts learned parameters of a pre-trained model to a new model. This assumes that DNNs can get similar feature representations from similar domains. Thus, through transferring parts of the DNN layers together with pre-trained parameters and/or hyperparameters, the pre-trained model is used as a base model to further train on target domain data and solve different learning tasks. Particularly, parameter transfer has gained popularity in computer vision and natural language processing, where large models are pre-trained on large datasets (Bommasani et al., 2022). In natural language processing, BERT (Devlin et al., 2019) and GPT-3 (Brown et al., 2020) that are based on the transformer architecture (Vaswani et al., 2017) can be fine-tuned for a variety of natural language processing tasks, including content generation (Dou et al., 2022), language translation (Sun et al., 2021), question answering (Glass et al., 2020), and summarization (Alexandr et al., 2021). Yosinski et al. (2014) investigated the general transferability of DNNs. Experiment results show that transferring features from source to target domain leads to improved generalization in networks compared to those trained solely on the target dataset. Unlike the typical way of fine-tuning a pre-trained model, Guo et al. (2019) propose the adaptive fine-tuning approach SpotTune to find the optimal fine-tuning strategy for the target task. Specifically, a policy network is used to make routing decisions on whether to pass the target instance through the pre-trained model. The results show SpotTune is effective in most cases by using a hybrid of parameter and instance transfer. Sager et al. (2022) propose an unsupervised domain adaptation for vertebrae detection in 3D CT volumes by transferring knowledge across domains during each batch of the training process.

2.2.3 Mapping transfer

Mapping transfer refers to learning a related feature representation for the target domain by feature transformation, which includes feature alignment, feature mapping, and feature encoding (Zhuang et al., 2021). The goal is to reduce feature discrepancies between source and target domains by minimizing the distance between the distribution of mapped features in the latent space. There are various criteria to measure the distribution difference, including Wasserstein distance (Shen et al., 2018), Kullback-Leibler Divergence (Dai et al., 2007), etc. Among them, Maximum Mean Discrepancy (MMD) (Tzeng et al., 2014) is most frequently adopted in mapping transfer from the surveyed papers. The MMD is calculated as the difference between the mean embeddings of the samples in a reproducing kernel Hilbert space associated with a chosen kernel function. Added to the target loss function, it measures the difference between two probability distributions and serves as a powerful tool for comparing the similarity of complex, high-dimensional datasets using a wide variety of kernel functions.

Some previous work focusing on transferred feature extraction/dimensionality reduction using MMD has been done. Long et al. (2017) base their Joint Adaptation Network on MMD, in which the joint distributions of multiple domain-specific layers across domains are aligned. In addition, an adversarial training version was adopted to make distributions of the source and target domains more distinguishable. Similarly, Long et al. (2015) adopted multi-layer adaptation and proposed Deep Adaptation Networks (DAN). In DAN models, the first three convolutional layers are used to extract general features. For the last three layers, multi-kernel MMD is used to bridge the cross-domain discrepancy and learn transferable features. Zhang et al. (2015) also based on MMD and proposed a Deep Transfer Network in which two types of layers are used to obtain domain invariant features across domains. The shared feature extraction layers learn a shared feature subspace between the source and the target samples, and the discrimination layer is then used to match conditional distributions by classifier transduction. Venkateswara et al. (2017) proposed Deep Adaptation Hash network, which is fine-tuned from the VGG-F (Chatfield et al., 2014) network. Multi-kernel MMD loss trains the Deep Adaptation Hash to learn feature representations that align the source and target domains.

2.2.4 Domain-adversarial transfer

Inspired by Generative Adversarial Networks (GANs) (Goodfellow et al., 2014; Schmidhuber, 2020), the goal here is to extract a transferable feature representation that is indiscriminative between source and target domain through adversarial training. Adversarial transfer mainly focuses on domain adaptation problems. Tzeng et al. (2015) adopt a domain confusion loss across the source and target domains to learn a domain invariant representation. Ganin et al. (2017) propose a new domain adaptation architecture by adding a domain classifier after feature extraction layers. A gradient reversal layer is used to ensure the similarity of the feature distributions over source and target domains.

