A Survey of Medical Imaging Modalities and AI Technologies for Enhanced Clinical Decision Support

www.surveyx.cn

Abstract

Medical imaging modalities such as X-ray, MRI, and CT are integral to modern diagnostics, offering detailed internal views crucial for effective patient management. The integration of AI technologies, particularly deep learning and multimodal large language models (LLMs), has revolutionized the interpretation and analysis of these imaging modalities, enhancing clinical decision support systems. This survey examines the convergence of AI with medical imaging, highlighting AI's role in improving diagnostic accuracy and workflow efficiency, especially during the COVID-19 pandemic. AI-driven models have demonstrated significant potential in automating image classification and reconstruction, addressing challenges like class imbalance and data quality, and enhancing diagnostic precision through innovative approaches such as vision-language processing. Despite these advancements, challenges persist, including data annotation, computational demands, and interoperability issues, underscoring the need for standardized benchmarks and robust validation frameworks. Ethical and privacy concerns also necessitate careful consideration to ensure responsible AI deployment in healthcare. Future research should focus on optimizing AI algorithms for low-dose imaging, expanding data diversity, and enhancing model scalability to further integrate AI into clinical settings. By addressing these challenges, AI promises to significantly enhance medical imaging capabilities, leading to improved patient outcomes and more personalized healthcare solutions.

1 Introduction

1.1 Importance of Medical Imaging Modalities

Medical imaging modalities, including X-ray, MRI, and CT, are essential for diagnosing and managing various health conditions by providing detailed internal body images. X-ray imaging is particularly crucial, facilitating the automatic classification of pulmonary diseases, including COVID-19 [1]. During the COVID-19 pandemic, chest X-ray (CXR) images became a cost-effective and rapid diagnostic tool, aiding clinicians in the timely diagnosis of pneumonia and other thoracic conditions [2]. However, traditional diagnostic methods often fail to capture prediction uncertainties, a limitation that deep neural networks are designed to address [3].

The spectral characteristics of X-rays are vital for imaging tasks, such as Monte Carlo-based radiation dose calculations, which are essential for patient safety during diagnostic procedures [4]. Despite their widespread use, medical image datasets frequently face class imbalance, particularly in COVID-19 detection datasets, necessitating innovative approaches to effectively synthesize positive examples [5].

In pediatric care, X-ray imaging is indispensable for diagnosing conditions like pneumonia, a leading cause of mortality in children under five. Accurate detection of conditions such as pneumoperitoneum on chest X-rays is crucial for urgent surgical interventions [6]. Additionally, challenges in lung cancer

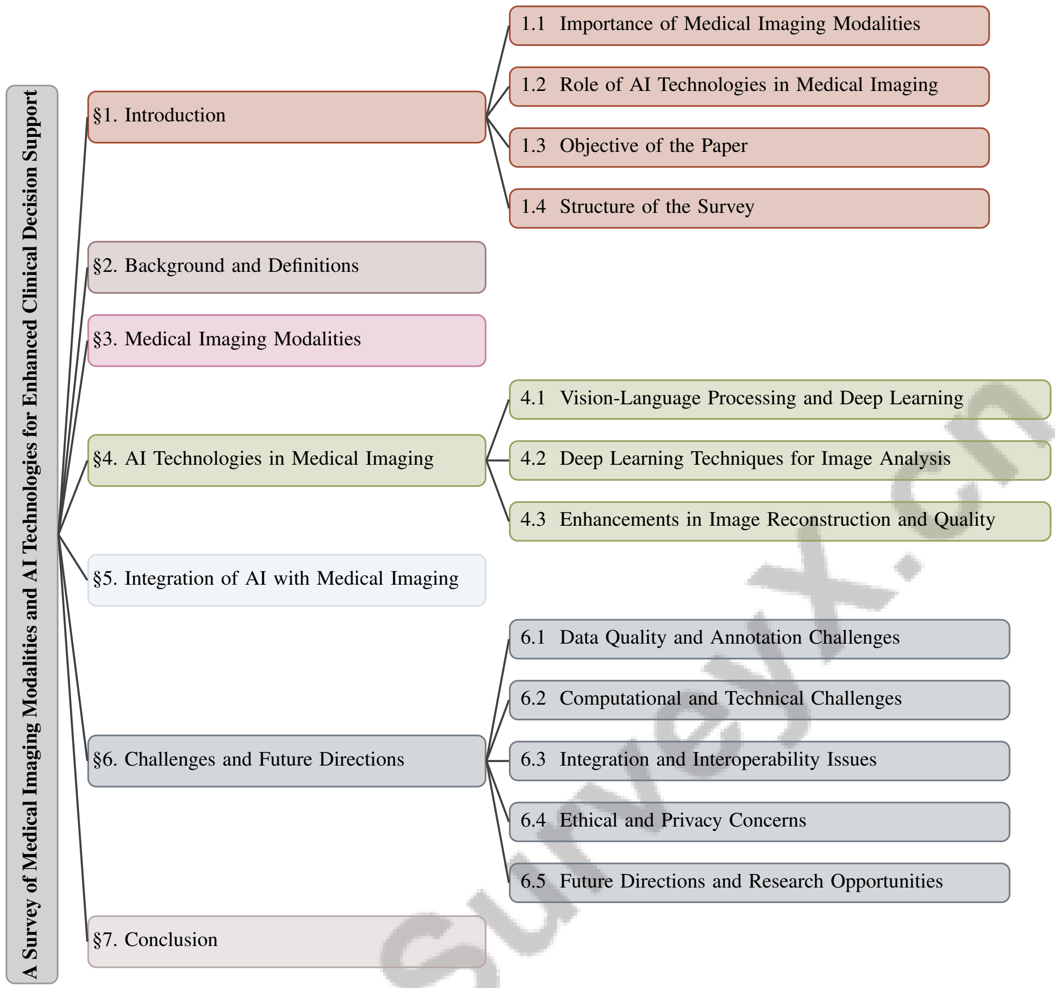


Figure 1: chapter structure

detection via CXR highlight the need for advanced techniques to reduce the manual analysis burden on radiologists [7].

