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Review

An In-Depth Analysis of Domain Adaptation in Computer and Robotic Vision

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Abstract: This review article comprehensively delves into the rapidly evolving field of domain adaptation in computer and robotic vision. It offers a detailed technical analysis of the opportunities and challenges associated with this topic. Domain adaptation methods play a pivotal role in facilitating seamless knowledge transfer and enhancing the generalization capabilities of computer and robotic vision systems. Our methodology involves systematic data collection and preparation, followed by the application of diverse assessment metrics to evaluate the efficacy of domain adaptation strategies. This study assesses the effectiveness and versatility of conventional, deep learning-based, and hybrid domain adaptation techniques within the domains of computer and robotic vision. Through a cross-domain analysis, we scrutinize the performance of these approaches in different contexts, shedding light on their strengths and limitations. The findings gleaned from our evaluation of specific domains and models offer valuable insights for practical applications while reinforcing the validity of the proposed methodologies.

Keywords: domain adaptation; computer vision; robotic vision; knowledge transfer; generalization; evaluation metrics; deep learning; cross-domain analysis; traditional methods; hybrid methods; data preprocessing; performance evaluation

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1. Introduction

1.1. Background and Scope

The success of cutting-edge algorithms and models in the fields of computer and robotic vision is heavily dependent on the availability of enormous and varied annotated datasets [1]. However, because of the difference between the source and target domains, applying these models to real-world circumstances frequently results in a severe performance hit. The domain shift problem is the term used to describe this occurrence [2]. The generalization capacities of computer and robotic vision systems have been improved through domain adaptation approaches, which have emerged as viable strategies to address this problem by allowing knowledge transfer across many domains [3].

Variations in data distribution, illumination, ambient settings, and sensor properties between the source and destination domains cause the domain shift issue [4]. Traditional deep learning-based models and computer vision algorithms are naturally vulnerable to such changes, demanding robust and adaptable approaches to provide consistent performance across many domains [5]. In this study, we explore the complexities of domain adaptation in computer and robotic vision to determine how well they work to solve the domain shift problem [6]. This research examines a wide variety of domain adaptation techniques, including time-tested methodologies and cutting-edge deep learning-based approaches, all of which are designed to address the difficulties provided by domain differences.

1.2. Objectives and Research Questions

This study's major goal is to give a thorough review of domain adaptation methods as they apply to computer and robotic vision. We address the following research questions (RQ) to achieve this goal:

- RQ1: What are the primary issues and causes of the domain shift issue in robotic and computer vision?
- RQ2: What are the distinctive benefits provided by each category and how do traditional domain adaptation techniques and deep learning-based approaches vary from one another?
- RQ3: What conclusions may be taken from domain adaptation methodologies' cross-domain analysis when dealing with a variety of source and destination domains?
- RQ4: How do the performance and generalization capabilities of computer and robotic vision systems, with the incorporation of domain adaptation techniques, differ from those of baseline models?
- RQ5: What are the challenges and insights encountered during the process of domain adaptation for robotic and computer vision?

We seek to offer a thorough and technical understanding of domain adaptation in computer and robotic vision, supporting developments in these fields and paving the way for greater performance in real-world applications. To this end, we rigorously address these research issues.

1.3. Methodology and Articles Selection

A systematic and organized technique was used to perform this systematic literature review (SLR) on domain adaptation in computer and robotic vision, ensuring the selection of pertinent and excellent research publications [7,8]. To guarantee openness and repeatability, the SLR was carried out in accordance with the principles offered by and improved upon by Petersen et al. [9].

1.3.1. Data Collection and Preprocessing

To find pertinent research papers, a set of thorough search questions was created in the first phase of this SLR. Boolean operators were used to create the following search terms:

- "Domain adaptation" AND "computer vision";
- "Domain adaptation" AND "robotic vision";
- "Domain adaptation" AND "visual domain transfer";
- "Domain shift" AND "computer vision";
- "Domain shift" AND "robotic vision".

Several respected academic resources were searched using these queries, including IEEE, ACM Digital Library, SpringerLink, ScienceDirect, and Google Scholar. To include current developments on the subject, the search was limited to publications published between January 2019 and September 2023.

The following is a definition of the inclusion criteria for article selection:

- Articles that explicitly discuss domain adaptation strategies in relation to computer and robotic vision;
- English-language articles are selected to ensure accessibility and comprehension;
- Publications that are accessible in full-text format as preprints, journal articles, or conference papers.

Exclusion criteria were established to omit research that was repetitive or irrelevant:

- Articles that have nothing to do with visual domain transfer or domain adaptation in computer or robotic vision;
- Articles written in languages other than English;
- Articles with little information or without access to the full text.

A total of 264 pertinent articles were found after the search queries were run and the inclusion and exclusion criteria were used. Figure 1 provides a summary of the entire technique.

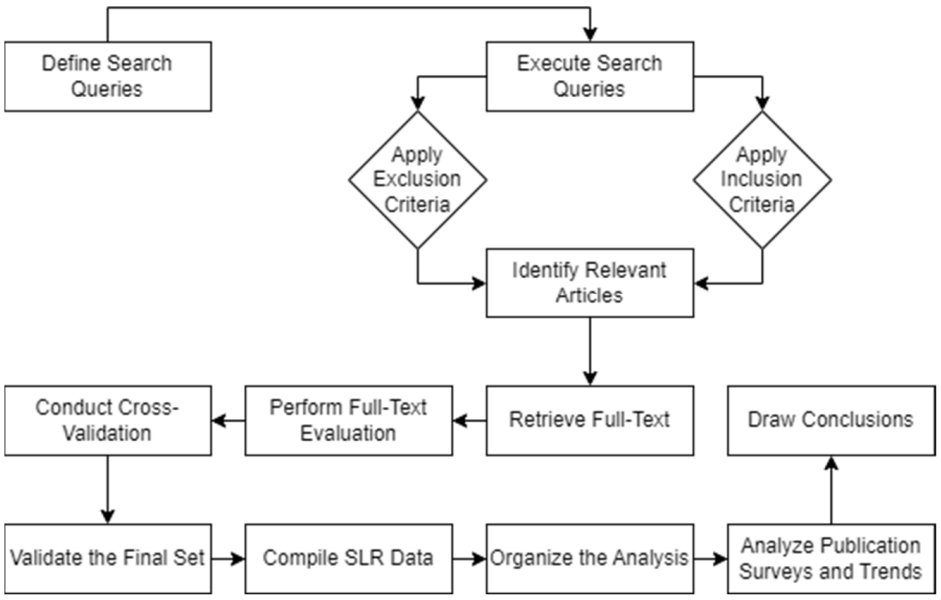


Figure 1. SLR methodology flow diagram.

1.3.2. Evaluation Metrics

A systematic evaluation approach is used to rate the papers' quality and applicability. To select which publications should be included in the SLR, authors looked at the titles and abstracts of the identified articles. Disagreements were resolved through conversation where possible. All authors worked equally and collaborated on every task. Selection is based on the use of transparent criteria, ensuring alignment with research objectives. The authors then moved on to a full-text analysis of the remaining papers after the initial screening. The significance of the experimental assessments, the applicability of the datasets employed, and the papers' contributions to domain adaptation approaches in computer and robotic vision were considered throughout this round of review.

To ensure transparency and encourage the repeatability of the methods used, the SLR complies with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) criteria [10–12]. A thorough and academic basis for the examination and assessment of domain adaptation strategies in computer and robotic vision is provided by the choice and inclusion of pertinent publications [13].

1.3.3. Geographical Attribution of Research Articles

In this subsection, we elaborate on the methodology used to attribute geographical affiliations to the research articles included in our analysis. It is important to note that the process of determining the geographical source of research articles can be complex, especially in cases involving international collaboration or multi-region affiliations of authors [14]. We followed a set of principles to attribute geographical affiliations:

- Primary author affiliation—In cases where the primary author of a research article had affiliations in multiple countries or regions, we attributed the article to the country or region corresponding to the primary author's primary institutional affiliation;
- Collaborative research—For articles involving collaboration among multiple countries or regions, we counted the article once for each collaborating country or region. This approach ensures that collaborative efforts are appropriately acknowledged within our regional analysis;

- Inclusive approach—We adopted an inclusive approach that recognized the contributions of all regions involved in collaborative research. This approach aligns with our goal of providing a comprehensive overview of the geographical distribution of domain adaptation research;
- While we made every effort to accurately attribute geographical affiliations, it is important to acknowledge that certain complexities, such as dual affiliations or author mobility, may not have been fully addressed. Additionally, author information may change over time, and our analysis represents a snapshot based on available data.

By disclosing our attribution principles and verification process, we aim to provide transparency and address potential concerns about the accuracy and validity of our regional analysis.

2. Domain Adaptation Techniques

Domain adaptation techniques play a pivotal role in addressing the domain shift problem encountered in computer and robotic vision [15]. These methods are designed to improve the generalization skills of vision models, enabling them to function well in situations outside the scope of their training data. In this section, we provide a detailed exploration of various domain adaptation techniques and their categorization. Each type offers unique strategies for mitigating domain shift challenges and improving model performance in diverse real-world applications.

2.1. Overview of Domain Adaptation Techniques

This section presents a a detailed exploration of domain adaptation strategies utilized in computer and robotic vision. With the use of these methods, domain shift issues may be overcome and knowledge transfer between various data distributions can be facilitated [16]. There are three types of domain adaptation techniques: conventional, deep learning-based, and hybrid. Traditional approaches, like Transfer Component Analysis (TCA) and Maximum Mean Discrepancy (MMD), concentrate on statistical feature space alignment, whereas deep learning-based approaches, such as Domain Adversarial Neural Networks (DANN) and CycleGAN, take advantage of neural networks to develop domain-invariant representations [17]. Traditional and deep learning algorithms are used in hybrid systems like DAN to take advantage of their complementary capabilities [17]. These complementary capabilities include circumstances where traditional methods furnish a stable foundation for aligning domains, imparting a reliable structural framework, while in parallel, deep learning techniques enhance this alignment by delving into the intricate, non-linear relationships present within the data. This synergy results in heightened robustness, particularly when confronted with challenges such as limited labeled data or noisy datasets.

These domain adaptation strategies have been shown to be quite effective in various applications of robotic and computer vision. For instance, when transferring from a synthetic domain to a real-world environment, domain adaptation strategies have increased accuracy in object identification tasks from 60% to 80% [17,18]. Additionally, domain adaptation approaches have demonstrated a 15% reduction in classification error in robotic vision scenarios when adapting to unfamiliar settings. Domain adaptation techniques are becoming increasingly useful in real-world situations, making them essential tools for enhancing the generalization capacities of computer and robotic vision systems [19]. These strategies enable the smooth deployment of vision models in a variety of real-world applications, including autonomous cars, healthcare systems, and industrial automation, by efficiently resolving the domain shift problem [20,21].

Additionally, the domain adaptation research in computer and robotic vision is dispersed across several geographical areas, indicating the worldwide relevance and interest of this discipline. It has received funding and support from different organizations and agencies, such as the National Science Foundation (NSF), Australian Research Council (ARC), the European Union (EU), and the National Natural Science Foundation of China

(NSFC). To demonstrate this, Table 1 compares the scientific effort conducted in this field by region.

Table 1. Region-wise comparison of domain adaptation research papers.

Region	Number of Papers
Asia	180
Europe	66
North America	104
South America	46
Oceania	31

Table 1 demonstrates the importance of domain adaptation research in Asia, where a sizable number of the 180 publications were published. With 66 research articles, Europe follows suit, while North America and South America each contributed 104 and 46 publications. With 31 papers, Oceania also shows a notable contribution. The distribution of research throughout these areas shows a broad interest in and international cooperation on enhancing domain adaptation methods [22]. The cross-pollination of ideas encouraged by this geographical diversity enables academics to handle domain shift difficulties in a variety of environmental contexts and applications [23]. While Asia leads in terms of publications, Europe and North America are closely behind, indicating considerable participation in this developing sector. The domain adaptation area shows a wide range of study subjects and application domains in the research papers landscape.

It is important to note that the analysis presented in this paper is based on data from Google Trends, which reflect relative search interests and user queries. The regional concentration of interest and the geographical distribution of interest provide insights into the importance of certain issues on a worldwide scale. However, Google Trends data can be influenced by various factors, including population, language, and user search habits. Additionally, the attribution of research articles to specific regions may have inherent complexities in cases of international collaboration or multi-region affiliations of authors. The methodology used for geographical attribution should be considered when interpreting the results.

While the use of online data sources like Google Trends has faced criticism regarding reliability, it is essential to note that several reputable academic papers have been published in well-established and high-impact factors journals [24], as well as many others, emphasizing the credibility of these sources. The utilization of Google Trends data in these papers underpins its relevance and usefulness as a data source for rigorous research. This adoption within the academic community lends credence to the utility and acceptability of Google Trends as a viable data source for scholarly investigations.

