A Survey of Medical Imaging Domain Adaptation and Machine Learning in Healthcare

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Abstract

The convergence of medical imaging, domain adaptation, and machine learning represents a transformative shift in healthcare diagnostics, enhancing accuracy, efficiency, and interpretability. This survey paper examines the integration of deep learning methodologies, such as convolutional and generative adversarial networks, in medical image analysis, addressing the challenges of domain adaptation and generalization across varied clinical environments. The paper highlights advancements in machine learning techniques, including transfer learning and federated learning, which mitigate data scarcity and privacy concerns. Emphasis is placed on the interpretability of AI models and the integration of explainable AI (XAI) techniques to facilitate clinical acceptance. The survey also explores the role of multi-modal data fusion in improving diagnostic accuracy, exemplified by the integration of MRI, CT, and PET modalities. Challenges such as data heterogeneity, ethical considerations, and the integration of AI into clinical workflows are discussed, alongside future directions focusing on the development of robust, generalizable, and interpretable models. The paper underscores the potential of these technologies to revolutionize healthcare delivery, improve diagnostic tools, and support precision medicine through enhanced decision-making processes. By providing a comprehensive overview of current methodologies and future research directions, this survey aims to support clinicians in leveraging AI-driven innovations for improved patient outcomes.

1 Introduction

1.1 Interdisciplinary Field Overview

The convergence of medical imaging, domain adaptation, and machine learning represents a transformative advancement in healthcare diagnostics, enhancing both accuracy and efficiency. This interdisciplinary domain leverages the strengths of various medical imaging modalities—such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and ultrasound—to provide critical insights into patients' physiological and pathological conditions. These techniques facilitate precise disease diagnosis and prediction, improve understanding of clinical outcomes, and can be integrated with electronic health records (EHR) through advanced artificial intelligence (AI) methods, enabling comprehensive patient health analyses. Recent developments in deep learning and multimodal data fusion have significantly augmented the diagnostic capabilities of these imaging modalities, making them essential tools in contemporary medical practice [1, 2, 3, 4, 5]. The incorporation of deep learning algorithms has revolutionized medical image analysis, allowing for the extraction of complex patterns and features often overlooked by human experts.

Domain adaptation is crucial for addressing variability and domain shifts across diverse imaging environments. Techniques have been developed to ensure that models trained on labeled source domains can be effectively applied to unseen target domains, enhancing model robustness and applicability in varied clinical contexts [6]. This adaptability is particularly important in automatic

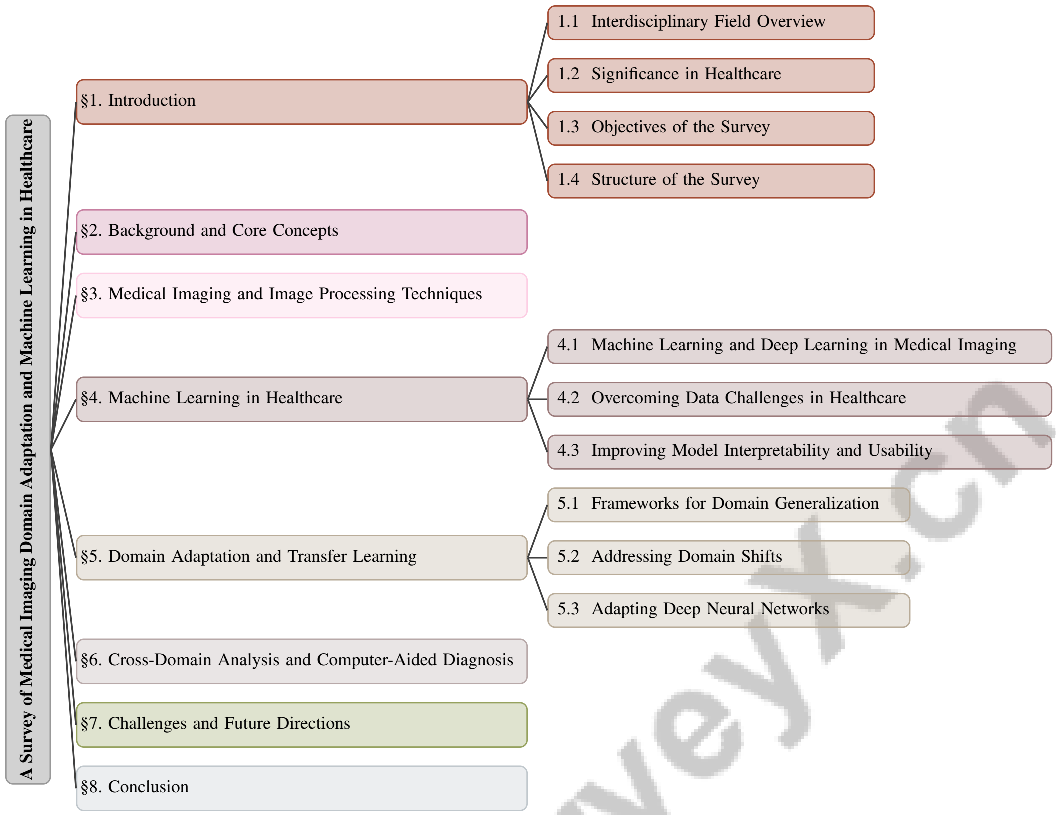


Figure 1: chapter structure

diagnosis models from medical images, where existing methods primarily focus on tabular data [7]. The challenge of domain shift, which significantly impacts the predictive performance of machine learning models across different sites and populations, is a critical consideration in this field [8].

The integration of machine learning algorithms has further advanced the field by achieving efficient and accurate segmentation in biomedical imaging, emphasizing the convergence of medical imaging and machine learning [9]. The application of these technologies in multimodal cancer detection and myocardial infarction detection highlights their potential to revolutionize healthcare delivery through enhanced diagnostic accuracy.

Combining medical imaging, domain adaptation, and machine learning is paving the way for robust, generalizable, and privacy-conscious diagnostic solutions. This convergence not only facilitates the development of accurate diagnostic tools but also promotes seamless integration of machine learning into healthcare systems. Nonetheless, challenges remain, including the need for extensive validation and complexities surrounding domain adaptation, explainability, and fairness [10].