Ajakan et al. (2015) propose a domain adversarial DNN in which a domain regressor is applied to learn a domain invariant feature representation. Tzeng et al. (2017) use an unsupervised domain adaptation method that combines adversarial learning with discriminative feature learning.

3 Time series analysis for industrial processes

Time series analysis encompasses statistical techniques to analyze and interpret sequential temporal data. In the context of industrial processes, time series analysis plays a crucial role in automating monitoring and controlling the efficiency, quality, and performance of these processes. Specifically, the analysis of time series data can be used for anomaly detection, forecasting, process control, performance assessment, and maintenance scheduling to increase the efficiency of the process.

Anomaly detection According to Hawkins (1980), an outlier is as an observation that deviates significantly from other observations in a way that it is likely that it was generated by a different mechanism. In this survey, we focus on time series data collected from machine sensor readings in the context of industrial applications, either univariate (only one variable is recorded over time) or multivariate (several simultaneously recorded measurements). Time series anomalies might occur for various reasons, including internal factors (e.g., temporary sensor error, machinery malfunction) and external factors (e.g. human error, ambient temperature). They can be divided into three categories (Choi et al., 2021; Chalapathy and Chawla, 2019): point anomalies, contextual anomalies, and collective anomalies. Point anomalies are isolated samples that deviate significantly from the normal behavior of that time series, which can be seen on the left of Fig. 3, e.g., a sudden spike in a pressure reading from a manufacturing machine sensor. These point anomalies can be caused by temporal sensor error, human error, or abnormal machinery operations. Contextual anomalies represent data points that deviate from normal ones only in their current context, and an example can be seen in the middle of Fig. 3. Collective anomalies are a set of data points that in their entirety (but not individually) are abnormal with respect to the entire time series, as shown on the right of Fig. 3.

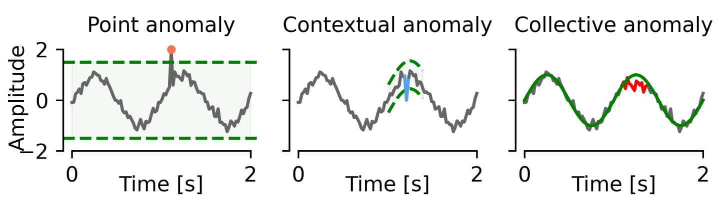

Figure 3: Three time series anomaly types. Gray lines represent recorded time series signals, and dashed green lines are *a priori* set thresholds of normal operations. The red dots and the red line indicate anomalies. Point anomalies are single values that fall outside of a pre-set range (left panel). Contextual anomalies are samples that deviate from current context (middle panel). Collective anomalies are defined as a series of data points that all fall within the range of operation but jointly are not expected (right panel).

Challenges regarding detecting time series anomalies persist due to two specific properties: First, the *complexity of time series data*. As the automation level of industrial processes and the complexity of industrial systems increases, univariate time series data become insufficient and inefficient in representing any industrial process in its entirety. Hence, more sensors are installed to monitor the whole process, making it necessary in turn to detect anomalies from multivariate time series, which poses particular challenges since it requires consideration of temporal dependencies and relationships between variables and modalities. Second, the *dynamic variability* of industrial processes can pose difficulties in detecting anomalies due to fluctuations in the process caused by varying input or environmental conditions such as material, temperature, pressure, and humidity, which lead to domain shifts.

Process automation The tasks described above are combined to automate industrial processes. For example, after the detection of an anomaly, another model that captures the relationship between time course and different failure modes or drifts may be exploited for predictive maintenance. For example, in injection molding process monitoring, anomaly detection models are used to analyze recorded sensor data from injection molding machines to detect bad parts and identify the root cause of anomalies (Tercan et al., 2018). There are two basic ways to detect anomalies: for supervised anomaly detection, labels (normal/abnormal) are needed per time series to build a binary classifier (Görnitz et al., 2013). For unsupervised anomaly detection, an anomaly score or confidence value that is conditioned purely on normal data can be used to differentiate abnormal from normal instances (Zhang et al., 2023; Audibert et al., 2020; Stadelmann et al., 2019).