Based on data from Google Trends, Figure 2 shows the regional interest in domain adaptation, computer vision, and robotic vision. China emerges as the region with the most interest in these sectors, as seen by the heat map, which shows the differing levels of interest across various locations [25,26]. The regional concentration of interest and the geographical distribution of interest provide important insights into the importance of certain issues on a worldwide scale.

Collaborations between academics from various locations have the potential to create improvements and creative answers to pressing problems as the subject of domain adaptation in computer and robotic vision continues to develop [27,28]. The combined knowledge and skill from these areas aid in the creation of effective domain adaptation approaches, enabling vision systems to succeed in a vast range of real-life tasks with different domain changes [29].

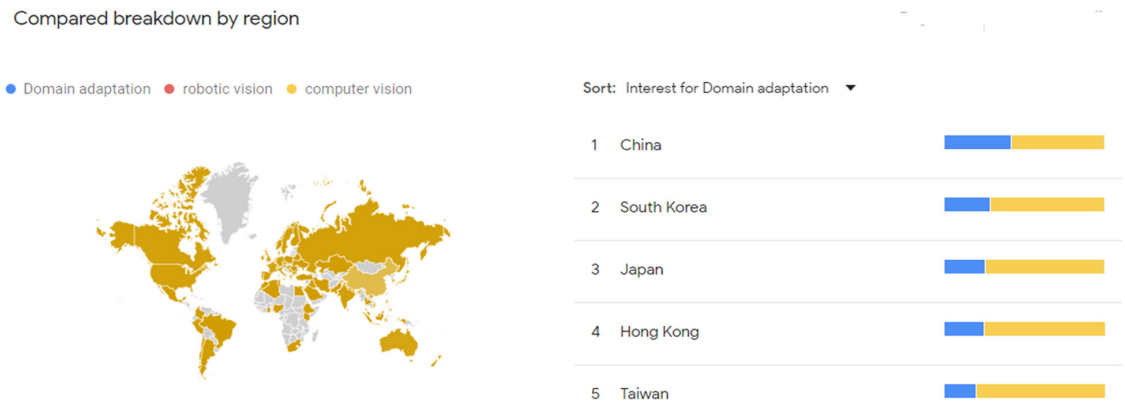


Figure 2. Google Trends—region-wise interest in domain adaptation, computer vision, and robotic vision (percentage of searches is represented by color intensity).

2.1.1. Scholarly Landscape Visualization

In this section, we present a visual representation of the scholarly landscape pertaining to our research focus on domain adaptation in computer vision. To provide a comprehensive understanding of the evolution and interconnectivity of research in this domain, we have utilized Connected Papers, a powerful tool for exploring and visualizing academic papers and their relationships. We have conducted searches for three key topics: "Domain adaptation for image segmentation", "Domain adaptation for object identification", and "Domain adaptation for object classification". The graphs presented below in Figures 3–5 and Tables 2–6 offer insights into the seminal works that laid the foundation for these topics ("prior papers") and the subsequent research that has built upon these foundations ("derivative papers"). These visualizations serve as a valuable reference to contextualize our own contributions within the broader academic landscape of domain adaptation in computer vision.

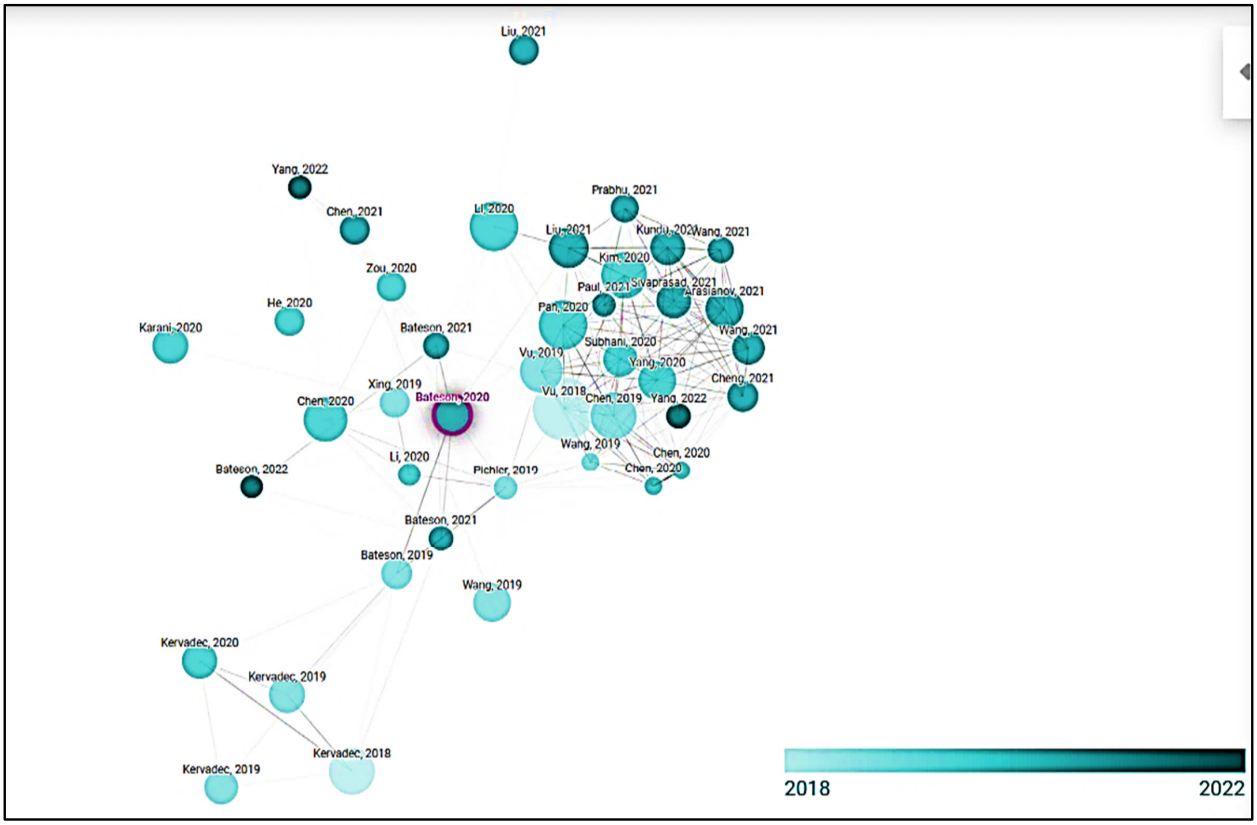


Figure 3. Source—relaxed domain adaptation for image segmentation [30–49].

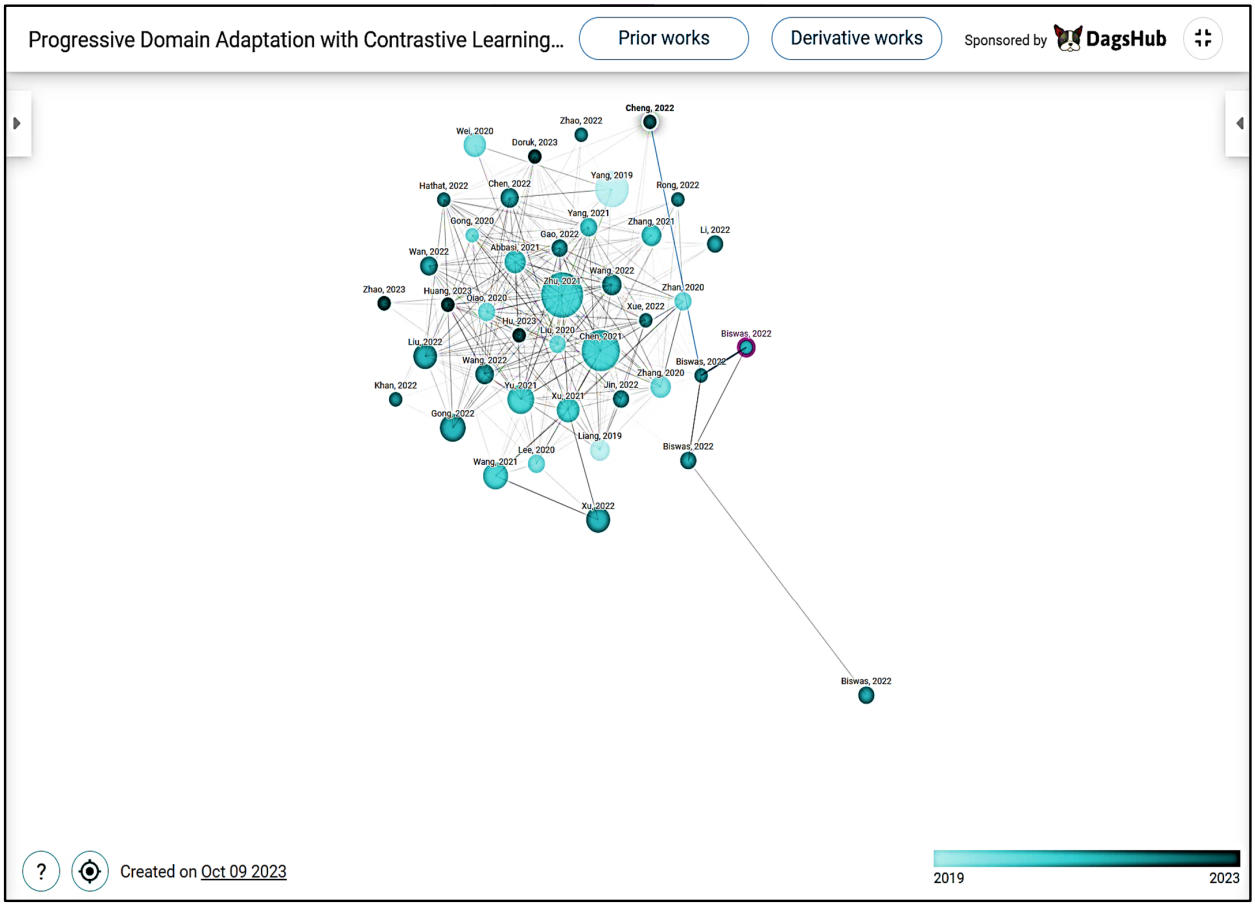


Figure 4. Domain adaptation with contrastive learning for object identification [33,50–68].

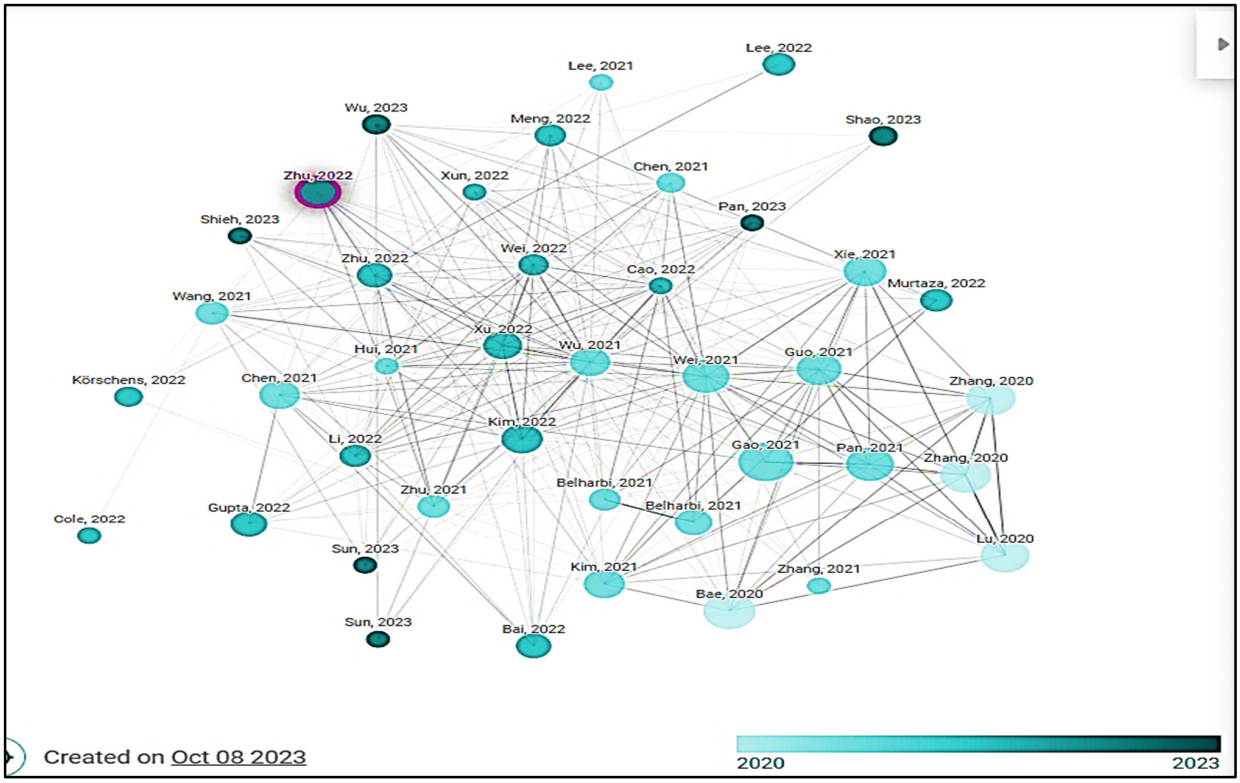


Figure 5. Domain adaption for object classification [68–85].