1.2 Significance in Healthcare

The integration of machine learning and deep learning techniques into medical imaging has fundamentally transformed healthcare by significantly enhancing diagnostic accuracy and workflow efficiency [11]. These technologies alleviate the challenges posed by increasing workloads and the subjective nature of traditional image assessments, streamlining diagnostic processes in radiology [12]. AI's capacity to process and analyze complex datasets is crucial for early disease detection, promoting precision medicine and reducing mortality rates associated with conditions such as cancer.

Despite these advancements, challenges persist, particularly regarding the availability of large-scale labeled datasets and the heterogeneity of multi-center data, which impact diagnostic accuracy [13]. The scarcity of labeled data presents a significant barrier to developing robust machine learning models, especially in surgical data science, where context-aware models are essential for improved outcomes. Furthermore, trust and explainability of deep learning algorithms are paramount for clinical acceptance, significantly influencing diagnostic accuracy and user confidence [14].

Multimodal data fusion enhances diagnostic accuracy by leveraging the strengths of multiple imaging modalities, effectively addressing the limitations of single-modality models [15]. This approach is particularly beneficial in multi-organ analysis, where deep learning techniques are increasingly integral [10]. AI-based diagnostic tools have shown substantial improvements in healthcare outcomes, as evidenced by their rapid and accurate diagnosis of conditions like COVID-19 pneumonia [6].

Current research has significantly improved the accuracy and efficiency of medical image analysis, enabling faster and more reliable diagnoses [16]. The proposed framework embraces data disharmony rather than seeking invariant representations, thereby enhancing model adaptation and generalization [8]. Deep learning approaches, including convolutional neural networks (CNNs) and generative adversarial networks (GANs), have been instrumental in advancing medical imaging applications [17]. Nonetheless, challenges such as data scarcity, ethical constraints in data sharing, and healthcare professionals' reluctance to adopt AI due to concerns about reliability and interpretability continue to pose significant barriers [14].

The integration of AI in medical imaging holds promise for significantly enhancing diagnostic accuracy and efficiency. Ongoing research is essential for overcoming existing limitations in medical imaging technologies and enhancing their generalizability across diverse clinical settings. This includes advancing incremental learning methods that allow models to adapt dynamically to new data while retaining previously learned information, as well as exploring innovative data augmentation techniques to expand the diversity of training datasets. Addressing the challenges of data scarcity and variability in imaging devices is crucial for developing robust AI-powered diagnostic systems that effectively bridge the gap between artificial intelligence and clinical practice [8, 18, 19, 20, 21].

1.3 Objectives of the Survey

This survey aims to provide a comprehensive analysis of the integration of medical imaging, domain adaptation, and machine learning to enhance diagnostic accuracy and efficiency within healthcare systems. A primary objective is to explore advancements in deep learning methodologies, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative adversarial networks (GANs), and long short-term memory networks (LSTMs) as applied to medical image analysis [11]. The survey addresses challenges associated with domain adaptation and generalization, particularly in multi-source imaging scenarios, to improve the robustness and applicability of machine learning models across diverse clinical environments [8].

A significant focus is placed on the interpretability of AI models, providing an overview of various explainable AI (XAI) techniques applied in medical imaging [22]. This includes understanding how AI models can be rendered interpretable to facilitate better visualization, understanding, and decision-making in medical practice [12]. By integrating these techniques, the survey endeavors to enhance the transparency and trust of AI systems in clinical settings.

The survey aims to develop comprehensive frameworks that effectively integrate non-functional requirements (NFRs) such as Efficiency, Accuracy, Interoperability, Reliability, Usability, Adaptability, and Fairness into medical imaging applications. This integration is intended to enhance the applications' overall effectiveness and facilitate their acceptance within clinical workflows, addressing the increasing demands on diagnostic imaging departments and the challenges posed by a shortage of qualified personnel. By engaging with key stakeholders, the survey seeks to identify critical NFRs that can improve the implementation of AI solutions in medical imaging, ultimately bridging the gap between advanced technology and practical clinical use [23, 8, 24, 4]. By achieving these objectives, the survey aims to provide a holistic understanding of the field, supporting clinicians in image interpretation and improving diagnostic performance.

1.4 Structure of the Survey

This survey is structured to provide a comprehensive evaluation of both traditional and modern machine learning approaches, with a particular emphasis on deep learning methodologies and specific convolutional neural network (CNN) architectures, assessing their effectiveness across various medical imaging tasks [1]. The paper is organized into several sections, each focusing on distinct technological advancements and their applications in medical imaging.

The survey begins with an introduction outlining the convergence of medical imaging, domain adaptation, and machine learning, highlighting their significance in enhancing diagnostic accuracy and efficiency. Following this, the background section delves into core concepts such as image processing, transfer learning, and computer-aided diagnosis, providing a foundational understanding of the field.

Subsequent sections explore specific methodologies. The section on medical imaging and image processing techniques discusses various imaging modalities and the role of image processing in improving image quality and interpretability. This is followed by an examination of machine learning applications in healthcare, emphasizing deep learning's contributions to medical imaging technologies.

The survey subsequently analyzes domain adaptation and transfer learning, essential methodologies for mitigating challenges posed by domain shifts and enhancing model robustness across diverse imaging environments. This analysis highlights the significance of addressing distribution shifts, leveraging techniques such as continuous domain adaptation and similarity-based transfer learning to improve model generalization in medical imaging tasks. By examining the intricate relationships between source and target domains, the survey underscores the importance of effective feature reuse and robust clustering algorithms in achieving superior performance across various imaging datasets [8, 25, 26, 27, 28]. This is complemented by a discussion on cross-domain analysis and computer-aided diagnosis, where the integration of multi-modal and cross-domain techniques enhances diagnostic accuracy and outcomes.

Finally, the survey addresses challenges and future directions, discussing ethical considerations, integration into clinical workflows, and potential technological advancements. This structured approach categorizes research into distinct technological advancements, such as visualization (Cinematic Rendering), understanding (AI and machine learning), procedural support, and decision support [12], providing a holistic view of the current landscape and future prospects in medical imaging and machine learning.The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Conceptual Frameworks and Taxonomies

The intersection of medical imaging, domain adaptation, and machine learning is structured by conceptual frameworks and taxonomies that elucidate methodologies and applications critical to these fields. A primary classification divides AI methods into supervised and unsupervised learning, essential for navigating AI innovations in healthcare [29]. Domain generalization (DG) enhances model robustness by leveraging multiple source domains to generalize to unseen test domains, crucial for diverse clinical settings [30]. Understanding domain shifts, such as covariate and concept shifts, is vital for maintaining model performance across varied environments [31].