4 Industrial applications

4.1 Overview

Currently, deep transfer learning approaches are popular in the field of computer vision and natural language processing because of the large available datasets. This popularity is not as pronounced for industrial time series data, likely due to the lack of publicly available data and the domain-specific differences between such data, making the field a less easy target for general gains. Fortunately, in recent years a growing number of deep transfer learning approaches have been applied in industry to solve anomaly detection tasks, such as fault diagnosis (Li et al., 2022), quality management (Ma et al., 2019), manufacturing process monitoring (Tercan et al., 2018), network/software security (Rosenberg et al., 2018), and infrastructure monitoring (Pan et al., 2023). These can be mapped onto the core industrial domains of manufacturing process and infrastructure monitoring, predictive maintenance, and energy management. Table 2 presents a compact comparison of the related works using deep transfer learning approaches to solve these tasks.

Figure 4 illustrates the quantity structure of the connections between industrial applications and the deep transfer learning approaches based on our literature survey. The Sankey diagram shows every path that connects the four dimensions of the methodology-problem-landscape within the surveyed literature. The broader the path is, the more papers are related to that element. The goal is to give an overview of how deep transfer learning is applied to industrial problems in the recent literature and specifically show with these four dimensions: (1) which deep transfer learning approaches are actually used in practice; (2) what the main industrial domains for time series anomaly detection are; (3) what deep transfer learning category these domains belong to; and (4) what labels are available in source and target domain.

Key observations from Figure 4 are: Regarding deep transfer learning approaches, parameter transfer is much more frequently used than any other deep transfer learning approach across all surveyed industrial applications since fine-tuning a pre-trained model on target data is more straightforward to implement by taking advantage of the pre-trained model on the source dataset and usually without fundamental modification on the model architecture. It is noteworthy that instance transfer and adversarial transfer do not appear in the diagram. Apparently, these two deep transfer learning approaches are not considered the optimal choice for respective time series anomaly detection tasks in the industry. The difficulty lies in implementing and training these scarcely researched approaches in the industrial field, as indicated by the findings. Regarding industrial applications, hybrid approaches of parameter and mapping transfer can be seen in predictive maintenance. Regarding deep transfer learning categories, most industrial applications use inductive TL, indicating they focus on leveraging labeled source and target data to solve the target task, i.e., use supervised learning.

Table 2: A compact overview of industrial applications that used deep transfer learning for time series anomaly detection.