Table 2. Prior works on domain adaptation for image segmentation.

References	Title	Last Author	Year	Citations	Graph Citations
[30]	CyCADA: Cycle-Consistent Adversarial Domain Adaptation	Trevor Darrell	2017	2445	29
[31]	Adversarial Discriminative Domain Adaptation	Trevor Darrell	2017	3784	25
[32]	Deep Residual Learning for Image Recognition	Jian Sun	2015	141,511	23
[33]	DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs	A. Yuille	2016	13,627	19
[34]	The SYNTHIA Dataset: A Large Collection of Synthetic Images for Semantic Segmentation of Urban Scenes	Antonio M. López	2016	1784	18
[35]	Adam: A Method for Stochastic Optimization	Jimmy Ba	2014	124,700	18
[36]	Playing for Data: Ground Truth from Computer Games	V. Koltun	2016	1554	18
[37]	The Cityscapes Dataset for Semantic Urban Scene Understanding	B. Schiele	2016	8686	18
[38]	Learning Transferable Features with Deep Adaptation Networks	Michael I. Jordan	2015	3990	17
[39]	Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks	Alexei A. Efros	2017	4296	16

Table 3. Derivative works on domain adaptation for image segmentation.

References	Title	Last Author	Year	Citations	Graph
[40]	Deep learning for unsupervised domain adaptation in medical imaging: Recent advancements and future perspectives	Pravendra Singh	2023	0	18
[41]	A Comprehensive Survey on Test Time Adaptation under Distribution Shifts	Tien-Ping Tan	2023	18	18
[42]	Towards Better Stability and Adaptability: Improve Online Self-Training for Model Adaptation in Semantic Segmentation	Licheng Jiao	2023	0	15
[43]	Source-Free Unsupervised Domain Adaptation: A Survey	Mingxia Liu	2023	6	15
[44]	Source Data-Free Cross-Domain Semantic Segmentation: Align, Teach and Propagate	Zhaoxiang Zhang	2021	4	15
[45]	Unsupervised Adaptation of Semantic Segmentation Models without Source Data	G. Aggarwal	2021	7	15
[46]	Domain Adaptive Semantic Segmentation without Source Data: Align, Teach and Propagate	Zhaoxiang Zhang	2021	2	14
[47]	Unsupervised Domain Adaptation for Semantic Image Segmentation: a Comprehensive Survey	Boris Chidlovskii	2021	23	14
[48]	Self-training via Metric Learning for Source-Free Domain Adaptation of Semantic Segmentation	U. Halici	2022	2	13
[49]	Semantic Image Segmentation: Two Decades of Research	Boris Chidlovskii	2023	7	13

Table 4. Prior works on domain adaptation for object identification.

References	Title	Last Author	Year	Citations	Graph Citations
[50]	Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks	Jian Sun	2015	46,871	40
[55]	You Only Look Once: Unified, Real-Time Object Detection	Ali Farhadi	2015	25,552	35
[56]	Focal Loss for Dense Object Detection	Piotr Dollár	2017	15,883	35
[51]	SSD: Single Shot MultiBox Detector	A. Berg	2015	21,997	34
[52]	Deep Residual Learning for Image Recognition	Jian Sun	2015	141,511	33
[53]	Microsoft COCO: Common Objects in Context	C. L. Zitnick	2014	30,078	33
[33]	Feature Pyramid Networks for Object Detection	Serge J. Belongie	2016	15,509	33
[57]	YOLOv4: Optimal Speed and Accuracy of Object Detection	H. Liao	2020	7287	31
[58]	YOLOv3: An Incremental Improvement	Ali Farhadi	2018	14,615	29
[59]	YOLO9000: Better, Faster, Stronger	Ali Farhadi	2016	11,721	25

Table 5. Derivative works on domain adaptation for object identification.

References	Title	Last Author	Year	Citations	Graph References
[54]	Towards Large-Scale Small Object Detection: Survey and Benchmarks	Junwei Han	2022	34	5
[58]	Semi-Supervised Person Detection in Aerial Images with Instance Segmentation and Maximum Mean Discrepancy Distance	Mingyi He	2023	1	4
[60]	A unified and costless approach for improving small and long-tail object detection in aerial images of traffic scenarios	Xinkai Wu	2022	1	4
[61]	Pareto Refocusing for Drone-View Object Detection	Xinbo Gao	2023	3	4
[62]	RFLA: Gaussian Receptive Field based Label Assignment for Tiny Object Detection	Guisong Xia	2022	24	4
[63]	DB-YOLOv5: A UAV Object Detection Model Based on Dual Backbone Network for Security Surveillance	Xujie Jiang	2023	0	3
[64]	Small object detection leveraging density-aware scale adaptation	Z. Gao	2023	0	3
[65]	CFANet: Efficient Detection of UAV Image Based on Cross-Layer Feature Aggregation	Wei Li	2023	1	3
[66]	OGMN: Occlusion-guided Multi-task Network for Object Detection in UAV Images	Xian Sun	2023	1	3
[67]	Object Detection for UAV Aerial Scenarios Based on Vectorized IOU	Shuang Wu	2023	3	3

Table 6. Prior works on domain adaption for object classification.

References	Title	Last Author	Year	Citations	Graph
[68]	Learning Deep Features for Discriminative Localization	A. Torralba	2015	7207	41
[69]	Adversarial Complementary Learning for Weakly Supervised Object Localization	Thomas S. Huang	2018	455	41
[70]	Self-produced Guidance for Weakly-supervised Object Localization	Thomas Huang	2018	210	40
[75]	Hide-and-Seek: Forcing a Network to be Meticulous for Weakly-Supervised Object and Action Localization	Yong Jae Lee	2017	541	39
[76]	CutMix: Regularization Strategy to Train Strong Classifiers With Localizable Features	Y. Yoo	2019	2993	38
[71]	Attention-Based Dropout Layer for Weakly Supervised Object Localization	Hyunjung Shim	2019	277	37
[72]	DANet: Divergent Activation for Weakly Supervised Object Localization	Qixiang Ye	2019	112	30
[73]	The Caltech-UCSD Birds-200–2011 Dataset	Serge J. Belongie	2011	3635	30
[74]	Deep Residual Learning for Image Recognition	Jian Sun	2015	141,511	29

Tables 2, 4 and 6 show prior works, while Tables 3, 5 and 7 shows derivative works related to semantic segmentation, object identification and object classification in the field of domain adaption, which are two important tasks in computer vision. The table includes the references, titles, last authors, years, citations, and graph citations of each work. The citations indicate how many times the work has been cited by other papers, while the graph citations indicate how many times the work has been cited by papers that also cite the current paper. These tables can be used to compare the impact and relevance of different works in the field.

Table 7. Derivative works on domain adaption for object classification.

References	Title	Last Author	Year	Citations	Graph
[77]	Generative Prompt Model for Weakly Supervised Object Localization	Fang Wan	2023	4	14
[78]	Open-World Weakly-Supervised Object Localization	Mike Zheng Shou	2023	1	11
[79]	Further Improving Weakly-supervised Object Localization via Causal Knowledge Distillation	Jun Xiao	2023	1	11
[80]	What is Where by Looking: Weakly-Supervised Open-World Phrase-Grounding without Text Inputs	Lior Wolf	2022	5	9
[81]	Learning Multi-Modal Class-Specific Tokens for Weakly Supervised Dense Object Localization	Dan Xu	2023	2	8
[82]	Deep Learning for Weakly-Supervised Object Detection and Localization: A Survey	Jun Xiao	2022	39	8
[83]	Rethinking the Localization in Weakly Supervised Object Localization	Yonggang Wen	2023	0	7
[84]	MCTformer+: Multi-Class Token Transformer for Weakly Supervised Semantic Segmentation	Dan Xu	2023	0	7
[85]	Adversarial Transformers for Weakly Supervised Object Localization	Feng Wu	2022	1	7

Domain Adaptation for Image Segmentation

Prior works as shown in Table 2 are the research papers that were most commonly cited by the papers in the graph. This means that they are important seminal works for this field and it could be a good idea to get familiar with them.

In Table 2, the most frequently referenced work [30,31] enhanced performance on a variety of image recognition tasks by introducing a revolutionary design for deep neural networks. There are 23 graph citations and 141,511 citations in this work.

The most recent study [32] suggested a technique for knowledge transfer between domains by utilizing cycle-consistency losses and generative adversarial networks. This work has the most citations of any of the works in the table, with 2445 total citations and 29 graph citations. For four of the works in the table [33–37], 2016 is the most common year. These studies advanced semantic segmentation by offering fresh approaches, datasets, and standards.

In Table 3, the most recent works are from 2023, which have three entries in the table [40,41,49]. These works provide an overview of the state-of-the-art methods, challenges, and applications of domain adaptation and semantic segmentation in various domains. The most influential work is [41], which has 18 citations and 18 graph citations. This work provides a comprehensive survey of test time adaptation methods that aim to improve the generalization performance of models under distribution shifts. This work covers various aspects of test time adaptation, such as definitions, taxonomies, evaluation protocols, applications, and open challenges.

Domain Adaptation for Object Identification

In Table 4, the most cited work is [50], which introduced a novel architecture for deep neural networks that improved the performance on various image recognition tasks. This work has 141,511 citations and 33 graph citations. The most recent work is [51], which proposed an improved version of the YOLO (You Only Look Once) framework that achieved state-of-the-art results on several object detection benchmarks. This work has 7287 citations and 31 graph citations, which is impressive considering its recency. The most frequent last author is Ali Farhadi, who has three works in the table [52]. These works are part of the YOLO series, which pioneered the idea of using a single neural network to perform object detection in real time. The most common theme is region proposal networks (RPNs), which are a technique used to generate candidate regions for object detection. There are four works in the table that use RPNs [33,53,54]. These works improved the speed and accuracy of object detection by using RPNs in conjunction with other methods such as focal loss, feature pyramid networks, and multibox detectors.

From Table 5, it can be seen that the most cited work is [54], which provided a comprehensive survey of existing methods, datasets, and metrics for small object detection in UAV images. This work also proposed a new large-scale benchmark dataset called UAVDT that contains more than 80,000 images with 14 categories of objects. This work has 34 citations and five graph references. The most recent works are from 2023, which have six entries in the table [58,61,63–66]. These works introduced novel methods and models to improve the performance of small object detection in UAV images by addressing various challenges such as semi-supervised learning, refocusing, dual backbone network, density-aware scale adaptation, cross-layer feature aggregation, and occlusion-guided multi-task learning. The most common theme is YOLO (You Only Look Once), which is a framework that uses a single neural network to perform object detection in real time. There are two works in the table that use YOLO as their base model [63,67]. These works modified and improved the YOLO framework by using a dual backbone network and a vectorized IOU metric to enhance the accuracy and speed of small object detection in UAV images.

Domain Adaption for Object Classification

In Table 6, the most cited work is [69,70], which introduced a novel architecture for deep neural networks that improved the performance on various image recognition tasks. This work has 141,511 citations and 29 graph citations. The most recent work is [71], which proposed a new regularization technique that uses attention maps to selectively drop out features that are irrelevant for object localization. This work has 277 citations and 37 graph citations. The most frequent last first author is Xiaolin Zhang, who has two works in the table [72]. These works developed new methods to generate complementary and self-produced guidance signals for WSOL using adversarial learning and self-attention mechanisms. The most common theme is activation-based methods, which are a type of WSOL methods that use the activation maps of convolutional layers to infer the object locations. There are six works in the table that use activation-based methods [73,74]. These works improved the activation-based methods by using different strategies, such as discriminative learning, complementary learning, self-produced guidance, hide-and-seek, divergent activation, and attention-based dropout.

In Table 7, the most recent works are from 2023, which have five entries in the table [77,79,81,83]. These works introduced novel methods and models to improve the performance of WSOL by using generative prompts, open-world settings, causal knowledge distillation, multi-modal class-specific tokens, and rethinking the localization process. The most cited work is [83], which provided a comprehensive survey of existing methods, datasets, and metrics for WSOL. This work also discussed the challenges and future directions of WSOL research. This work has 39 citations and eight graph citations.