Transfer learning addresses the challenge of limited labeled data in medical image classification. Techniques that adapt CNNs pre-trained on large datasets like ImageNet for specific tasks, such as ultrasound kidney detection, demonstrate transfer learning's effectiveness [32]. The impact of pre-training on datasets like ImageNet versus RadImageNet is also evaluated for medical image classification tasks [4].

The survey categorizes explainability approaches into model-specific versus model-agnostic, global versus local, and pre-model versus post-model methods [33]. This taxonomy is crucial for enhancing AI model interpretability and transparency in clinical practice. The classification of histopathology WSIs with staining variations emphasizes the need for robust unsupervised domain adaptation techniques. Approaches like fine-tuning the Stable Diffusion model for medical imaging, utilizing both quantitative metrics and radiologist evaluations, enhance image quality and clinical relevance [34].

Challenges are categorized into data-related issues, evaluation shortcomings, and publication practices that may compromise research integrity, offering a framework for addressing these obstacles [35].

This comprehensive approach enables leveraging these technologies for improved diagnostic and therapeutic outcomes.

2.2 Techniques and Methodologies

Medical imaging, domain adaptation, and machine learning employ diverse techniques to address healthcare data analysis complexities. Federated learning facilitates decentralized deep learning model training across institutions while preserving data privacy, crucial for mitigating performance loss due to data heterogeneity [36, 37, 38, 39]. Flexible Federated Learning (FFL) allows collaborative training on heterogeneous datasets by sharing a common feature extraction backbone with local classification heads.

Domain adaptation (DA) and domain generalization (DG) techniques manage domain shifts and enhance model robustness across imaging environments. These include alignment techniques, data manipulation strategies, and feature disentanglement approaches. Model-based Domain Adaptation (MBDA) addresses reliance on specific diffusion-weighted images (DWI) [40]. Structure Preserving Cycle-GAN (SP Cycle-GAN) integrates segmentation loss to maintain structural integrity in medical scans [41]. Unsupervised domain adaptation frameworks for cross-modality liver segmentation enhance accuracy via joint adversarial learning and self-learning. Boundary-Weighted Domain Adaptive Neural Network (BOWDA-Net) improves prostate MR image segmentation using boundary-sensitive transfer learning [42].

Transfer learning strategies, organized by source datasets and transfer types, are pivotal. Pre-trained networks as feature extractors with small target dataset-trained classifiers exemplify this approach. A two-dimensional CNN architecture uses transfer learning from VGG-Net for ECG signal classification [43]. The benchmark evaluates transfer learning effectiveness in medical imaging, focusing on feature reuse and other factors [28]. A novel 2.5D deep neural network combining supervised domain adaptation with knowledge distillation enhances prostate segmentation accuracy [44].

Incremental learning dynamically updates model weights to generalize new data without forgetting existing knowledge, crucial for continuous performance improvement [21]. The benchmark compares foundation models in few-shot and zero-shot learning scenarios across medical imaging datasets [45].

These methodologies advance healthcare machine learning by addressing data heterogeneity and privacy challenges through approaches like patchwork learning, integrating diverse biomedical data while preserving confidentiality. They enhance diagnostic model interpretability and accuracy through task-specific adaptations and advanced data augmentation, improving robustness and generalizability across clinical applications [19, 46, 47].

3 Medical Imaging and Image Processing Techniques

Category	Feature	Method
Image Processing Techniques	Prediction Reliability	DCA[48]
	Noise and Feature Enhancement	SIFA[49], DSMM[50]

Table 1: Summary of image processing techniques employed in medical imaging, highlighting specific features and associated methods. The table outlines the use of DCA for prediction reliability and the application of SIFA and DSMM for noise reduction and feature enhancement in medical images.

This section delves into the essential role of diverse imaging modalities in medical diagnostics and treatment. By examining the characteristics and applications of these modalities, we establish a foundation for understanding image processing techniques that enhance medical image quality and interpretability. Table 1 presents a concise overview of image processing techniques that are integral to enhancing the quality and interpretability of medical images, detailing the methods used for prediction reliability and noise and feature enhancement. Convolutional neural networks and data augmentation strategies are pivotal in improving diagnostic accuracy and efficiency. Furthermore, the integration of foundation models and generative AI is discussed as a pathway to future advancements in clinical radiology practices [19, 51, 4, 47, 52]. Table 3 offers a detailed comparison of various medical imaging modalities, image processing techniques, and feature and data fusion strategies, underscoring their significance in improving diagnostic accuracy and image quality.

To illustrate the hierarchical structure of medical imaging and image processing techniques, Figure 2 categorizes the primary modalities, such as MRI and CT, alongside image processing methods designed for quality and clarity enhancement. Additionally, it highlights feature and data fusion techniques that contribute to comprehensive image analysis and improved diagnostic accuracy. This visual representation serves as a valuable reference as we begin with an overview of the primary medical imaging modalities used in healthcare.