Reference	Industrial task	Industrial domain	Deep transfer learning approach	Transfer learning problem setting	Deep learning framework	Source data type	Source label	Target label
Maschler et al., 2021	Industrial metal forming anomaly detection	Predictive maintenance	Parameter transfer	Inductive	CNN	Multiple sources	✓	✓
Wen and Keyes, 2019	Monitoring systems Anomaly detection	Predictive maintenance	Parameter transfer	Inductive	U-Net	Multiple sources	✓	✓
Xu et al., 2019	Car body-side production line fault diagnosis	Predictive maintenance	Parameter transfer	Inductive	SAE	Multiple source	✓	✓
Mao et al., 2020	Rotation bearings fault detection	Predictive maintenance	Mapping transfer	Transductive	Auto-encoder	Multiple sources	✓	✗
Wang et al., 2021	Industrial control systems anomaly detection	Predictive maintenance	Parameter transfer	Inductive	ResNet8	Single source	✓	✓
Canizo et al., 2019	Service elevator fault detection	Predictive maintenance	Parameter transfer	Inductive	CNN+RNN	Multiple sources	✓	✓
Yao et al., 2022	Nuclear power plants fault detection	Predictive maintenance	Parameter transfer	Inductive	CNN	Multiple sources	✓	✓
Li et al., 2023	Building energy systems fault diagnosis	Predictive maintenance	Parameter transfer	Inductive	CNN	Multiple source	✓	✓
Serradilla et al., 2021	Press machine production prediction	Predictive maintenance	Parameter transfer	Inductive	CNN	Single source	✓	✓
Zgraggen et al., 2021	Wind turbine fault detection	Predictive maintenance	Parameter transfer	Inductive	CNN	Single source	✓	✓
Zabin et al., 2023	Industrial machine operating fault detection	Predictive maintenance	Parameter transfer	Inductive	CNN+LSTM	Single source	✓	✓
Liao et al., 2021	Machine turning operations classification	Manufacturing process monitoring	Parameter transfer	Inductive	VGG-19, ResNet	Single source	✓	✓
Lockner and Hopmann, 2021	Injection molding process quality control	Manufacturing process monitoring	Parameter transfer	Inductive	FCN	Multiple sources	✓	✓
Tercan et al., 2018	Injection molding process quality control	Manufacturing process monitoring	Parameter transfer	Inductive	FCN	Single source	✓	✓
Tercan et al., 2019	Injection molding process anomaly detection	Manufacturing process monitoring	Parameter transfer	Inductive	FCN	Multiple sources	✓	✓
Lockner et al., 2022	Injection molding process anomaly detection	Manufacturing process monitoring	Parameter transfer	Inductive	FCN	Multiple sources	✓	✓
Gellrich et al., 2021	Aluminum gravity die casting quality prediction	Manufacturing process monitoring	Parameter transfer	Inductive	FCN	Single source	✓	✓
Abdallah et al., 2021	Digital agriculture and smart manufacturing systems anomaly detection	Manufacturing process monitoring	Parameter transfer	Inductive	LSTM	Single source	✓	✓
Abdallah et al., 2023	Manufacturing testbeds anomaly detection	Manufacturing process monitoring	Parameter transfer	Inductive	LSTM, RNN	Single source	✓	✓
Maschler et al., 2021	Industrial metal (pump) forming anomaly detection	Manufacturing process monitoring	Parameter transfer	Inductive	LSTM	Single source	✓	✓
Panjapornpon et al., 2023	Petrochemical production process anomaly detection	Energy saving	Parameter transfer	Inductive	LSTM, CNN, FCN	Single source	✓	✓
Liang et al., 2018	Electricity consumption anomaly detection in aluminium extrusion processes	Energy saving	Parameter transfer	Inductive	FCN	Single source	✗	✓
Copiaco et al., 2023	Building's energy consumption anomaly detection	Energy saving	Parameter transfer	Inductive	MAlexNet-40	Single source	✓	✓
Xu et al., 2021	Power consumption anomaly detection	Energy saving	Mapping transfer	Transductive	Cluster-based DAN	Single source	✓	✗
Simone and Amigoni, 2021	Building's power consumption anomaly detection	Energy saving	Parameter transfer	Inductive	LSTM	Single source	✓	✓
Xiong et al., 2018	Aircraft flight anomaly detection	Infrastructure facilities monitoring	Parameter transfer	Inductive	LSTM	Single source	✓	✓
Pan et al., 2023	Anomaly identification for bridge groups	Infrastructure facilities monitoring	Parameter transfer	Inductive	CNN	Single source	✓	✓
Dhillon and Haque, 2020	Network intrusion detection	Infrastructure facilities monitoring	Parameter transfer	Inductive	CNN+LSTM	Single source	✓	✓

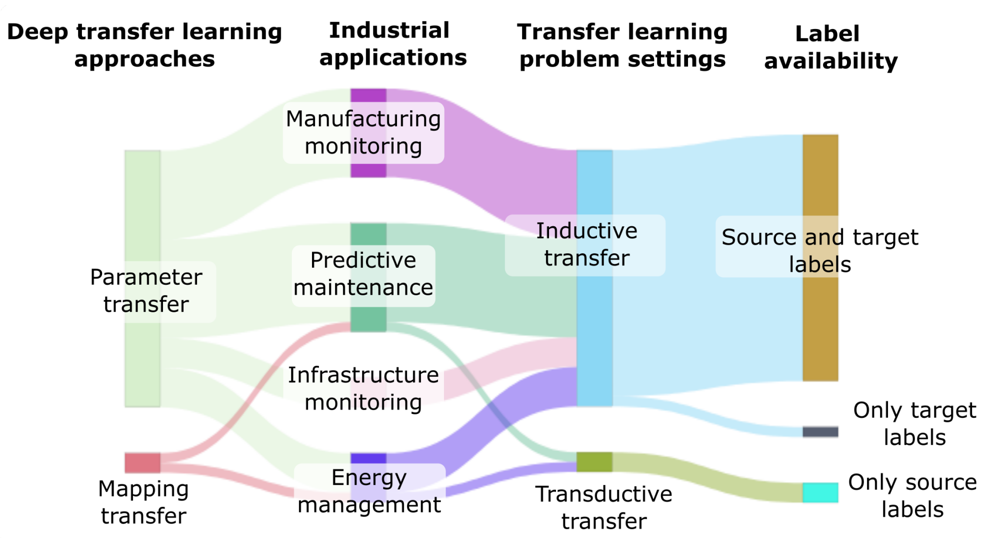

Figure 4: Overview of quantity structure of transfer learning problem setting, deep transfer learning approach categories, and label availability in the surveyed industrial domains.