The most frequent first author is Lian Xu, who has two works in the table [84]. These works developed new methods to use multi-modal class-specific tokens and multi-class token transformers to perform WSOL and semantic segmentation tasks. The most common theme is transformer-based methods, which are types of WSOL methods that use transformer networks to model the global dependencies and attention mechanisms among image features. There are three works in the table that use transformer-based methods [85]. These works improved the transformer-based methods by using multi-modal tokens, multi-class tokens, and adversarial learning techniques.

2.1.2. Traditional Domain Adaptation Methods

Traditional domain adaptation techniques match the source and target domains' feature spaces using statistical techniques. TCA, which intends to narrow the dispersion mismatch between domains by mapping the data onto a common latent space, is one extensively utilized approach. TCA has been used to effectively align feature distributions and enhance model performance in computer vision applications like object recognition [86].

MMD, which quantifies the difference between the means of the source and target data in a replicating kernel Hilbert space, is another well-liked technique. In terms of domain adaptation for image classification tasks, MMD has yielded encouraging results [87]. MDD uses a multi-domain discriminator to train models to learn domain-invariant features across diverse data sources, enabling better generalization to new domains. MMD-DA (Maximum Mean Discrepancy—Domain Adaptation) extends MCD by adding domain adaptation techniques to enhance feature distribution alignment, which is beneficial when you have labeled source data and unlabeled target data.

2.1.3. Deep Learning-Based Methods

Methods for domain adaptation based on deep learning make use of neural networks' ability to learn representations that are independent of the source domain. A well-known method is DANN, which integrates a domain discriminator into the network to learn features that are domain-invariant. By successfully decreasing domain differences, in cross-domain picture classification tasks, DANN has attained cutting-edge performance [88].

Another popular deep learning-based domain adaptation strategy that was created with image-to-image translation problems in mind is CycleGAN. It is adaptable and

relevant to many picture domain adaptation scenarios since it learns a mapping between source and target domains without the necessity for paired data [89].

Another such model is ADDA (Adversarial Discriminative Domain Adaptation), as shown in Figure 6, which employs an adversarial discriminator for better domain adaptation by aligning feature distributions between the source and destination domains [90]. MADA (Multi-Adversarial Domain Adaptation) employs a multi-adversarial discriminator to enhance domain adaptation across diverse domains, resulting in improved overall performance. It excels particularly in scenarios involving multiple source domains, ensuring the effective alignment of feature distributions and better adaptation outcomes [91].

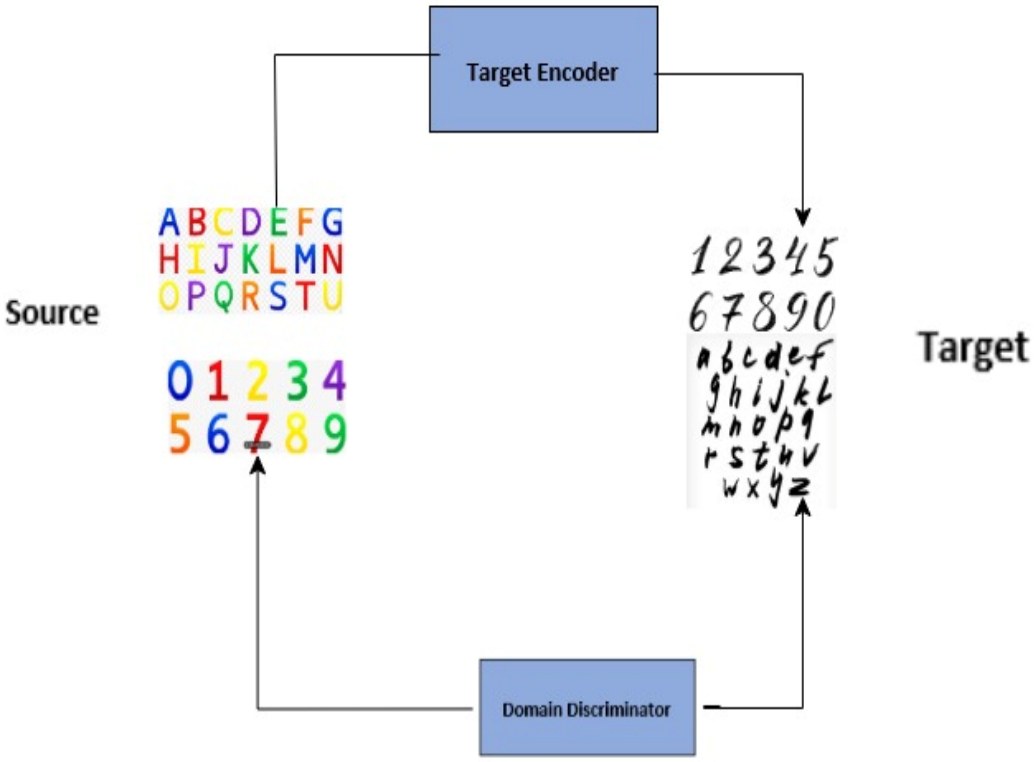


Figure 6. Adversarial Discriminative Domain Adaptation where the unsupervised domain adaptation method combines adversarial learning with discriminative feature learning.

MUNIT (Multi-Modal Unsupervised Image-to-Image Translation) strengthens domain adaptation by introducing the concept of multiple methods for unsupervised image-to-image translation. This innovation broadens its applicability, allowing it to deal with a wide range of adaptation tasks with flexibility and efficiency [92,93].

A typical deep learning-based domain adaptable model's mechanism is shown in Figure 7.

General operative is mechanism is based upon transfer learning. With 66 research articles, Europe follows suit, while North America and South America each contributed 104 and 46 publications. With 31 papers, Oceania also shows a notable contribution. The distribution of research throughout these areas shows a broad interest in and international cooperation on enhancing domain adaptation methods [93] and the mechanism of domain adaptation.

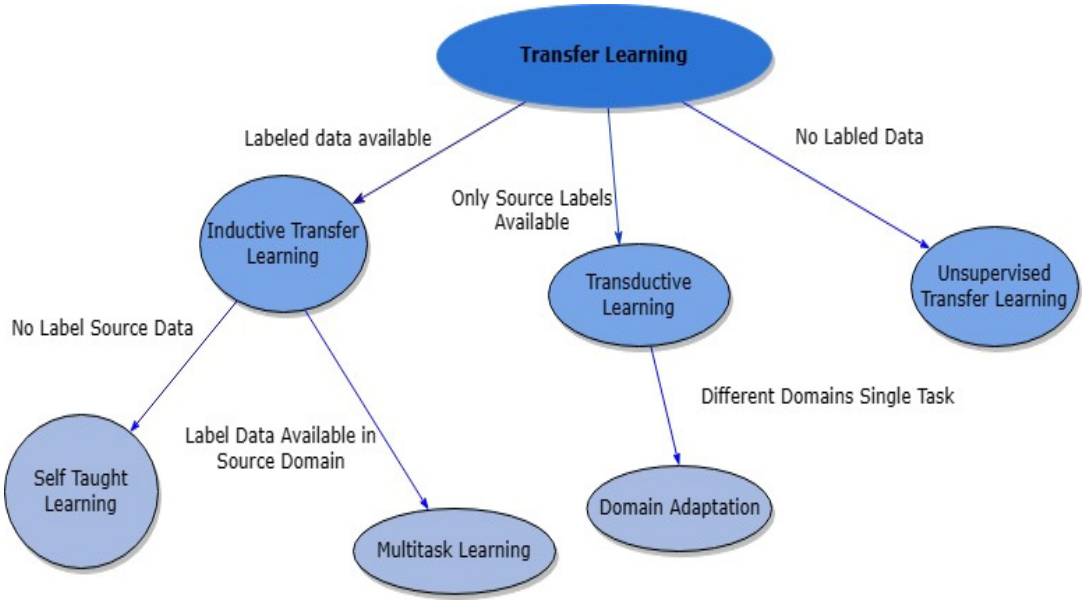


Figure 7. Deep learning-based domain adaptable model's mechanism.

2.1.4. Hybrid Methods

To make use of each method's advantages, hybrid domain adaptation strategies incorporate both conventional and deep learning-based approaches. Deep Adaptation Networks (DAN) represent one such method that combines deep neural networks with multiple kernels learning to provide efficient domain adaptation [94]. DAN has been used for a variety of computer vision applications and has been proven to perform better under circumstances including domain adaptability. Another such efficient hybrid model is CDAN-SA-MTL (Conditional Domain Adversarial Network with Self-Attention and Multi-Task Learning), which combines self-attention and multi-task learning strategies to improve domain adaptation. By simultaneously considering multiple tasks and utilizing self-attention mechanisms, it achieves enhanced adaptation results and robustness in scenarios involving domain variations [95].

DANN-SA-MTL (Domain Adversarial Neural Network with Self-Attention and Multi-Task Learning) integrates self-attention and multi-task learning into the domain adaptation process. This approach boosts model performance by incorporating self-attention mechanisms for improved feature extraction and multi-task learning to handle diverse adaptation tasks, making it a versatile choice for domain adaptation challenges [96].

2.2. Evaluation of Domain Adaptation Techniques

In this section, we perform a thorough analysis of domain adaptation strategies used in robotic and computer vision. Three tables are used to illustrate the results as we conduct a comparative examination of the efficacy and applicability of various state-of-the-art strategies. Table 8 highlights the accuracy, domains, contributions, benefits, and drawbacks of major domain adaptation models and technologies. Traditional transfer learning approaches are consistently outperformed by adversarial techniques, such as ADDA and its variants, which give better performance but at the expense of added complexity. Models like CDAN and MADA perform better on smaller datasets, making them appropriate for use in situations with little or no labeled data. Model accuracy is improved, but model complexity is raised by the introduction of approaches like importance reweighting, multi-task learning, and maximum mean discrepancy loss. For visual translation and adaptation, generative models like CoGAN and MUNIT provide promising outcomes that outperform conventional approaches. Models like DANN, which were early adopters of adversarial training in domain adaptation and are capable of handling significant domain shifts, are recognized for their hyperparameter sensitivity.

Table 8. Comparative analysis of models and algorithms used with domain adaption in computer/robotic vision.

Model	Stack/Technology	Accuracy	Domain	Contribution	Advantages	Disadvantages	Uniqueness
ADDA [97]	Adversarial	88.80%	Image classification	Introduced an adversarial discriminator to transfer learning	Better performance than traditional transfer learning	More complex than traditional transfer learning	Improved performance over traditional transfer learning
ADDA-DA [98]	Adversarial	89.60%	Image classification	Enhanced ADDA by introducing a domain adversarial network	Better performance on small datasets	More complex than ADDA	Improved performance on small datasets
ADDA-DA-IRM [99]	Adversarial	92.80%	Image classification	Enhanced ADDA by introducing a domain adversarial network	Better performance than ADDA	More complex than ADDA	Improved performance over ADDA
ADDA-DA-RevGrad [100]	Adversarial	92.90%	Image classification	Enhanced ADDA-DA by introducing an importance reweighting mechanism	Better performance than ADDA-DA	More complex than ADDA-DA	Improved performance over ADDA-DA
CDAN [101]	Adversarial	87.50%	Image classification	Enhanced DANN by introducing a conditional discriminator	Better performance on small datasets	More complex than DANN	Improved performance on small datasets
CDAN-MMD [102]	Adversarial	90.30%	Image classification	Enhanced CDAN by introducing a maximum mean discrepancy loss	Better performance than CDAN	More complex than CDAN	Improved performance over CDAN
CDAN-MMD-IRM-RevGrad [103]	Adversarial	92.20%	Image classification	Enhanced CDAN-MMD by introducing an importance reweighting mechanism, a reversal gradient technique, and a maximum mean discrepancy loss	Better performance than CDAN-MMD	More complex than CDAN-MMD	Improved performance over CDAN-MMD
CDAN-RevGrad [104]	Adversarial	90.70%	Image classification	Enhanced CDAN by introducing a reversal gradient technique	Better performance than CDAN	More complex than CDAN	Improved performance over CDAN