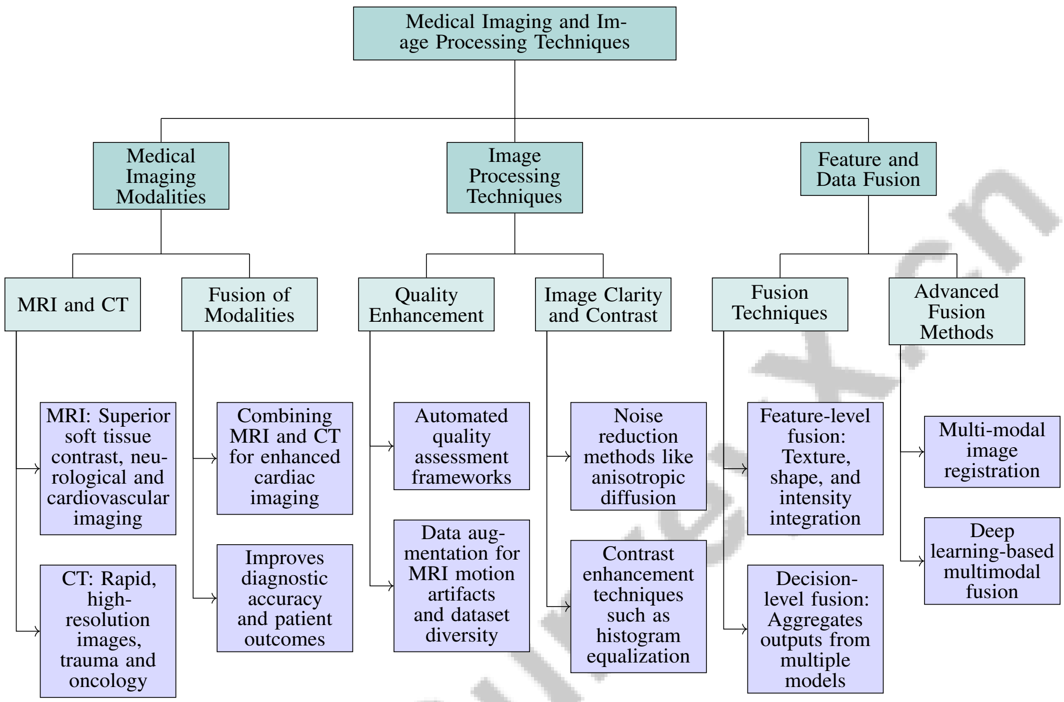


Figure 2: This figure illustrates the hierarchical structure of medical imaging and image processing techniques, categorizing the primary modalities (MRI and CT), image processing methods for quality and clarity enhancement, and feature and data fusion techniques for comprehensive image analysis and improved diagnostic accuracy.

3.1 Medical Imaging Modalities

Method Name	Imaging Techniques	Diagnostic Applications	Technological Integration
DSMM[50]	Mri And CT	Neurology, Oncology	AI Advancements
SIFA[49]	MR And CT	Segmentation Tasks	Adversarial Learning
DCA[48]	Medical Imaging Datasets	Improve Diagnostic Accuracy	AI Advancements

Table 2: This table presents a comparative analysis of various methods integrating medical imaging techniques with technological advancements. It highlights the specific diagnostic applications of each method, focusing on the incorporation of AI and adversarial learning to enhance diagnostic accuracy and efficiency.

Medical imaging modalities like Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are indispensable for diagnosis and treatment planning. Table 2 illustrates the integration of MRI and CT imaging modalities with advanced technologies, demonstrating their diagnostic applications and the role of AI in improving medical imaging outcomes. MRI offers superior soft tissue contrast crucial for neurological and cardiovascular imaging, while CT provides rapid, high-resolution images beneficial in trauma and oncology [50]. The Multi-Modality Whole Heart Segmentation Challenge 2017 highlights the potential of combining MRI and CT for enhanced cardiac imaging [49]. This fusion of modalities improves diagnostic accuracy and patient outcomes. Evaluation of datasets such as RSNA and DDSM across CNN architectures underscores the need for modality-specific calibration to refine diagnostic tools [48]. MRI and CT's extensive use in diagnostics supports clinical decisions from disease detection to treatment monitoring, with AI advancements further enhancing image interpretation [53, 54].

3.2 Image Processing Techniques

Image processing techniques enhance medical image quality and interpretability, improving diagnostic accuracy and clinical decisions. Techniques such as automated quality assessment frameworks and data augmentation address challenges like MRI motion artifacts and dataset diversity. Convolutional neural networks and advanced algorithms help distinguish diagnostic from non-diagnostic images, supporting reliable treatment plans [19, 1, 51]. Noise reduction methods, such as anisotropic diffusion, enhance image clarity in MRI and CT by minimizing noise while preserving structural details [50]. Contrast enhancement techniques like histogram equalization improve visibility, aiding in detecting subtle pathological changes in modalities like mammography [48]. Segmentation techniques, crucial for treatment planning, partition images into meaningful regions using methods like thresholding [49]. Feature extraction identifies attributes within images, integral to CAD systems that differentiate normal from pathological states [48]. These techniques transform raw images into diagnostic resources, enhancing diagnostic tool robustness through data augmentation and deep learning [19, 55, 1].

3.3 Feature and Data Fusion

Feature and data fusion integrate features and data from multiple sources, enhancing image analysis and diagnostic accuracy. This technique combines diverse feature sets and merges decisions from various modalities for comprehensive assessments, improving image quality and reducing redundancy [3, 56, 57]. Feature-level fusion integrates features before classification, combining texture, shape, and intensity into a single vector, enhancing machine learning model robustness [57]. Decision-level fusion aggregates outputs from multiple models, providing a consensus decision more reliable than individual predictions, especially when models perform variably across datasets [57]. Advanced fusion techniques, such as multi-modal image registration, enhance visualization and analysis of anatomical structures, improving clinical applicability for diagnosis [58, 56]. These methods are employed in CAD systems to enhance disease detection by integrating information from MRI, CT, and PET scans. Feature and data fusion are crucial for improving medical image analysis, integrating diverse information to enhance diagnostic accuracy and clinical decision-making. These techniques, including deep learning-based multimodal fusion, strengthen the classification and interpretation of complex images, addressing challenges like incomplete data and optimizing network architectures. Their integration promises significant advancements in clinical applications, improving image quality and supporting informed clinical decisions [58, 56, 57].

Feature	Medical Imaging Modalities	Image Processing Techniques	Feature and Data Fusion
Purpose	Diagnosis And Treatment	Image Quality Enhancement	Comprehensive Assessments
Techniques Used	Mri And CT	Noise Reduction, Segmentation	Feature, Decision-level Fusion
Outcomes Improved	Diagnostic Accuracy	Interpretability	Diagnostic Accuracy

Table 3: This table provides a comparative analysis of medical imaging modalities, image processing techniques, and feature and data fusion methods. It highlights the purpose, techniques used, and outcomes improved for each category, emphasizing their roles in enhancing diagnostic accuracy and image interpretability. The table serves as a comprehensive reference for understanding the integration and impact of these methods in clinical practice.