4.2 Manufacturing process monitoring

Manufacturing process monitoring is crucially important to ensure high-quality products and low rejection rates. For example, in injection molding machines, sensors are installed to detect molding conditions in the cavity, such as cavity pressure and temperature. These signals are used to analyze in particular the mold filling and solidification process for each produced part. Such cyclic processing data can also be seen in metal machining (cutting force signal) or joining of parts (joining force signal). Currently, parameter transfer is predominantly used for manufacturing processes (Lockner and Hopmann, 2021; Tercan et al., 2018, 2019; Lockner et al., 2022; Maschler et al., 2021; Abdallah et al., 2021, 2023; Hsieh et al., 2019; Maschler et al., 2021).

In injection molding, parameter transfer is applied to transfer the knowledge from one or more source domains to solve tasks in a target domain (Lockner and Hopmann, 2021; Tercan et al., 2019; Lockner et al., 2022). Similarly, Tercan et al. (2018) build a bridge between simulated data and real data using parameter transfer in injection molding. Maschler et al. (2021) compare different DNNs for anomaly detection tasks on metal forming datasets. Further, they propose a deep transfer learning framework aiming to transfer knowledge between tasks. However, the proposed architecture is not validated. Later, Maschler et al. (2021) apply continuous learning on the same dataset by transferring knowledge from several source tasks to a target task to train a deep learning algorithm capable of solving both source and target tasks. Abdallah et al. (2021, 2023) apply parameter transfer to monitor operation status of manufacturing testbeds with vibration sensor data. Hsieh et al. (2019) transfer knowledge across three chambers in a production line to detect anomalous time series data. Results show reduced training time and improved detection accuracy through transfer learning.

4.3 Predictive Maintenance

Predictive maintenance aims to predict the necessity of maintenance before production is negatively impacted by a failure. Tasks involve monitoring equipment to anticipate maintenance requirements (i.e., predict likely future failure) to optimize maintenance schedules (Serradilla et al., 2022). Time series anomaly detection is often used in respective systems to identify abnormal patterns or behaviors in operation that may indicate the need for maintenance, such as increasing noise, vibrations, etc.

Mao et al. (2020) use mapping transfer with a Sparse Auto-Encoder (SAE) for motor vibration anomaly detection. A transformation from the source and target space to a common latent feature space is learned by MMD to make the feature distribution of two domains as identical as possible. Similarly, Wen et al. (2019) also used mapping transfer with an SAE architecture for fault detection of rotation bearings, using an MMD regularizer to extract a common feature representation. Subsequently, they propose a new MU-Net architecture to deal with multivariate time series anomaly detection tasks (Wen and Keyes, 2019). First, they pre-train a U-Net (Ronneberger et al., 2015) on a large time series dataset for an anomaly detection task. Then, they propose a new model MU-Net, built upon U-Net, wherein each channel they can use the pre-trained U-Net through fine-tuning to transfer knowledge for multivariate time series anomaly detection.

In another application, parameter transfer is used to predict the remaining useful life for tools in manufacturing (Sun et al., 2019). An SAE network is first trained to predict the remaining useful life of a cutting tool on retrospectively acquired data in an offline process. The trained network is then transferred to production with a new tool in operation for online remaining useful life prediction. A 2D CNN-LSTM (Hochreiter and Schmidhuber, 1997) hybrid architecture for fault detection is presented. The model is trained on a fault dataset, and then parameter transfer is applied to target datasets with a different set of conditions. The result shows that transfer learning based hybrid deep learning significantly reduces the training time and is highly suitable for real-time industrial fault diagnosis in various environments. Similarly, parameter transfer is implemented to reduce the gap between different industrial environments (Zabin et al., 2023; Xu et al., 2019). Xu et al. (2019) use a stacked SAE to extract general features from source data and a digital-twin-assisted fault diagnosis approach is presented to transfer knowledge from virtual space to physical space for real-time use. Here, a DNN model is first fully trained in virtual space and then migrated to the physical space using deep transfer learning for real-time use.