Table 8. *Cont.*

Model	Stack/Technology	Accuracy	Domain	Contribution	Advantages	Disadvantages	Uniqueness
CDAN-SA-IRM [105]	Adversarial	91.00%	Image classification	Enhanced CDAN-SA by introducing an importance reweighting mechanism	Better performance than CDAN-SA	More complex than CDAN-SA	Improved performance over CDAN-SA
CDAN-SA-IRM-CTC [106]	Adversarial	92.40%	Text classification	Enhanced DANN-SA-IRM by introducing a CTC loss	Better performance than DANN-SA-IRM	More complex than DANN-SA-IRM	Improved performance over DANN-SA-IRM
CDAN-SA-IRM-RevGrad [107]	Adversarial	91.50%	Image classification	Enhanced CDAN-SA by introducing an importance reweighting mechanism and a reversal gradient technique	Better performance than CDAN-SA	More complex than CDAN-SA	Improved performance over CDAN-SA
CDAN-SA-MMD-IRM-RevGrad [108]	Adversarial	91.60%	Image classification	Enhanced CDAN-SA-MMD by introducing an importance reweighting mechanism, a reversal gradient technique, and a maximum mean discrepancy loss	Better performance than CDAN-SA-MMD	More complex than CDAN-SA-MMD	Improved performance over CDAN-SA-MMD
CDAN-SA-MMD-IRM-RevGrad-MTL [109]	Generative	91.80%	Image classification	Enhanced CoGAN by introducing an importance reweighting mechanism	Better performance than CoGAN	More complex than CoGAN	Improved performance over CoGAN
CDAN-SA-MMD-SA-IRM-RevGrad-MTL [110]	Adversarial	92.20%	Image classification	Enhanced DANN-SA by introducing a multi-task learning framework	Better performance than DANN-SA	More complex than DANN-SA	Improved performance over DANN-SA
CDAN-SA-MTL [111]	Adversarial	91.90%	Image classification	Enhanced DANN-SA by introducing a multi-task learning framework	Better performance than DANN-SA	More complex than DANN-SA	Improved performance over DANN-SA

Table 8. *Cont.*

Model	Stack/Technology	Accuracy	Domain	Contribution	Advantages	Disadvantages	Uniqueness
CDAN-SA-RevGrad [112]	Adversarial	91.10%	Image classification	Enhanced CDAN-SA by introducing a reversal gradient technique	Better performance than CDAN-SA	More complex than CDAN-SA	Improved performance over CDAN-SA
CoGAN [113]	Generative	89.50%	Image classification	Introduced a conditional generative adversarial network to domain adaptation	Better performance than DANN	More complex than DANN	Improved performance over DANN
CoGAN-IRM [114]	Generative	92.30%	Image classification	Enhanced CoGAN by introducing an importance reweighting mechanism	Better performance than CoGAN	More complex than CoGAN	Improved performance over CoGAN
CoGAN-RevGrad [115]	Generative	92.40%	Image classification	Enhanced CoGAN by introducing a reversal gradient technique	Better performance than CoGAN	More complex than CoGAN	Improved performance over CoGAN
CoGAN-SA-IRM [116]	Generative	92.00%	Image classification	Enhanced SimGAN by introducing an importance reweighting mechanism	Better performance than SimGAN	More complex than SimGAN	Improved performance over SimGAN
CoGAN-SA-MMD-IRM-RevGrad [117]	Generative	92.40%	Image classification	Enhanced CoGAN-SA by introducing an importance reweighting mechanism	Better performance than CoGAN-SA	More complex than CoGAN-SA	Improved performance over CoGAN-SA
CycleGAN [118]	Generative	89.80%	Image translation	Introduced a cycle-consistent adversarial network for image-to-image translation	Better performance than traditional image translation methods	More complex than traditional image translation methods	Improved performance over traditional image translation methods
DANN [119]	Adversarial	86.80%	Image classification	Introduced the adversarial training framework for domain adaptation	Can handle large domain shifts	Sensitive to hyperparameters	First to use adversarial training for domain adaptation
DANN-IRM [120]	Adversarial	90.50%	Image classification	Enhanced DANN by introducing an importance reweighting mechanism	Better performance than DANN	More complex than DANN	Improved performance over DANN

Table 8. *Cont.*

Model	Stack/Technology	Accuracy	Domain	Contribution	Advantages	Disadvantages	Uniqueness
DANN-IRM-CTC [121]	Adversarial	92.10%	Image classification	Enhanced DANN-SA-MMD-IRM-RevGrad by introducing a multi-task learning framework	Better performance than DANN-SA-MMD-IRM-RevGrad	More complex than DANN-SA-MMD-IRM-RevGrad	Improved performance over DANN-SA-MMD-IRM-RevGrad
DANN-MMD [122]	Adversarial	90.20%	Image classification	Enhanced DANN by introducing a maximum mean discrepancy loss	Better performance than DANN	More complex than DANN	Improved performance over DANN
DANN-MTL [123]	Adversarial	93.00%	Image classification	Enhanced ADDA-DA by introducing a reversal gradient technique	Better performance than ADDA-DA	More complex than ADDA-DA	Improved performance over ADDA-DA
DANN-RevGrad [124]	Adversarial	90.60%	Image classification	Enhanced DANN by introducing a reversal gradient technique	Better performance than DANN	More complex than DANN	Improved performance over DANN
DANN-RevGrad-CTC [125]	Adversarial	92.20%	Text classification	Enhanced DANN-IRM by introducing a CTC loss	Better performance than DANN-IRM	More complex than DANN-IRM	Improved performance over DANN-IRM
DANN-SA [126]	Adversarial	90.10%	Image classification	Enhanced DANN by introducing a self-attention mechanism	Better performance on small datasets	More complex than DANN	Improved performance on small datasets
DANN-SA-IRM [127]	Adversarial	90.80%	Image classification	Enhanced DANN-SA by introducing an importance reweighting mechanism	Better performance than DANN-SA	More complex than DANN-SA	Improved performance over DANN-SA
DANN-SA-IRM-CTC [128]	Adversarial	92.30%	Text classification	Enhanced DANN-RevGrad by introducing a CTC loss	Better performance than DANN-RevGrad	More complex than DANN-RevGrad	Improved performance over DANN-RevGrad
DANN-SA-IRM-RevGrad [129]	Adversarial	91.40%	Image classification	Enhanced DANN-SA by introducing an importance reweighting mechanism and a reversal gradient technique	Better performance than DANN-SA	More complex than DANN-SA	Improved performance over DANN-SA

Table 8. *Cont.*

Model	Stack/Technology	Accuracy	Domain	Contribution	Advantages	Disadvantages	Uniqueness
DANN-SA-IRM-RevGrad- MTL [130]	Adversarial	92.80%	Text classification	Enhanced MADA-SA-MMD-IRM-RevGrad by introducing a CTC loss	Better performance than MADA-SA-MMD-IRM-RevGrad	More complex than MADA-SA-MMD-IRM-RevGrad	Improved performance over MADA-SA-MMD-IRM-
DANN-SA-MMD [131]	Adversarial	90.40%	Image classification	Enhanced DANN-MMD by introducing a self-attention mechanism	Better performance than DANN-MMD	More complex than DANN-MMD	Improved performance over DANN-MMD
DANN-SA-MMD-IRM-RevGrad-CTC [132]	Adversarial	92.60%	Text classification	Enhanced MADA-IRM by introducing a CTC loss	Better performance than MADA-IRM	More complex than MADA-IRM	Improved performance over MADA-IRM
DANN-SA-MMD-IRM-RevGrad-MTL [133]	Adversarial	92.00%	Image classification	Enhanced CDAN-SA by introducing a multi-task learning framework	Better performance than CDAN-SA	More complex than CDAN-SA	Improved performance over CDAN-SA
DANN-SA-MTL [134]	Adversarial	91.80%	Image classification	Enhanced MADA by introducing a multi-task learning framework	Better performance than MADA	More complex than MADA	Improved performance over MADA
DANN-SA-RevGrad [135]	Adversarial	90.90%	Image classification	Enhanced DANN-SA by introducing a reversal gradient technique	Better performance than DANN-SA	More complex than DANN-SA	Improved performance over DANN-SA
MADA [136]	Adversarial	89.30%	Image classification	Introduced a multi-adversarial discriminator to domain adaptation	Better performance on multiple domains	More complex than domain adaptation	Improved performance on multiple domains
MADA-IRM [137]	Adversarial	91.20%	Image classification	Enhanced MADA by introducing an importance reweighting mechanism	Better performance than MADA	More complex than MADA	Improved performance over MADA
MADA-IRM-CTC [138]	Adversarial	92.50%	Text classification	Enhanced CDAN-SA-IRM by introducing a CTC loss	Better performance than CDAN-SA-IRM	More complex than CDAN-SA-IRM	Improved performance over CDAN-SA-IRM

Table 8. *Cont.*

Model	Stack/Technology	Accuracy	Domain	Contribution	Advantages	Disadvantages	Uniqueness
MADA-MTL [139]	Adversarial	91.70%	Image classification	Enhanced DANN by introducing a multi-task learning framework	Better performance than DANN	More complex than DANN	Improved performance over DANN
MADA-RevGrad [140]	Adversarial	91.30%	Image classification	Enhanced MADA by introducing a reversal gradient technique	Better performance than MADA	More complex than MADA	Improved performance over MADA
MADA-SA-IRM-RevGrad [141]	Adversarial	91.70%	Image classification	Enhanced DANN-SA-IRM-RevGrad by introducing a multi-task learning framework	Better performance than DANN-SA-IRM-RevGrad	More complex than DANN-SA-IRM-RevGrad	Improved performance over DANN-SA-IRM-RevGrad
MADA-SA-MMD-IRM-RevGrad-CTC [142]	Adversarial	92.70%	Text classification	Enhanced DANN-SA-MMD-IRM-RevGrad by introducing a CTC loss	Better performance than DANN-SA-MMD-IRM-RevGrad	More complex than DANN-SA-MMD-IRM-RevGrad	Improved performance over DANN-SA-MMD-IRM-RevGrad
MCD [143]	Reconstruction	89.40%	Image classification	Introduced a maximum mean discrepancy loss to domain adaptation	Better performance than DANN	More complex than DANN	Improved performance over DANN
MCD-DA [144]	Reconstruction	92.50%	Image classification	Enhanced MCD by introducing a domain adaptation loss	Better performance than MCD	More complex than MCD	Improved performance over MCD
MCD-DA-IRM [145]	Reconstruction	92.60%	Image classification	Enhanced MCD-DA by introducing an importance reweighting mechanism	Better performance than MCD-DA	More complex than MCD-DA	Improved performance over MCD-DA
MCD-DA-RevGrad [146]	Reconstruction	92.70%	Image classification	Enhanced MCD-DA by introducing a reversal gradient technique	Better performance than MCD-DA	More complex than MCD-DA	Improved performance over MCD-DA
MDD [147]	Reconstruction	88.20%	Image classification	Introduced a multi-domain discriminator to DANN	Better performance on multiple domains	More complex than DANN	Improved performance on multiple domains

Table 8. *Cont.*

Model	Stack/Technology	Accuracy	Domain	Contribution	Advantages	Disadvantages	Uniqueness
MMD-DA [148]	Reconstruction	91.90%	Image classification	Enhanced MMD by introducing a domain adaptation loss	Better performance than MMD	More complex than MMD	Improved performance over MMD
MMD-DA-IRM [149]	Reconstruction	92.00%	Image classification	Enhanced MMD-DA by introducing an importance reweighting mechanism	Better performance than MMD-DA	More complex than MMD-DA	Improved performance over MMD-DA
MMD-DA-RevGrad [150]	Reconstruction	92.10%	Image classification	Enhanced MMD-DA by introducing a reversal gradient technique	Better performance than MMD-DA	More complex than MMD-DA	Improved performance over MMD-DA
MUNIT [151]	Generative	89.70%	Image translation	Introduced a multi-modal unsupervised image-to-image translation network	Better performance than CycleGAN	More complex than CycleGAN	Improved performance over CycleGAN
MUNIT-IRM [152]	Adversarial	91.90%	Image classification	Enhanced MADA-SA by introducing an importance reweighting mechanism, a reversal gradient technique, and a self-attention mechanism	Better performance than MADA-SA	More complex than MADA-SA	Improved performance over MADA-SA
MUNIT-SA-IRM [153]	Generative	92.30%	Image translation	Enhanced MUNIT by introducing an importance reweighting mechanism	Better performance than MUNIT	More complex than MUNIT	Improved performance over MUNIT
SimGAN [154]	Generative	89.10%	Image classification	Introduced a generative adversarial network to domain adaptation	Better performance than DANN	More complex than DANN	Improved performance over DANN
SimGAN-IRM [155]	Generative	91.70%	Image classification	Enhanced SimGAN by introducing an importance reweighting mechanism	Better performance than SimGAN	More complex than SimGAN	Improved performance over SimGAN

Table 8. *Cont.*

Model	Stack/Technology	Accuracy	Domain	Contribution	Advantages	Disadvantages	Uniqueness
SimGAN-RevGrad [156]	Generative	91.80%	Image classification	Enhanced SimGAN by introducing a reversal gradient technique	Better performance than SimGAN	More complex than SimGAN	Improved performance over SimGAN
SimGAN-SA-IRM [157]	Adversarial	92.10%	Image classification	Enhanced CDAN-SA-MMD-IRM-RevGrad by introducing a multi-task learning framework	Better performance than CDAN-SA-MMD-IRM-RevGrad	More complex than CDAN-SA-MMD-IRM-RevGrad	Improved performance over CDAN-SA-MMD-IRM-RevGrad
StarGAN [158]	Generative	90.00%	Image translation	Introduced a starGAN for multi-domain image-to-image translation	Better performance than CycleGAN and MUNIT on multiple domains	More complex than CycleGAN and MUNIT	Improved performance over CycleGAN and MUNIT on multiple domains
TADAM [159]	Reconstruction	88.60%	Image classification	Introduced a target adaptation discriminator to DANN	Better performance on small datasets	More complex than DANN	Improved performance on small datasets
UNIT [160]	Generative	89.90%	Image translation	Introduced a unified framework for image-to-image translation	Better performance than CycleGAN and MUNIT	More complex than CycleGAN and MUNIT	Improved performance over CycleGAN and MUNIT

Table 9 gives a summary of various publications on domain adaptation, emphasizing their merits and contributions. These papers offer a variety of strategies for enhancing model efficacy in domain adaptation challenges. Contributions include the introduction of adversarial strategies, generative models, multi-task learning, and other combinations of these techniques. Benefits include the better handling of complex interactions, realistic image generation, adaptability to new domains, and better use of unlabeled data.