4 Machine Learning in Healthcare

4.1 Machine Learning and Deep Learning in Medical Imaging

Machine learning (ML) and deep learning (DL) have significantly advanced medical imaging, enhancing diagnostic precision and operational efficiency. Convolutional Neural Networks (CNNs) are pivotal in this domain, excelling in tasks like myocardial infarction detection through transfer learning, which improves classification accuracy [43]. Deep neural networks (DNNs) are equally impactful, particularly in segmenting optic nerve and orbital tumors from CT scans [59]. The integration of DL with transfer learning is crucial for overcoming data scarcity, as demonstrated by AI tools for COVID-19 diagnosis from X-ray and CT images, which showcase adaptability in urgent healthcare scenarios [15].

Few-Shot Learning (FSL) enhances DL models with limited labeled data, exemplified by the Polyformer model's superior performance in chest X-ray pathology detection [60]. Collaborative training methods, like Flexible Federated Learning (FFL), further improve classification accuracy in decentralized data contexts [15]. DL methods also facilitate complex mappings between imaging modalities, improving image quality and reducing the need for multiple scans [11]. Explainable AI (XAI) techniques, combining DL with interpretability methods, enhance diagnostic accuracy and trustworthiness in applications like leukemia detection [17]. XAI improves AI model interpretability, aiding visualization and decision-making in clinical workflows [12], addressing the opaque nature of deep learning models [33].

Innovative domain adaptation techniques, such as EdgeCycleGAN, preserve critical edge information during image translation, essential for maintaining diagnostic accuracy across diverse imaging environments [61]. Similarly, SP Cycle-GAN ensures structure preservation in the translation process [41]. Incremental learning approaches, like Hard Example Mining, adapt network weights to new data while retaining prior knowledge, highlighting potential for continuous model improvement [21]. ML and DL are driving advancements in medical imaging technologies, addressing data scarcity and enhancing healthcare delivery quality, emphasizing the need for standardized methodologies and ethical considerations related to interpretability and generalization [10].

4.2 Overcoming Data Challenges in Healthcare

The integration of ML and DL in medical imaging faces challenges due to data scarcity and privacy concerns, particularly in rare diseases where large datasets are scarce [45]. Privacy regulations further complicate data collection, imposing strict controls to safeguard patient confidentiality [62]. This scarcity is exacerbated by the need for specialized medical expertise in data annotation and the complexity of standardizing data across imaging modalities [16].

Transfer learning and self-supervised learning offer promising strategies to mitigate these challenges, leveraging pre-trained models and unlabeled data to enhance model generalization and reduce computational costs [16]. However, the domain gap between natural and medical images necessitates innovative domain adaptation strategies. Privacy-preserving methodologies, such as federated learning, enable decentralized model training across institutions, preserving patient privacy while facilitating robust ML model development [16]. Synthetic data generation through generative models also aids in augmenting limited real-world data, contributing to more balanced datasets [62].

The computational demands of traditional multimodal deep learning techniques present hurdles, particularly in low-resource environments like Low and Middle-Income Countries (LMICs). Recent research proposes using vector embeddings from single-modal foundation models and multi-modal Vision-Language Models (VLMs) as efficient alternatives, reducing computational costs while maintaining performance [63, 64]. Overcoming these challenges requires innovative data handling techniques and robust domain adaptation strategies to enhance ML and DL technologies' effectiveness and acceptance in clinical settings, ultimately improving healthcare outcomes.

4.3 Improving Model Interpretability and Usability

Enhancing ML model interpretability and usability in clinical settings is crucial for widespread adoption and trust among healthcare professionals. The complexity of AI models, particularly deep learning systems, often results in 'black boxes' with limited transparency [22]. This opacity can hinder clinical adoption, as clinicians need a clear understanding of AI outputs to integrate these tools into diagnostic workflows [33].

To improve model interpretability, explainable AI (XAI) techniques have been developed to elucidate model predictions, providing multimodal explanations that blend visual and textual information, thereby enhancing the transparency and trustworthiness of healthcare AI systems [65]. These explanations assist clinicians in understanding model predictions, facilitating informed decision-making. Model-agnostic interpretability methods, such as Local Interpretable Model-agnostic

Explanations (LIME) and Shapley Additive Explanations (SHAP), offer a granular view of model behavior, allowing clinicians to assess AI-driven insights' reliability and relevance [33].

User-centric design principles are essential for improving AI models' usability in clinical settings. Tailoring AI interfaces to align with healthcare professionals' workflow and cognitive processes ensures AI tools are intuitive and seamlessly integrate into existing systems. By prioritizing user experience and interface design, AI developers can enhance ML models' accessibility and practicality, supporting their effective utilization in healthcare environments [22]. Enhancing ML model interpretability and usability is vital for establishing trust and fostering acceptance among clinicians, enabling them to comprehend these models' decision-making processes. This is particularly important in high-stakes medical contexts, where integrating human-centered design principles can bridge the knowledge gap between ML developers and clinical stakeholders. By prioritizing user research and empirical evaluations, ML systems can be tailored to meet healthcare professionals' specific needs, increasing successful implementation likelihood and improving patient care outcomes [65, 22, 47, 46, 66]. Leveraging explainable AI techniques and prioritizing user-centric design can significantly enhance AI integration into clinical practice, leading to improved diagnostic accuracy and patient outcomes.

5 Domain Adaptation and Transfer Learning

5.1 Frameworks for Domain Generalization

Domain generalization frameworks are crucial for developing ML models that perform consistently across diverse, unseen domains, particularly in medical imaging's heterogeneous landscape. Distribution shifts, including covariate and concept shifts, pose significant challenges, potentially degrading model performance in new clinical environments. The Distant Domain Transfer Learning (DDTL) approach mitigates these issues by enabling knowledge transfer between disparate domains, reducing negative transfer typically seen in traditional methods [7].

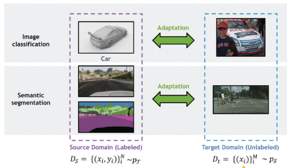
The SpotTUnet framework enhances adaptability by selectively fine-tuning or reusing pre-trained CNN layers based on target domain data [67]. Similarly, the Cross-Domain Error Minimization (CDEM) framework integrates empirical error minimization, distribution alignment, and discriminative learning, addressing the scarcity of labeled medical imaging data [68]. Zhou et al.'s dual-normalization model improves cross-modality segmentation by leveraging augmented source-similar and source-dissimilar images [60]. Mahmood et al. employ adversarial training to transform real medical images into synthetic-like representations, facilitating synthetic dataset use for DL model training [13]. The Source-Free Domain Adaptation framework enhances performance and fairness by minimizing label-free entropy loss on target-domain data, guided by a domain-invariant prior from anatomical information [69].