The surveyed literature proves that deep transfer learning is a research field that could simplify the life cycle of predictive maintenance systems and facilitate DNN model reusability by reducing the required data and training time, helping adapt them to solve similar tasks.

4.4 Energy management

Energy management deals with systems that detect abnormal excessive consumption caused by end-users' unusual behavior or malfunction of faulty devices or systems (Copiaco et al., 2023). The goal is to develop automatic, quick-responding, accurate, and reliable fault detection to save energy and build environmentally friendly systems. Energy anomaly detection systems monitor data during energy generation, transmission, and utilization, in order to ensure normal energy consumption. Xu et al. (2021) design a cluster-based deep adaptation layer to improve a deep adaptation network, effectively reducing the mismatch in transfer learning of spinning power consumption anomaly detection. Liang et al. (2018) successfully build an electricity consumption time series anomaly detection method in aluminum extrusion. Parameter transfer is applied to transfer domain knowledge from another data-sufficient domain. They also find it unnecessary when the target data is sufficient because transferring knowledge decreases prediction accuracy.

4.5 Infrastructure facilities monitoring

Infrastructure facilities monitoring refers to monitoring and maintaining the conditions of infrastructure facilities, such as bridges, buildings, and networks. This can include detecting potential issues or failures. The goal is to minimize the impact of failures on the public or the environment. Pan et al. (2023) apply parameter transfer to make full use of the similarity of the anomalous patterns across different bridges and transfer the knowledge obtained by a CNN model to a small part of target data, achieving high accuracy anomaly detection across bridges. Dhillon and Haque (2020) present a parameter transfer approach towards building a network intrusion detection system based on CNN and LSTM.

5 Discussion

5.1 Challenges

Label availability Deep transfer learning is built upon deep learning, which usually requires a large amount of labeled data, the more data a model has available for learning, the better it can generalize to new examples. In real-world industrial time series anomaly detection tasks, collecting data is probably easy, but collecting labels is much more expensive and time-consuming, sometimes prohibitively so, leading to the unavailability of sufficient labeled data. Self-supervised learning can be used to re-label a large amount of unlabeled data and thus facilitate transfer learning process. Thus, anomaly detection models usually need to learn in an unsupervised or semi-supervised mode (Goldstein and Uchida, 2016).

Deep learning for imbalanced data Even if the labels can be collected, anomalies can be extremely rare by design, which poses the risk of training with extremely imbalanced data. A practical problem for anomaly detection in industry is the extremely imbalanced data distribution, in which normal samples dominate in data and abnormal samples only share a small percentage in the whole dataset. Prior research has proven that the effect of class imbalance on classification performance by using deep learning is detrimental (Buda et al., 2018). However, most research studies still ignore such problems, which can result in poor performance regarding the minority class, i.e., abnormal data are misclassified as normal.

Missing relevant data Another problem is missing relevant data, i.e, some information that has a significant effect on the process from case to case is not even recorded or is too complex to record (i.e. part geometry, machine geometry, or environmental conditions in injection molding processes).

Domain shift Domain shifts lie at the heart of the deep transfer learning problem, but the dynamic changes in many industrial processes, up to an apparent dissimilarity of source and target data, make the transfer learning task particularly challenging.

Effectiveness of deep transfer learning The general effectiveness of deep transfer learning is limited by the difficulty of determining which knowledge or to what extent the knowledge should be transferred from source to target task. Unlike natural language processing, pretraining a language model on a large corpus of text data can help the model learn the statistical patterns and semantic and syntactic representations of words and sentences, which can be used for new natural language processing tasks with a few data. For industrial time series, due to data privacy, large available public datasets usually do not exist, or they cannot be used even because of a large domain gap between different datasets and tasks. In this case, transferring all of the knowledge may not be beneficial, as it may be irrelevant. In the worst case, this can lead to negative transfer (Pan and Yang, 2010; Smith-Jentsch et al., 2001), in which the extracted knowledge harms the new task-learning. This requires assessing how source and target tasks are related, carefully selecting the knowledge to be transferred, and selecting the proper means to implement this transfer.