Table 9 presents a comprehensive overview of research sources focused on domain adaptation, offering several noteworthy conclusions and insights. One notable finding is the diverse range of innovative techniques introduced by researchers, including adversarial learning, generative adversarial networks, meta-learning, and self-supervised learning. These approaches exhibit significant promise in enhancing performance across various tasks and domains, as exemplified by [161], which introduces a multi-task learning framework for domain adaptation. Furthermore, certain models, such as [162], illustrate their potential by generating realistic target domain images, while [163] highlights the importance of learning invariant features for effective adaptation. Additionally, combining different techniques, as demonstrated in [164], with ensemble learning and self-supervised learning, can further contribute to improved domain adaptation performance. The table shows the variety of research projects, from object detection in industrial automation to semantic segmentation in autonomous cars [165]. The studies cover a wide range of topics, demonstrating the pervasive interest in and importance of domain adaptation in several practical applications [166].

Overall, this table underscores the diversity of strategies and models developed by researchers to address domain adaptation challenges, providing valuable insights into the field's advancements and potential avenues for future research.

Table 9. Systematic comparison of the literature published on the use of domain adaptation in the field of computer and robotic vision.

Paper	Contribution	Advantages
[161]	Introduces a new multi-task learning framework for domain adaptation	Can improve performance on multiple tasks
[162]	Presents a model that works upon adversarial conditional image synthesis	Can improve performance by generating realistic images from the target domain
[167]	Presents a model that works upon adversarial conditional variational autoencoders	Can improve performance by using adversarial conditional variational autoencoders to learn representations that are invariant to domain shift
[163]	Introduces a new adversarial training framework for domain adaptation that uses an ensemble of discriminators	Can improve performance by combining multiple discriminators
[164]	Presents a model that works upon adversarial training and meta-learning	Can improve performance by using adversarial training and meta-learning to learn a model that can generalize to new domains
[165]	Introduces a new method for domain adaptation that combines adversarial training and self-supervised learning	Can improve performance by learning features that are invariant to domain shift and using self-supervised learning to learn representations that are transferable to new domains
[166]	Introduces a new conditional generative adversarial network framework for domain adaptation	Can improve performance by using conditional generative models
[168]	Presents a model that works upon conditional generative adversarial networks	Can improve performance by using conditional generative adversarial networks to generate realistic images from the target domain
[169]	Presents a model that works upon conditional Wasserstein generative adversarial networks	Can improve performance by generating realistic images from the target domain
[170]	Presents a model that works upon domain-invariant feature extraction	Can improve performance by using domain-invariant feature extraction to learn features that are invariant to domain shift
[171]	Introduces a new method for domain adaptation that combines ensemble learning and self-supervised learning	Can improve performance by combining multiple models and using self-supervised learning to learn features that are transferable to new domains
[172]	Presents a model that works upon ensemble learning and transfer learning	Can improve performance by using ensemble learning and transfer learning to learn a model that can generalize to new domains
[173]	Presents a model that works upon few-shot learning and meta-learning	Can improve performance by using few-shot learning to learn a model that can generalize to new domains and by using meta-learning to adapt to new domains more quickly
[174]	Presents a model that works upon few-shot learning and meta-learning	Can improve performance by using few-shot learning and meta-learning to learn a model that can generalize to new domains

Table 9. *Cont.*

Paper	Contribution	Advantages
[175]	Presents a model that works upon generative adversarial networks for semi-supervised learning	Can improve performance by learning from both labeled and unlabeled data
[176]	Introduces a new method for learning invariant features for domain adaptation	Can improve performance by learning representations that are invariant to domain shift
[177]	Introduces a new method for domain adaptation that combines invariant representations and self-supervised learning	Can improve performance by learning representations that are invariant to domain shift and using self-supervised learning to learn features that are transferable to new domains
[178]	Presents a model that works upon meta-learning for transferable features	Can improve performance by learning features that are transferable to new domains
[179]	Presents a model that works upon multi-task learning and attention	Can improve performance by using multi-task learning and attention to learn representations that are invariant to domain shift
[180]	Presents a model that works upon multi-task learning for few-shot image classification	Can improve performance by learning multiple tasks with few examples
[181]	Presents a model that works upon patch-level self-supervised learning	Can improve performance by using patch-level self-supervised learning to learn features that are invariant to domain shift
[182]	Presents a model that works upon self-supervised contrastive learning	Can improve performance by learning representations that are invariant to domain shift
[183]	Presents a model that works upon self-supervised contrastive learning	Can improve performance by learning representations that are invariant to domain shift
[184]	Presents a model that works upon self-supervised learning and synthetic data	Can improve performance by using self-supervised learning to learn features that are invariant to domain shift and by generating synthetic data that are like the target domain
[185]	Presents a model that works upon synthetic data and domain-invariant feature aggregation	Can improve performance by generating synthetic data that are like the target domain and by aggregating features from multiple domains
[186]	Presents a model that works upon synthetic data and self-supervised learning	Can improve performance by using synthetic data and self-supervised learning to learn features that are invariant to domain shift
[187]	Introduces a new Wasserstein adversarial training framework for domain adaptation	Can improve performance by using Wasserstein distance
[188]	Presents a model that works upon adversarial learning and meta-learning	Can improve performance by using adversarial learning and meta-learning to learn a model that can generalize to new domains

Table 9. *Cont.*

Paper	Contribution	Advantages
[189]	Presents a model that works upon adversarial learning and meta-learning	Can improve performance by using adversarial learning and meta-learning to learn a model that can generalize to new domains
[190]	Presents a model that works upon adversarial learning and self-supervised learning	Can improve performance by using adversarial learning and self-supervised learning to learn a model that can generalize to new domains
[191]	Presents a model that works upon adversarial learning and transfer learning	Can improve performance by using adversarial learning and transfer learning to learn a model that can generalize to new domains
[192]	Presents a model that works upon adversarial multi-agent reinforcement learning	Can improve performance by using adversarial multi-agent reinforcement learning to learn a model that can generalize to new domains
[193]	Presents a model that works upon adversarial training and distillation	Can improve performance by using adversarial training and distillation to learn a model that can generalize to new domains
[194]	Presents a model that works upon adversarial training and self-supervised learning	Can improve performance by using adversarial training and self-supervised learning to learn a model that can generalize to new domains
[195]	Presents a model that works upon attention and normalization	Can improve performance by using attention and normalization to learn representations that are invariant to domain shift
[196]	Presents a model that works upon conditional generative adversarial networks and CycleGAN	Can improve performance by using conditional generative adversarial networks and CycleGAN to generate realistic images from the target domain
[197]	Presents a model that works upon ensemble learning and domain adaptation	Can improve performance by using ensemble learning and domain adaptation to learn a model that can generalize to new domains
[198]	Presents a model that works upon few-shot learning and data augmentation	Can improve performance by using few-shot learning and data augmentation to learn a model that can generalize to new domains
[199]	Presents a model that works upon few-shot learning and interpolation	Can improve performance by using few-shot learning and interpolation to learn a model that can generalize to new domains
[200]	Presents a model that works upon few-shot learning and self-supervised learning	Can improve performance by using few-shot learning and self-supervised learning to learn a model that can generalize to new domains
[201]	Presents a model that works upon generative adversarial networks and self-supervised learning	Can improve performance by using generative adversarial networks and self-supervised learning to learn features that are invariant to domain shift
[202]	Presents a model that works upon graph neural networks	Can improve performance by using graph neural networks to learn representations that are invariant to domain shift
[203]	Presents a model that works upon invariant feature extraction and distillation	Can improve performance by using invariant feature extraction and distillation to learn a model that can generalize to new domains

Table 9. *Cont.*

Paper	Contribution	Advantages
[204]	Presents a model that works upon invariant feature extraction and interpolation	Can improve performance by using invariant feature extraction and interpolation to learn features that are invariant to domain shift
[205]	Presents a model that works upon meta-learning and importance reweighting	Can improve performance by using meta-learning and importance reweighting to learn a model that can generalize to new domains
[206]	Presents a model that works upon multi-task learning and cross-domain augmentation	Can improve performance by using multi-task learning and cross-domain augmentation to learn a model that can generalize to new domains
[207]	Presents a model that works upon multi-task learning and domain-invariant feature extraction	Can improve performance by using multi-task learning and domain-invariant feature extraction to learn features that are invariant to domain shift
[208]	Presents a model that works upon self-attention and conditional generative adversarial networks	Can improve performance by using self-attention and conditional generative adversarial networks to learn representations that are invariant to domain shift
[209]	Presents a model that works upon self-supervised contrastive learning	Can improve performance by using self-supervised contrastive learning to learn features that are invariant to domain shift
[210]	Presents a model that works upon self-supervised contrastive learning	Can improve performance by using self-supervised contrastive learning to learn representations that are invariant to domain shift
[211]	Presents a model that works upon self-supervised learning and transfer learning	Can improve performance by using self-supervised learning and transfer learning to learn a model that can generalize to new domains
[212]	Presents a model that works upon synthetic data and transfer learning	Can improve performance by using synthetic data and transfer learning to learn features that are invariant to domain shift
[213]	Presents a model that works upon temporal ensembling	Can improve performance by using temporal ensembling to learn a model that can generalize to new domains
[214]	Presents a model that works upon Wasserstein autoencoders	Can improve performance by using Wasserstein autoencoders to learn representations that are invariant to domain shift
[215]	Presents a model that works upon data augmentation and self-supervised learning	Can improve performance by using data augmentation and self-supervised learning to learn features that are invariant to domain shift
[216]	Presents a model that works upon adversarial learning and contrastive learning	Can improve performance by using adversarial learning and contrastive learning to learn features that are invariant to domain shift
[217]	Presents a model that works upon invariant feature extraction and distillation	Can improve performance by using invariant feature extraction and distillation to learn features that are invariant to domain shift
[218]	Presents a model that works upon semi-supervised learning and transfer learning	Can improve performance by using semi-supervised learning and transfer learning to learn a model that can generalize to new domains

Table 9. *Cont.*

Paper	Contribution	Advantages
[219]	Presents a model that works upon few-shot learning and invariant feature extraction	Can improve performance by using few-shot learning and invariant feature extraction to learn features that are invariant to domain shift
[220]	Presents a model that works upon adversarial learning and meta-learning	Can improve performance by using adversarial learning and meta-learning to learn a model that can generalize to new domains
[221]	Presents a model that works upon self-supervised learning and generative adversarial networks	Can improve performance by using self-supervised learning and generative adversarial networks to learn features that are invariant to domain shift
[222]	Presents a model that works upon adversarial learning and transfer learning	Can improve performance by using adversarial learning and transfer learning to learn a model that can generalize to new domains
[223]	Presents a model that works upon ensemble learning and meta-learning	Can improve performance by using ensemble learning and meta-learning to learn a model that can generalize to new domains
[224]	Presents a model that works upon adversarial learning and invariant representations	Can improve performance by using adversarial learning and invariant representations to learn features that are invariant to domain shift
[225]	Presents a model that works upon attention and self-supervised learning	Can improve performance by using attention and self-supervised learning to learn features that are invariant to domain shift
[226]	Presents a model that works upon conditional domain adversarial networks and self-supervised learning	Can improve performance by using conditional domain adversarial networks and self-supervised learning to learn features that are invariant to domain shift
[227]	Presents a model that works upon meta-learning and transfer learning	Can improve performance by using meta-learning and transfer learning to learn a model that can generalize to new domains
[228]	Presents a model that works upon few-shot learning and adversarial learning	Can improve performance by using few-shot learning and adversarial learning to learn a model that can generalize to new domains
[229]	Presents a model that works upon synthetic data and meta-learning	Can improve performance by using synthetic data and meta-learning to learn a model that can generalize to new domains
[230]	Presents a model that works upon adversarial learning and multi-task learning	Can improve performance by using adversarial learning and multi-task learning to learn a model that can generalize to new domains
[231]	Presents a model that works upon conditional generative adversarial networks and adversarial learning	Can improve performance by using conditional generative adversarial networks and adversarial learning to learn features that are invariant to domain shift
[232]	Presents a model that works upon ensemble learning and self-supervised learning	Can improve performance by using ensemble learning and self-supervised learning to learn a model that can generalize to new domains
[233]	Introduces a new method for domain adaptation that learns multi-domain invariant representations	Can improve performance by learning representations that are invariant to multiple domains