Juodelyte et al.'s Medical Imaging Contextualized Confounder Taxonomy (MICCAT) systematically evaluates confounders, revealing robustness differences between models pre-trained on natural versus medical datasets [70]. These frameworks significantly advance domain generalization in medical imaging AI, equipping models to adapt to clinical environments while addressing fairness and bias mitigation [71, 8, 72].

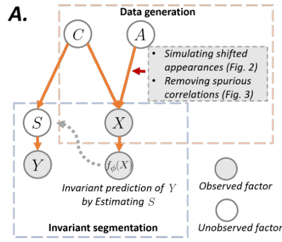
As shown in Figure 3, various frameworks for domain generalization illustrate the versatility of domain adaptation and transfer learning techniques. The first illustration highlights the adaptation of semantic segmentation for both image classification and segmentation tasks, enhancing classification accuracy. The second example emphasizes robust data generation processes by simulating shifted appearances and eliminating spurious correlations. The third image showcases an unsupervised domain adaptation framework for liver tumor classification, demonstrating the model's ability to transfer knowledge to an unseen domain. Together, these examples underscore the potential of domain adaptation and transfer learning in addressing domain generalization challenges, paving the way for more resilient ML models [73, 74, 72].

5.2 Addressing Domain Shifts

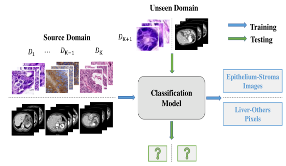
Addressing domain shifts in medical imaging is vital due to variations in data distributions from differing imaging modalities, protocols, and patient demographics across clinical sites. Such shifts can degrade ML model performance, affecting diagnostic accuracy and decision-making. A primary challenge is identifying which network layers should be fine-tuned to adapt effectively to the target



(a) Adaptation of Semantic Segmentation for Image Classification and Semantic Segmentation[73]



(b) Simulating Shifted Appearances and Removing Spurious Correlations in Data Generation and Invariant Segmentation[74]



(c) Unsupervised Domain Adaptation for Liver Tumor Classification[72]

Figure 3: Examples of Frameworks for Domain Generalization

domain, as layers respond variably to domain shifts [67]. Significant shifts from imaging modality differences can severely hinder models not designed for such variability [60].

Unsupervised domain adaptation (UDA) techniques leverage unlabeled data to enhance model learning and address distribution challenges, though the scarcity of annotated target domain images often limits effectiveness [61]. Innovative approaches like domain translators, exemplified by FLARE, project source domain data into a latent space to bolster robustness against domain shifts [15].

Some approaches excel in generalizing across various institutional data, improving segmentation accuracy over existing methods [44]. However, the lack of structure preservation mechanisms can lead to suboptimal segmentation in adapted images [41]. Techniques ensuring critical anatomical structure preservation during adaptation are essential.

Moreover, the risk of forgetting previously learned knowledge when fine-tuning models with new data, especially in the imbalanced and variable medical imaging domain, poses a significant challenge [21]. Incremental learning techniques can mitigate this risk, enabling models to adapt to new data while retaining prior information.

Effectively managing domain shifts requires integrating sophisticated adaptation techniques, comprehensive data augmentation strategies, and structural integrity preservation mechanisms. This multifaceted approach is crucial for enhancing DL model robustness, improving performance across varying clinical settings, and ultimately leading to better patient outcomes in medical imaging [71, 8, 75, 76].

5.3 Adapting Deep Neural Networks

Adapting deep neural networks (DNNs) to new imaging domains is essential for ensuring robust performance and generalizability across diverse clinical environments. A significant challenge is effectively aligning domain distributions to maintain model accuracy and reliability. The CatDA method illustrates using shallow networks for domain alignment, offering a computationally efficient alternative to resource-intensive DL approaches [77]. This simplicity and effectiveness make CatDA particularly suitable for scenarios with limited resources.

Integrating cross-domain error minimization into adaptation is promising, as exemplified by the Cross-Domain Error Minimization (CDEM) framework, which combines empirical error minimization, distribution alignment, and discriminative learning for enhanced model performance [68]. The Source-Free Domain Adaptation framework introduces a novel method utilizing weak supervision and anatomical priors, enabling effective adaptation without source data [69]. This innovation is beneficial in medical imaging, where source data access may be restricted due to privacy or availability.

Boundary information is critical in adapting DNNs, as shown by the Boundary-Weighted Domain Adaptive Neural Network (BOWDA-Net), which enhances the model's ability to address target domain challenges like unclear boundaries and insufficient training data [42].

These strategies highlight diverse methodologies for adapting DNNs to new imaging domains, addressing challenges like data scarcity, domain shifts, and model generalization. Future research should focus on advancing innovative adaptation techniques in DL for medical applications, emphasizing integrating multimodal data sources, such as electronic health records and medical imaging, for more accurate and personalized diagnostics. Researchers must also consider the ethical implications of implementing DL technologies in clinical settings, ensuring these systems enhance diagnostic capabilities while prioritizing patient safety and privacy. Addressing these challenges can significantly improve patient outcomes and contribute to healthcare delivery effectiveness [78, 46, 5, 2].

6 Cross-Domain Analysis and Computer-Aided Diagnosis

In computer-aided diagnosis, the integration of cross-domain analysis and multi-modal data is critical for enhancing diagnostic accuracy. This section examines methodologies for combining diverse data sources to improve diagnostic outcomes and inform clinical decision-making. The subsequent subsection delves into how these techniques enhance diagnostic accuracy, providing insights into their implications in medical imaging.

6.1 Enhancing Diagnostic Accuracy with Multi-modal and Cross-domain Techniques

Incorporating data from multiple domains enhances diagnostic accuracy in medical imaging by offering a comprehensive view through the integration of various information sources. Multi-modal data integration, encompassing both imaging and non-imaging information, supports a holistic diagnostic approach. Tools like Barttender facilitate simultaneous visualization of diverse data types, providing an interpretable framework for clinical decision-making [79].