5.2 Directions for anomaly detection solution design

Data preprocessing How data preprocessing should be conducted is an open question. For industrial applications, some researchers consider directly using time series data as input for training to be inefficient, thus suggesting deriving or selecting features from time series data by statistical methods or human experience to decrease the complexity of the dataset dramatically. On the other hand, this crops a lot of potentially useful information, e.g., the time series trend. Some researchers use machine parameters as features of the manufacturing process instead of using process data collected by sensors (Lockner and Hopmann, 2021; Tercan et al., 2018, 2019; Lockner et al., 2022). Others try different transformations of raw time series data, a common way being to transform 1D time series data to 2D image data (Liao et al., 2021; Wang et al., 2021; Zabin et al., 2023) or transforming time domain signals otherwise into the frequency domain (Lukic et al., 2016). However, as large-scale computation power and storage become cheaper and more accessible, it is becoming increasingly common to use deep learning techniques to directly process time series data (Xu et al., 2019; Maschler et al., 2021).

Data augmentation Data augmentation is useful for deep learning models because it can help to prevent overfitting. For deep transfer learning, when a model becomes too closely adapted to the specifics of the source domain, it may not be able to generalize well to some examples in the task domain. One important technique is to acquire effective synthetic data, e.g., using a simulation process or model to explore potential anomalous conditions by simulating industrial processes under parameters that cannot yet be experienced in the real-world. High fidelity and reliability of simulation data can provide training data at low cost and mitigate the problem of insufficient samples for deep transfer learning (Xu et al., 2019). Another way to generate effective synthetic data is to use GANs. GANs are trained on normal data only to generate indistinguishable samples from which abnormal samples are distinguished during the testing stage of the overall anomaly detection system based on their deviating data distribution (Jiang et al., 2019). To increase the number of anomalous samples and thus the robustness of the anomaly detection model, the technique of adversarial perturbation known from computer vision (Goodfellow et al., 2015) can be used.

Data imbalance DNNs perform well when they are trained on balanced datasets. However, in practice, it is difficult to get sufficient anomalous data for anomaly detection tasks. For example, manufacturing process is usually in a healthy state due to the pre-designed and optimized operation. Several ways exist to address the imbalanced dataset for time series anomaly detection. To deal with data imbalance, one way is to oversample the minority class, i.e., to randomly replicate samples from the minority class to equalize the number of samples from each class in each batch. Synthetic Minority Over-sampling Technique is an advanced method that creates synthetic samples to force the decision region of the minority class to become more general (Chawla et al., 2002). This technique is widely used in anomaly detection tasks in industry (Ijaz et al., 2018; Mokhtari et al., 2021). Apart from oversampling, the resampling strategy is also frequently used to assign a higher probability to abnormal samples and evenly select the same amount of samples from both classes in each batch. Finally, a weighted loss can be used that balances the loss for the abnormal and normal class in supervised anomaly detection (Buda et al., 2018).

5.3 Directions for deep transfer learning implementation

When shall deep transfer learning be used? (1) Limited data availability: If the amount of data available for a specific task is limited, pre-training on related source data can learn general features that can be transferred to the specific learning task in the target domain. (2) Similar domains: deep transfer learning is well suited for similar source and target domains. (3) Limited resources (time and compute): Using parameter transfer here is recommended if pre-trained models exist.

When not to use deep transfer learning? (1) Different tasks: If the target learning task is vastly different from the source learning task, deep transfer learning may not be appropriate. For example, if one wants to train a model for natural language processing on a new dataset, using a pre-trained model that has been trained on image data will not be useful. (2) High domain shift: If there is a large difference between the source and the target domain, deep transfer learning may not be effective. This can happen when the data distributions, features, or labels are vastly different. (3) Abundance of labeled data: If there are enough data for the new task, it may be more effective to train a model from scratch (Liang et al., 2018).

What model architecture to choose? We suggest selecting the model architecture mainly depending on the data size and label availability, starting from a relatively small network and moving gradually to more complex DNNs. It is important to effectively capture the temporal dependencies and extract respective features of time series data. LSTMs are used heavily for detecting temporal dependencies in time series data (Zabin et al., 2023; Panjapornpon et al., 2023; Xiong et al., 2018). CNNs are also effective in extracting time series features (Yao et al., 2022; Zgraggen et al., 2021). For semi-supervised settings, CNN-based auto-encoders are trained to reconstruct the original data (Serradilla et al., 2021).