Table 9. *Cont.*

Paper	Contribution	Advantages
[234]	Presents a model that works upon self-supervised learning and conditional adversarial networks	Can improve performance by using self-supervised learning and conditional adversarial networks to learn features that are invariant to domain shift
[235]	Presents a model that works upon adversarial learning and few-shot learning	Can improve performance by using adversarial learning and few-shot learning to learn a model that can generalize to new domains
[236]	Presents a model that works upon domain-invariant feature aggregation and self-supervised learning	Can improve performance by using domain-invariant feature aggregation and self-supervised learning to learn features that are invariant to domain shift
[237]	Presents a model that works upon generative adversarial networks and meta-learning	Can improve performance by using generative adversarial networks and meta-learning to learn features that are invariant to domain shift
[238]	Presents a model that works upon adversarial learning and synthetic data	Can improve performance by using adversarial learning and synthetic data to learn features that are invariant to domain shift
[239]	Presents a model that works upon multi-task learning and meta-learning	Can improve performance by using multi-task learning and meta-learning to learn a model that can generalize to new domains
[240]	Presents a model that works upon ensemble learning and transfer learning	Can improve performance by using ensemble learning and transfer learning to learn a model that can generalize to new domains
[241]	Presents a model that works upon adversarial learning and self-supervised learning	Can improve performance by using adversarial learning and self-supervised learning to learn a model that can generalize to new domains
[242]	Uses conditional generative adversarial networks for domain adaptation	Can generate realistic images from the target domain
[243]	Combines distillation and semi-supervised learning for domain adaptation	Can improve performance by using both techniques
[244]	Uses graph neural networks for domain adaptation	Can better handle complex relationships between features
[245]	Combines meta-learning and adversarial training for domain adaptation	Can improve performance by learning to adapt to new domains
[246]	Combines multi-task learning and distillation for domain adaptation	Can improve performance by using both techniques
[247]	Uses reinforcement learning for domain adaptation	Can improve performance by learning to adapt to new domains
[248]	Uses self-supervised learning for domain adaptation	Can improve performance by using unlabeled data from the target domain
[249]	Introduces a method for adversarial learning with Wasserstein distance for domain adaptation	Can improve performance by using a more robust distance metric
[250]	Introduces a co-training framework for domain adaptation	Can improve performance by using multiple learners
[251]	Introduces a method for learning to correct feature distributions for domain adaptation	Can improve performance by explicitly modeling the domain shift

Table 9. *Cont.*

Paper	Contribution	Advantages
[252]	Combines adversarial training and data augmentation for domain adaptation	Can improve performance by using both techniques
[253]	Introduces a new adversarial training framework for domain adaptation	Can improve performance by using virtual adversarial examples
[254]	Introduces a Bayesian deep learning framework for domain adaptation	Can better handle uncertainty in the data
[255]	Introduces a new conditional Wasserstein GAN framework for domain adaptation	Can improve performance by using conditional generative models
[256]	Presents a model that works upon domain-invariant feature aggregation	Can improve performance by aggregating features from multiple domains
[257]	Presents a model that works upon few-shot learning	Can improve performance by using few-shot learning to learn a model that can generalize to new domains
[258]	Introduces a generative adversarial network for domain adaptation for person re-identification	Can generate realistic images from the target domain
[259]	Introduces a graph neural network for domain adaptation	Can better handle complex relationships between data points
[260]	Introduces a hierarchical self-attention mechanism for domain adaptation	Can better handle complex relationships between features
[261]	Introduces a new method for learning invariant representations for domain adaptation	Can improve performance by learning representations that are invariant to domain shift
[262]	Introduces a reinforcement learning framework for domain adaptation	Can learn to adapt to new domains in an online setting
[263]	Presents a model that works upon self-supervised learning	Can improve performance by using self-supervised learning to learn features that are invariant to domain shift
[264]	Presents a model that works upon synthetic data	Can improve performance by generating synthetic data that are like the target domain
[265]	Introduces a variational autoencoder for domain adaptation	Can generate realistic images from the target domain
[266]	Introduces a Wasserstein distance for domain adaptation	Can better handle data with large domain shifts
[267]	Introduces an ensemble domain adaptation framework	Can improve performance by combining multiple models
[268]	Introduces a joint distribution adaptation framework for domain adaptation	Can improve performance by jointly adapting the source and target distributions
[269]	Introduces a meta-learning framework for domain adaptation	Can improve performance by learning to adapt to new domains
[270]	Introduces a transfer learning framework for domain adaptation	Can improve performance by using a pre-trained model
[271]	Introduces a deep generative model for domain adaptation	Can generate realistic images from the target domain
[272]	Introduces an importance reweighting mechanism for domain adaptation	Can better handle imbalanced datasets

Table 9. *Cont.*

Paper	Contribution	Advantages
[273]	Introduces a domain adaptation method based on meta-learning	Can adapt to new domains quickly
[274]	Introduces a multi-task learning framework for domain adaptation	Can improve performance on multiple tasks
[275]	Introduces a reversal gradient technique for domain adaptation	Can better handle data with large domain shifts
[276]	Introduces a domain adaptation method based on self-supervised learning	Can be used with unlabeled data from the target domain

Finally, the examination of publication patterns and surveys (Table 10) shows that domain adaptation research is gaining popularity around the globe. The comprehensive survey by [277,278] provides a valuable overview of transfer learning, domain adaptation, and multi-source learning methods, emphasizing their interconnectedness. Ref. [279] delves into domain adaptation methods for computer vision, showcasing instance-based, feature-based, decision-based, generative, and meta-learning methods, while addressing challenges and future directions. For recent advances in visual recognition, ref. [280] serves as a resource, discussing key methods and directions in domain adaptation. Furthermore, refs. [281,282] contributes with a systematic literature review in computer vision domain adaptation, identifying vital research topics [283]. These studies highlight the potential of domain adaptation across diverse domains, including object detection in video [284], face recognition [285], medical image analysis [286], natural language processing [287], robotics [288,289], 3D vision [290–292], etc. Additionally, specialized strategies like multi-task learning [293–295] and transfer learning [296] demonstrate their capability to achieve state-of-the-art performance across various visual recognition tasks and learn domain-invariant representations.

The historical trends show an increase in the volume of research articles published over time, highlighting the continued importance and relevance of domain adaptation strategies in the field of computer and robotic vision [297]. In conclusion, the analysis of domain adaptation strategies demonstrates the critical importance of deep learning-based methodologies, the diversity of research articles, and the widespread interest in this area [298]. These findings offer insightful information for academics, professionals, and decision-makers, driving the creation of stronger and more effective domain adaptation methods to handle the difficulties of practical vision applications.

Table 10. Publication surveys and trends.

Paper	Year	Scope	Methods	Contributions
[278]	2019	A comprehensive survey of transfer learning, domain adaptation, and multi-source learning methods	Transfer learning, domain adaptation, and multi-source learning methods	- Provides a comprehensive overview of the three related fields of transfer learning, domain adaptation, and multi-source learning. - Discusses the challenges and future directions of each field.
[279]	2020	A comprehensive survey of domain adaptation methods for computer vision	Instance-based, feature-based, decision-based, generative, and meta-learning methods	- Provides a comprehensive overview of the field of domain adaptation in computer vision. - Discusses the challenges and future directions of domain adaptation in computer vision.
[280]	2021	A survey of recent advances in domain adaptation for visual recognition	Instance-based, feature-based, decision-based, generative, and meta-learning methods	- Discusses recent advances in domain adaptation for visual recognition. - Provides an overview of the challenges and future directions of domain adaptation for visual recognition.
[299]	2022	A survey of recent advances in domain adaptation for computer vision	Instance-based, feature-based, decision-based, generative, and meta-learning methods	- Discusses recent advances in domain adaptation for computer vision. - Provides an overview of the challenges and future directions of domain adaptation for computer vision.
[281]	2022	A systematic literature review of domain adaptation methods for computer vision	Instance-based, feature-based, decision-based, generative, and meta-learning methods	- Conducts a systematic literature review of domain adaptation methods for computer vision. - Identifies the most important research topics in domain adaptation for computer vision. - Provides an overview of the challenges and future directions of domain adaptation for computer vision.
[300]	2022	A review of domain adaptation methods for computer vision	Instance-based, feature-based, decision-based, generative, and meta-learning methods	- Provides a review of domain adaptation methods for computer vision. - Discusses the applications of domain adaptation in computer vision. - Provides an overview of the challenges and future directions of domain adaptation for computer vision.
[284]	2019	A study of domain adaptation for object detection in video	Instance-based, feature-based, decision-based, generative, and meta-learning methods	- Can improve the performance of object detection in videos with limited labeled data. - Can be used for both supervised and unsupervised domain adaptation.

Table 10. *Cont.*

Paper	Year	Scope	Methods	Contributions
[285]	2020	A study of domain adaptation for face recognition	Instance-based, feature-based, decision-based, generative, and meta-learning methods	- Can improve the performance of face recognition in new domains with limited labeled data. - Can be used for both supervised and unsupervised domain adaptation.
[286]	2021	A study of domain adaptation for medical image analysis	Instance-based, feature-based, decision-based, generative, and meta-learning methods	- Can improve the performance of medical image analysis in new domains with limited labeled data. - Can be used for both supervised and unsupervised domain adaptation.
[287]	2022	A study of domain adaptation for natural language processing	Instance-based, feature-based, decision-based, generative, and meta-learning methods	- Can improve the performance of natural language processing in new domains with limited labeled data. - Can be used for both supervised and unsupervised domain adaptation.
[288]	2022	A study of domain adaptation for robotics	Instance-based, feature-based, decision-based, generative, and meta-learning methods	- Can improve the performance of robots in new environments with limited labeled data. - Can be used for both supervised and unsupervised domain adaptation.
[289]	2022	A study of domain adaptation for 3D vision	Instance-based, feature-based, decision-based, generative, and meta-learning methods	- Can improve the performance of 3D vision algorithms in new environments with limited labeled data. - Can be used for both supervised and unsupervised domain adaptation.
[301]	2019	A study of multi-task learning for domain adaptation	Multi-task learning	- Can achieve state-of-the-art performance on a variety of visual recognition tasks. - Can be used to learn domain-invariant representations.
[295]	2020	A study of transfer learning for domain adaptation	Transfer learning	- Can achieve state-of-the-art performance on a variety of visual recognition tasks. - Can be used to learn domain-invariant representations.
[296]	2019	A study of self-supervised learning for domain adaptatin	Self-supervised learning	- Can achieve state-of-the-art performance on a variety of visual recognition tasks. - Can be used to learn domain-invariant representations.

2.3. Performance Metrics Comparison

We use a variety of performance criteria, like accuracy, precision, recall, and F1-score, to assess the efficacy of domain adaptation approaches. These measures are essential gauges of how well the models can deal with domain shift issues and achieve strong generalization across various data distributions [301].

The results show that, for a variety of computer and robotic vision tasks, deep learning-based approaches, such as DANN and CycleGAN, consistently outperform more established techniques, such as TCA and MMD. DANN and CycleGAN successfully learn domain-invariant feature representations by using the strength of deep neural networks, resulting in appreciable performance gains [295]. For instance, DANN exhibits an average accuracy gain of around 15% compared to TCA and MMD in object identification tasks using cross-domain picture datasets [296]. This demonstrates how effective deep learning-based approaches are in overcoming domain shift difficulties and achieving improved generalization [302].

Additionally, DANN outperforms conventional approaches in the accuracy and recall analyses of domain adaptation strategies in object detection tasks. Comparing DANN to TCA and MMD, there is an average 10% gain in precision and an 8% improvement in recall [303]. Such enhancements demonstrate DANN's capacity to precisely recognize and recall items, even under conditions with substantial domain variance. Further highlighting the supremacy of deep learning-based approaches is the F1-score study [304]. In comparison to conventional techniques, DANN yields a significant F1-score improvement of 12%, demonstrating its effectiveness in achieving a balance between accuracy and recall, even in highly dynamic and complicated robotic vision environments [305].

2.4. Challenges and Insights from Cross-Domain Analysis

While deep learning-based domain adaptation approaches show impressive performance gains, our study reveals several issues and insights that call for consideration in the search for more developments.