Cross-modality data augmentation enhances diagnostic precision by diversifying training datasets. Yang et al. demonstrated that such augmentation improves predictive performance, enriching datasets and bolstering model robustness [80]. This is particularly beneficial when single-modality data is insufficient for accurate diagnosis.

Advanced architectures, such as TransMed, model long-range dependencies across modalities, effectively integrating multi-modal images to enhance diagnostic accuracy [81]. Transfer learning further improves diagnostic accuracy across domains, with adapted CNNs achieving significant advancements, exemplified by an 86

In low-resource settings, vector embeddings democratize multimodal deep learning, enhancing AI adaptability and diagnostic accuracy across healthcare applications [64]. This approach utilizes limited data effectively, ensuring AI-driven tools remain accessible in resource-constrained environments.

Domain adaptation techniques, such as BOWDA-Net, enhance segmentation accuracy and delineate clearer boundaries in medical images [42]. Integrating multi-modal and cross-domain techniques significantly enhances diagnostic accuracy by leveraging diverse datasets, such as the MedIMeta, which standardizes datasets across domains for robust machine learning applications [82, 80, 58, 76].

6.2 Leveraging Multi-Modality Data

Integrating multi-modality data in medical imaging enhances diagnostic outcomes by synthesizing diverse information sources, providing a comprehensive view of patient health. This approach addresses single-modality limitations, improving diagnostic model robustness and accuracy [81]. Multi-modality fusion combines anatomical, functional, and molecular information, beneficial for complex diagnostic tasks requiring nuanced disease understanding.

Techniques like multi-modal image registration and fusion align data from different modalities, such as MRI, CT, and PET, yielding a unified anatomical and physiological landscape representation. This integration aids in identifying subtle pathological changes that may be overlooked when modalities are considered independently [83]. By leveraging each modality's strengths, clinicians achieve more accurate diagnoses and informed treatment planning.

Advanced machine learning architectures, particularly transformers, manage multi-modality data, capturing long-range dependencies among different data types. The TransMed model exemplifies this application, enhancing computer-aided diagnosis precision through effective multi-modal image integration [81]. Such models process complex data relationships, providing deeper insights into patient conditions and supporting precise clinical decision-making.

Integrating multi-modality data enhances AI model interpretability, offering richer analysis context and providing more transparent predictions essential for clinical acceptance [79]. Visualizing and interpreting multi-modal data in an integrated manner enables clinicians to draw informed conclusions, ultimately leading to improved patient outcomes.

The strategic integration of multi-modality data in medical imaging represents a transformative leap in diagnostic methodologies, harnessing diverse data sources—such as EHR, medical images, and multi-omics data—augmented by advanced AI techniques. This comprehensive approach enriches understanding of complex health conditions and facilitates personalized healthcare solutions, leading to improved disease diagnosis and prediction accuracy. Recent studies reveal a trend in fusing EHR and imaging data, with early fusion techniques demonstrating superior clinical outcomes, particularly in diagnosing neurological disorders. Leveraging machine learning algorithms, researchers create robust models capable of effectively analyzing multimodal datasets, paving the way for innovative healthcare delivery advancements [58, 2, 19, 3, 5].

6.3 Improving Visual Recognition Across Domains

Enhancing visual recognition across domains in medical imaging requires addressing challenges posed by domain shifts and imaging protocol variations. Developing robust techniques ensures consistent and accurate model performance. Domain adaptation and transfer learning strategies enhance visual recognition by adapting models trained in one domain to perform well in another, leveraging similarity information alongside features. Recent research suggests that formulating transfer learning as a clustering problem allows the use of a similarity network to learn category-agnostic pairwise constraints, significantly improving unsupervised domain adaptation and cross-task learning performance. Studies indicate that while transferring knowledge from domains like ImageNet is common, transfer learning effectiveness is influenced by data size, model capacity, and source-target domain distance, emphasizing feature reuse importance for successful outcomes [27, 28].

Adversarial training methods, like the CDEM framework, align feature distributions between source and target domains, minimizing discrepancies and enhancing model generalization across imaging environments [68]. Generative models, exemplified by the Source-Free Domain Adaptation framework, generate synthetic data resembling the target domain, enhancing model adaptability and fairness [69].

Boundary-sensitive techniques, like BOWDA-Net, improve recognition and delineation of complex anatomical structures across domains by focusing on boundary information during adaptation, preserving critical features and enhancing segmentation accuracy [42].

Incremental learning methods support visual recognition enhancement across domains by allowing models to continuously learn from new data without forgetting previously acquired knowledge, beneficial in dynamic clinical environments where data distributions evolve over time [21].

Improving visual recognition capabilities across domains in medical imaging necessitates a multi-faceted approach combining domain adaptation, transfer learning, adversarial training, and incremental learning. Implementing diverse data augmentation techniques, such as spatial transformations, color adjustments, and style transfer, enhances visual recognition model robustness and accuracy. These advancements address challenges related to limited and heterogeneous training datasets, improving models' ability to generalize across varying clinical scenarios, leading to superior diagnostic performance and better patient outcomes as models adapt to real-world complexities and variations in medical data [19, 84, 35].

7 Challenges and Future Directions

The incorporation of machine learning (ML) and deep learning (DL) in medical imaging introduces challenges that necessitate a focus on ethical considerations and practical deployment. Addressing these issues is crucial for ensuring that ML and DL applications are effective and ethically aligned with healthcare complexities. The following subsections explore these challenges and the ethical implications of integrating ML and DL in medical imaging.

7.1 Challenges and Ethical Considerations

The integration of ML and DL in medical imaging faces challenges such as data scarcity, privacy, and model explainability. A key issue is the dependence on large, annotated datasets, which are often scarce in healthcare, affecting model performance and generalizability [16]. The high costs and time required for data annotation, coupled with limited radiologist availability, exacerbate this problem [45]. Model performance variability due to dataset size, domain similarity, and architecture further complicates robust model development [45].

Privacy is a critical concern, especially with federated learning, which must balance patient confidentiality with collaborative model training across decentralized datasets. Although promising, federated learning's reliance on datasets that may not reflect all demographic variations can hinder model generalizability [8]. The complexity of integrating DL into clinical workflows and the interpretability of these models pose challenges, as they often function as 'black boxes' [16]. This opacity can impede clinical adoption, as interpretable AI models are essential for effective integration into diagnostic workflows [33].