Another aspect of deep transfer learning implementations is often the limited computing power of hardware platforms, such as embedded systems in industrial applications. Sensor data are typically acquired using resource-constrained edge processing devices that struggle with computationally intensive tasks, especially when updating a DNN model. One possible solution is federated learning, perhaps the most popular framework, mainly due to its feature of leveraging data while still preserving their privacy (Wang et al., 2018; Amiri and Gündüz, 2019). The technology enables a more collaborative approach to ML while preserving user privacy by storing data decentralized on distributed devices rather than on a central server. Combining deep transfer learning with federated learning is a promising and powerful combination in the abovementioned industrial applications.

Beyond transfer learning Foundation models such as transformers (Vaswani et al., 2017), diffusion models (Rombach et al., 2022) and SAM (Kirillov et al., 2023) demonstrate emerging properties such as in-context learning (Brown et al., 2020) and complex cross-modality conditioning. This is achieved by training complex and often auto-regressive models with massive amounts of data, although the precise mechanisms that lead to this are not well understood. Some of those models generalize to new settings and tasks, without an explicit element of transfer learning. Thus, the application of foundational models in industrial time series analysis has the potential to reduce and eventually eliminate the need to explicitly account for changes in the domain in modeling, and instead, the foundational models will provide the transfer capability. To not only detect anomalies but also identify failure modes and elicit an appropriate intervention, AI systems must have some form of understanding, a world model, or, in other words, the AI has to implicitly or explicitly model causal relations. Counterfactual inference incorporates causal relations between observations and interventions which allows making predictions of outcomes that were never seen during training (Vlontzos et al., 2023).

6 Conclusions

In this survey, we presented a comprehensive overview of (deep) transfer learning by defining transfer learning problem settings and categorizing the state-of-the-art deep transfer learning approaches. Equipped with this foundation, we selected representative examples of the landscape of fielded applications to provide practitioners with a guide to the field and possibilities of industrial time series anomaly detection. After carefully discussing open challenges, we gave practical directions for time series anomaly detection solution design and deep transfer learning implementation. We found that current applications focus on simple cases with simple datasets, neural network structures, and deep transfer learning schemes. Despite this, the survey suggests that deep transfer learning approaches have huge potential and promise for solving more complex and dynamic anomaly detection tasks in the industry. As the field is still in an early stage, more R&D is expected to fully realize the potential of deep transfer learning in increasingly complex settings. Future work should focus on developing robust transfer learning schemas and methods that can handle more complex and dynamic tasks. The following directions hold the greatest potential for future work:

Automatic selection of transferable features (Long et al., 2015) It refers to methods for selecting and transferring only the relevant knowledge from the base model. This could involve the use of techniques such as selective fine-tuning and distillation to identify the most important features and knowledge learned from source domains (Yosinski et al., 2014; Ge and Yu, 2017).

Investing into more complex deep transfer learning schemes and DNN architectures Most deep transfer learning approaches applied in industry focus on the parameter transfer approach as it is conceptionally the simplest and readily applicable by interdisciplinary teams without ML research experience. It seems promising to invest in testing more appropriate deep transfer learning approaches according to different use cases, such as mapping transfer, adversarial transfer, etc. The same applies to testing diverse DNN architectures besides straightforward ones.

Data-centric approach to real-time anomaly detection The data-centric approach focuses on improving ML models by ensuring high-quality labeled data (Stadelmann et al., 2022) using techniques such as re-labeling, re-weighting, or data augmentation (Luley et al., 2023). Currently, a human-in-the-loop solution is still needed, frameworks have been proposed to assist annotators with graph-based algorithms such as nearest neighbor graphs (Bai et al., 2021), decision trees (Liu et al., 2021), or factor graphs (Kang et al., 2022). Although these methods have proven to be effective, a more automated process is a goal for future research.

Integration with other ML methods To build robust AI approaches to solve time series anomaly detection in industry, only focusing on transfer learning will not be sufficient. Combinations with other ML approaches are needed in the future, such as continuous learning, meta-learning, and federated learning.

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