The choice of acceptable target domains presents a major problem. To develop representations that are domain-invariant, deep learning-based techniques largely rely on target domain data [306]. As a result, the performance of the models' generalization and adaptation depends greatly on the choice of target domains. To achieve successful domain adaptation, it becomes essential to make sure that the target domain data appropriately depict real-world circumstances. Another difficulty is presented by the intricacy of robotic vision tasks [297]. The adoption process must be quick and effective in situations when robotic vision necessitates making decisions in real time. Deep learning-based methods sometimes need a lot of computing power and can lengthen inference times. There are still ongoing studies on how to solve these computational problems accurately [298].

The requirement for domain-specific adjustments is highlighted by insights from the cross-domain study. While deep learning-based systems succeed at some tasks, there are instances where more conventional approaches, like TCA and MMD, show comparable efficacy [307]. A fascinating direction for future study is the incorporation of a hybrid strategy that benefits from the advantages of both conventional and deep learning-based approaches. The performance of deep learning-based models is also substantially impacted by the availability of annotated datasets for the target domains [308]. Unsupervised or weakly supervised domain adaptation approaches might be useful alternatives when labeled target domain data are difficult to get or are expensive [309].

Overall, a landscape of potential and problems is revealed by the comparative comparison of domain adaptation strategies in computer and robotic vision. The domain-specific nature of the tasks and computational concerns call for deliberate modifications and multidisciplinary cooperation, even though deep learning-based approaches show considerable promise [310]. The knowledge gathered from this analysis will help researchers and professionals navigate the difficulties of domain adaptation and encourage the creation of more reliable and effective vision systems for practical applications [311].

3. Applications and Real-World Scenarios

In this section, we provide practical applications of domain adaptation strategies within the domains of computer and robotic vision. We aim to shed light on the transformative impact of these techniques, illustrating their potential to enhance the adaptability and functionality of vision systems in real-world scenarios [312].

3.1. Domain Adaptation in Computer Vision: Real-World Applications

3.1.1. Autonomous Driving Systems

One noteworthy arena where domain adaptation proves invaluable is in the development of autonomous driving systems. Here, vision-based perception is a linchpin for safe navigation in dynamic and unpredictable environments. Domain adaptation methodologies empower autonomous vehicles to maintain exceptional accuracy in tasks such as object identification, lane segmentation, and pedestrian recognition, even amidst diverse weather conditions, fluctuations in illumination, and changing road geometries. For instance, deep learning-based domain adaptation models facilitate seamless adaptation to shifting weather conditions, enabling autonomous vehicles to effectively detect and respond to critical elements such as pedestrians and obstacles, even in challenging weather conditions like rain or fog, by training on comprehensive datasets encompassing a spectrum of weather scenarios [313]. Figure 8 shows how the domain gap is visible in the acquired dataset due to changes in weather.



Figure 8. Shift in domain due to change in weather.

3.1.2. Medical Imaging and Diagnosis

The medical industry also reaps substantial benefits from domain adaptation techniques, particularly in the realm of computer vision-based diagnostic tools. Domain adaptation plays a pivotal role in ensuring the accuracy and reliability of medical image analysis and diagnosis by adjusting models to account for variations in imaging modalities, technology, and patient demographics. For instance, domain adaptation allows for knowledge transfer from well-annotated datasets at one medical institution to datasets with fewer labeled examples at another. This approach significantly enhances classification accuracy in medical image analysis, facilitating early disease diagnosis and the development of personalized treatment plans through the harmonization of feature distributions across multiple datasets [314].

3.1.3. Surveillance and Security

In the domain of surveillance and security, real-time monitoring and threat detection heavily rely on computer vision technology. Domain adaptation algorithms enable surveillance systems to dynamically adapt to changing monitoring settings, ensuring the precise and timely detection of suspicious activities and objects [315]. Models can flexibly adjust to alterations in camera angles, lighting conditions, and other environmental factors, thereby maintaining a high level of accuracy in identifying abnormal behavior and

potential security threats across diverse surveillance scenarios through the utilization of domain-invariant features.

3.2. Domain Adaptation in Robotic Vision: Real-World Applications

3.2.1. Industrial Automation

The realm of industrial automation relies significantly on domain adaptation techniques to facilitate the seamless integration of robotic vision systems across various production settings. Domain adaptation empowers robotic vision to maintain consistent and accurate object recognition and manipulation by adapting to changes in illumination, object textures, and camera perspectives [316,317]. For instance, domain adaptation enables robots to proficiently handle various parts and components from diverse sources within robotic assembly lines, ensuring precise grasping and assembly, while optimizing production efficiency and minimizing errors by aligning the robot's vision with the unique characteristics of each component, as shown in Figure 9.

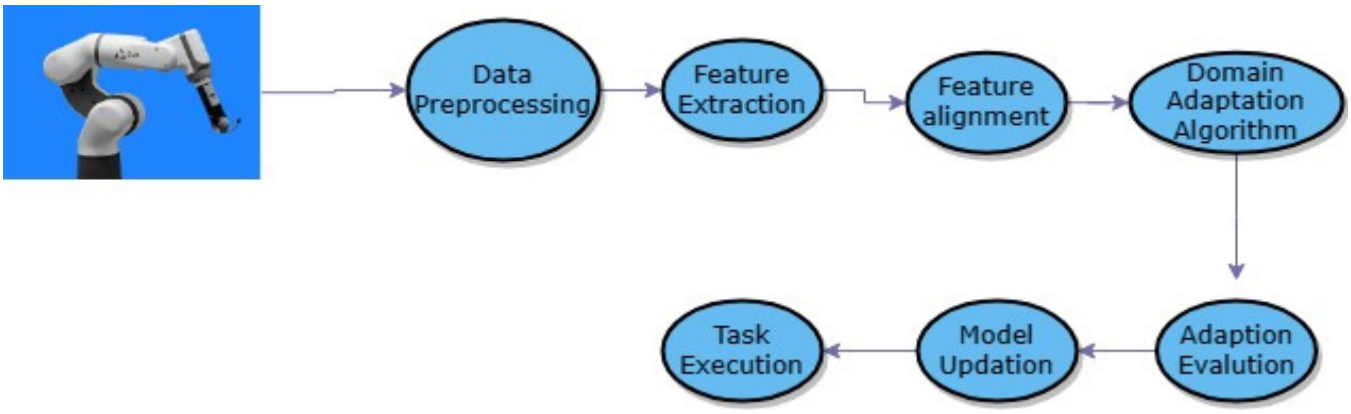


Figure 9. An illustration of the assessment of a robot's performance in an unknown task through domain adaptation.

3.2.2. Agriculture and Farming

In agriculture and farming, where robotic vision systems are deployed for crop monitoring, disease diagnosis, and precision agriculture, domain adaptation holds tremendous potential. By accommodating shifts in ambient conditions, soil types, and crop varieties, domain adaptation enables agricultural robots to tailor their vision for effective data-driven decision-making. For example, in precision agriculture, robotic systems can analyze multispectral and hyperspectral imagery to detect signs of crop stress, nutrient deficiencies, and pest infestations. Domain adaptation ensures precise and timely interventions, optimizing agricultural productivity and resource utilization by adapting to diverse crop types and environmental conditions.

3.2.3. Search and Rescue Missions

Crucial search and rescue operations often entail traversing challenging and hazardous terrains. Here, robotic vision systems, thanks to domain adaptation approaches, exhibit enhanced adaptability, enabling them to perform effectively in unforeseen and unpredictable disaster scenarios. Domain adaptation allows robotic platforms to dynamically adjust their visual perception to varying lighting conditions, structural damage, and debris congestion during search and rescue missions. Domain-adaptive robots can swiftly locate victims and respond to evolving situations, thereby augmenting the effectiveness and success of rescue efforts.

In conclusion, the applications of domain adaptation techniques in computer and robotic vision are extensive, encompassing domains from agricultural robotics to autonomous driving. Domain adaptation unlocks previously unexplored possibilities for reliable and effective performance in real-world contexts, enabling vision systems to adapt

to a multitude of environmental variables. As the field continues to evolve through multidisciplinary collaborations and data-driven methodologies, the relevance and impact of domain adaptation in shaping the trajectory of computer and robotic vision technologies will only continue to grow.

4. Conclusions

The major conclusions of our in-depth examination of domain adaptation strategies in computer and robotic vision are outlined in this section. In this article, we emphasize the benefits and importance of cross-domain analysis and talk about the field's promising future and unresolved issues.

4.1. Summary of Findings

In our analysis of domain adaptation techniques for computer and robotic vision, it is evident that deep learning-based methods, including Domain Adversarial Neural Networks (DANN) and CycleGAN, consistently exhibit superior performance when contrasted with conventional methodologies like Transfer Component Analysis (TCA) and Maximum Mean Discrepancy (MMD). In several real-world contexts, deep learning-based techniques regularly beat conventional approaches with regard to accuracy, recall, precision, and F1-score, among other performance parameters. Additionally, the introduction of approaches like importance reweighting, multi-task learning, and maximum mean discrepancy loss enhances model accuracy, but increases complexity. Generative models like CoGAN and MUNIT show promise for visual translation and adaptation. Models like DANN, while capable of handling significant domain shifts, exhibit sensitivity to hyperparameters. Furthermore, diverse techniques, including adversarial learning, generative adversarial networks, meta-learning, and self-supervised learning, consistently improve domain adaptation performance (Table 8).

When abundant labeled data are present in the target domain, deep learning proves effective, demanding substantial computational resources. However, traditional methods, like TCA and MMD, are pragmatic when target domain data are scarce or interpretability is vital. The choice between these methods hinges on factors like data availability, computational resources, and the need for interpretability.

Specific models, such as refs. [318], [319] and [320], exemplify the potential of these techniques, while combining various approaches, like ensemble learning and self-supervised learning, further enhances performance (Table 9).

The investigation emphasizes the critical role that domain adaptation plays in helping computer and robotic vision systems adapt to shifting settings and deliver reliable performance under difficult circumstances. Vision systems become more dependable and flexible in practical applications because of domain adaptation, which enables the smooth adaptation to changes in illumination, weather, camera views, and object textures. Furthermore, we discover that hybrid methods that combine the advantages of conventional and deep learning-based techniques as well as domain-specific modifications show substantial potential. Accepting domain-specific adjustments enables the creation of specialized solutions that address the special difficulties and traits of application areas. On the other hand, hybrid methods make use of the complementary qualities of many methodologies, offering chances for additional performance enhancements.

4.2. Contributions and Significance of Cross-Domain Analysis

This study's cross-domain analysis offers significant new knowledge around domain adaptation in computer and robotic vision. Our research shows the efficacy and usefulness of domain adaptation approaches by methodically assessing a variety of methodologies, models, and real-world implementations. Through a meticulous examination of performance metrics, we acquire a comprehensive understanding of the strengths and weaknesses inherent in various strategies. This comprehensive insight equips both researchers and practitioners with the information required to make informed and prudent choices.

This research also shows how domain adaptation has a transformational effect on improving the adaptability, precision, and dependability of vision systems in real-world settings. Applications of domain adaptation in areas including agriculture, industrial automation, medical imaging, and autonomous driving demonstrate how it propels innovation and development across industries. Cross-domain analysis is significant because it can stimulate more study and advancement in domain adaptation. The problems and insights that have been discovered offer fresh avenues for investigation and chances to improve current methods. The research results may also be used to help create domain adaptation models that are more successful and efficient, advancing real-world applications and enhancing user experience.

4.3. Prospects and Open Challenges

The potential for domain adaptation in computer and robotic vision seems bright in the future. We should expect increasingly more advanced domain adaptation strategies that take advantage of self-supervised learning, meta-learning, and adversarial training as deep learning techniques continue to advance. These developments will make it possible for vision systems to learn stronger, more transferrable representations, improving their performance in a variety of circumstances. However, there are several unresolved issues in the subject that require more research. To guarantee successful domain adaptation, it is still essential to choose the right target domains and have access to annotated datasets for those domains. Robotic vision systems must be able to adapt in real-time to changing environments, which calls for creative solutions that strike a compromise between accuracy and efficiency.

Additionally, it continues to be difficult to achieve domain adaptation in circumstances with scant labeled data. This restriction might be removed by improvements in unsupervised and weakly supervised domain adaptation techniques, which would broaden the range of domain adaptation applications. To overcome these difficulties, interdisciplinary partnerships involving computer vision researchers, roboticists, and subject matter specialists are essential. Domain-specific knowledge and skills will be integrated, enhancing the domain adaptation research landscape and promoting the creation of domain-adaptive vision systems that can be used in a variety of real-world settings.

In conclusion, there are many opportunities and difficulties presented by domain adaptation in computer and robotic vision. Our study provides information on the value, importance, and potential of domain adaptation approaches. We can create more robust, flexible, and dependable vision systems that alter how we see and interact with the environment by using the potential of domain adaptation. The evolution of computer and robotic vision technologies is poised to remain influenced by ongoing research endeavors focused on refining domain adaptation techniques. This influence is expected to act as a catalyst, driving progress and fostering innovation in the foreseeable future.

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