The intricate nature of deep neural networks (DNNs) complicates explainability, as these models may not explicitly represent knowledge. Regulatory requirements for transparency in decision-making necessitate models that clinicians can trust [33]. Moreover, some domain adaptation techniques require labeled source domain images, limiting their applicability where such data is unavailable [8].

Addressing these challenges requires developing models that are accurate, efficient, transparent, privacy-preserving, and ethically sound. Integrating diverse data sources and validating new technologies in clinical settings are essential for reliable and ethical deployment. Techniques like Incremental Example Mining (IEM), which adapts to new data while retaining existing knowledge, can enhance model flexibility [21]. Such strategies will advance the field toward more trustworthy AI-driven healthcare solutions.

7.2 Integration into Clinical Workflows

Integrating ML and DL technologies into clinical workflows involves challenges that must be addressed for effective adoption. Aligning AI tools with established clinical processes requires seamless integration that enhances clinical operations without disrupting existing practices [85].

Significant variability across clinical environments demands customization of ML models to accommodate diverse imaging protocols, equipment types, and patient demographics. This variability can hinder reproducibility and generalization, as models often overfit specific datasets and struggle across different hospitals and populations. Developing robust solutions involves data augmentation to enhance performance in heterogeneous settings [19, 23, 8, 4]. The lack of standardized deployment protocols further complicates this process, leading to inconsistencies in model performance. Additionally, DL models often require substantial computational resources and technical expertise, posing integration challenges, especially in resource-constrained environments.

Model interpretability is crucial for clinical workflow integration. Clinicians require transparent AI models to foster trust and enhance diagnostic processes. These models must provide insights into their decision-making mechanisms, aligning with human judgment, particularly in high-stakes environments [65, 22, 20, 4, 66]. Developing models that offer accurate predictions with decision-making insights is vital for clinician acceptance.

Addressing ethical and regulatory considerations is paramount. Ensuring compliance with healthcare standards and privacy regulations while facilitating the fusion of diverse data modalities, such as EHR and medical imaging, enhances AI applications' clinical relevance [5, 18, 20]. Implementing robust data governance frameworks that protect patient information while enabling effective AI-driven insights is essential.

Future research should focus on expanding benchmarks to include parameter-efficient fine-tuning (PEFT) techniques and exploring their integration into clinical workflows [85]. By addressing these challenges and advancing adaptable, interpretable, and compliant AI models, ML and DL technologies can significantly improve healthcare outcomes and operational efficiency.

7.3 Technological Advancements and Future Research Directions

The future of medical imaging and ML is poised for transformative advancements, emphasizing enhanced model robustness, interpretability, and adaptability across diverse clinical environments. Critical research involves integrating diverse datasets and developing benchmarks to refine transfer learning and self-supervised learning in medical imaging. This approach aims to improve ML model generalization and performance across tasks by addressing domain shift challenges and employing strategies like domain adaptation and data augmentation [19, 71, 8, 72].

Exploring advanced annotation techniques and innovative architectures for multimodal imaging is essential for enhancing model generalization through domain adaptation, potentially revolutionizing multimodal data use in clinical practice [16]. Future research will extend methodologies to detect a broader range of physiological signals and conditions, such as EEG, while enhancing data augmentation techniques to improve diagnostic accuracy [61].

Significant advancements in unsupervised and semi-supervised learning methods are anticipated, particularly through frameworks like SpotTUnet, which aim to tackle domain shifts and enhance model robustness [6]. Enhancing style augmentation techniques and exploring additional normalization strategies will improve generalization across medical imaging tasks [60].

The reverse domain adaptation paradigm offers promising applications to other modalities, improving automated segmentation and classification tasks [21]. Future research will investigate extending domain adaptation techniques to segment different organs across various modalities, broadening their applicability in medical image analysis [61].

Enhancing frameworks like FLARE by integrating sophisticated feature extraction techniques and leveraging additional data sources is another key research direction [8]. Exploring multiple input alterations and generalizing models trained on larger datasets will drive technological advancements [16].

Future research should prioritize developing interpretable models and exploring emerging trends, such as transformer architectures and multi-modal imaging, to enhance generalization capabilities [33]. These advancements are expected to significantly impact ML integration into healthcare, ultimately improving diagnostic accuracy and patient outcomes.

8 Conclusion

The convergence of medical imaging, domain adaptation, and machine learning heralds a pivotal shift in healthcare diagnostics, significantly advancing the precision, efficiency, and comprehensibility of imaging tasks. This survey highlights the transformative impact of these technologies, particularly emphasizing the efficacy of active learning frameworks in optimizing classification tasks with limited training data. Such methodologies achieve remarkable diagnostic accuracy, exemplified by frameworks like HAIL, which enhance multi-site MRI data harmonization, thereby preserving critical anatomical details for improved clinical outcomes in rare disease diagnosis.

Standardization efforts, such as the highdicom library, play a crucial role in seamlessly integrating machine learning models into clinical settings, promoting consistent image annotation exchange and advancing research reliability. Moreover, frameworks like LENS illustrate substantial advancements in lesion detection sensitivity, underscoring the importance of robust methodologies in addressing the complexities of clinical datasets.

The advent of transformers in medical imaging has set new benchmarks for performance, contingent upon optimal model architecture and data quality. The necessity for continuous AI model performance and fairness monitoring is evident, requiring comprehensive regulatory frameworks to ensure equitable healthcare applications. Notably, advanced imaging techniques are poised to enhance diagnostic precision and facilitate personalized medicine through innovative computational models.

Addressing biases in medical imaging AI remains a critical challenge, with proposed frameworks aiming to develop more equitable clinical decision-support tools. The exploration of generative models and deep learning advancements offers promising research directions, as evidenced by frameworks like FedLSM, which demonstrate significant potential in federated learning applications.

These findings underscore the transformative potential of AI technologies in healthcare, suggesting a paradigm shift in diagnostic and treatment paradigms, particularly within oncology. The integration of diverse data sources through innovative learning approaches enhances the clinical utility of machine learning models, ultimately improving patient care and health outcomes. Continued research and development are essential to validate and fully harness these technologies, paving the way for a revolutionized healthcare landscape.

AI-generated, for reference only.

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