The integration of artificial intelligence (AI) in medical diagnostics, particularly during the COVID-19 pandemic, underscores the evolving role of medical imaging modalities in enhancing diagnostic accuracy and patient care [8]. Advancements in imaging technology further solidify the importance of these modalities in clinical settings, paving the way for improved patient outcomes.

1.2 Role of AI Technologies in Medical Imaging

AI technologies are revolutionizing medical imaging by significantly improving the precision and efficiency of image interpretation. Deep learning techniques, especially convolutional neural networks (CNNs), have been pivotal in automating the classification and analysis of medical images. For instance, CNNs have effectively classified chest X-ray images into categories such as COVID-19, normal, and pneumonia, thereby enhancing radiologists' diagnostic capabilities. These advancements extend beyond classification, with CNNs also improving image reconstruction quality, surpassing the limitations of traditional methods like filtered backprojection [9].

The integration of deep learning algorithms has significantly enhanced the accuracy and speed of COVID-19 diagnosis using chest X-ray images, as demonstrated by recent methodologies [8]. Furthermore, the classification of textural medical images, such as diffuse lung diseases (DLDs), using deep convolutional neural networks (DCNNs) showcases AI's potential in addressing complex diagnostic challenges [10].

Despite these advancements, existing deep learning models often struggle with generalizability across different imaging systems, necessitating benchmarks to validate their performance [6]. The adoption of weakly-supervised learning approaches has further enhanced AI's capabilities in medical imaging by enabling simultaneous localization and classification of fractures without additional localization annotations [11]. Vision-language pre-training (VLP) models have emerged as crucial tools, integrating visual and textual information to provide a comprehensive understanding of diseases like osteoarthritis [12].

AI technologies have also tackled modality incongruity in Multimodal Federated Learning (MMFL) for medical vision and language-based disease detection [13]. The P2Med-MLLM benchmark exemplifies the integration of both text and image modalities, reflecting AI's role in enhancing the interpretation of medical imaging data [14].

During the COVID-19 pandemic, AI-driven models like CoroNet and DAD-COVID have shown significant potential by facilitating rapid screening and detection of the virus using chest X-ray images. These models leverage advanced deep learning techniques to enhance imaging data interpretation, supporting timely and accurate diagnosis [15].

Moreover, the development of visualization frameworks using Bayesian Convolutional Neural Networks has enabled uncertainty interpretation in predictions, crucial for enhancing the reliability of machine learning models in healthcare [3]. The automation of matching sentences in radiology reports to semi-structured representations using neural models further exemplifies AI's growing role in streamlining radiological workflows [16]. As AI technologies continue to evolve, their integration into medical imaging promises to further improve diagnostic accuracy and patient care outcomes.

1.3 Objective of the Paper

This paper aims to explore the integration of artificial intelligence (AI) technologies with medical imaging modalities to enhance diagnostic performance and clinical decision support systems. A significant focus is addressing challenges posed by class imbalance in medical imaging datasets, particularly chest X-ray images, which affect the performance of deep learning models used for classification tasks [17]. By leveraging advanced deep learning methodologies, such as those proposed by the COVID-MobileXpert, the paper seeks to optimize resource utilization and clinical workflow in managing COVID-19 patients [18].

Additionally, the paper evaluates the effectiveness of dimensionality reduction techniques in improving chest X-ray analysis for lung cancer detection, providing benchmarks for enhancing diagnostic accuracy [7]. It also aims to design automated diagnosis systems for COVID-19 using chest X-ray images, emphasizing deep learning's role in accelerating testing processes [8].

The investigation includes the integration of AI with medical imaging through frameworks like PRECISE, which generates patient-friendly summaries of radiology reports, thereby enhancing patient communication and understanding [19]. The evaluation of deep learning models in detecting pneumoperitoneum in chest radiographs is also a key focus, facilitating model comparisons across various imaging systems [6].

Furthermore, the paper aims to provide a homogeneous and balanced dataset for training deep learning models to accurately classify COVID-19 severity levels, addressing the need for standardized benchmarks in medical imaging [2]. Through these objectives, the paper underscores the importance of AI integration in advancing medical imaging research and improving clinical outcomes.

1.4 Structure of the Survey

This survey is meticulously structured to offer a comprehensive exploration of the integration of artificial intelligence (AI) technologies with medical imaging modalities. The paper begins with an introduction that highlights the significance of medical imaging modalities, such as X-ray, MRI, and CT, in clinical diagnostics and patient care, alongside the transformative role of AI technologies, particularly Multimodal Large Language Models (LLMs) and natural language processing, in enhancing the interpretation and analysis of medical imaging data.

Following the introduction, the background and definitions section provides an overview of core concepts and definitions pertinent to the survey, including X-ray, MRI, CT, Multimodal LLMs, and natural language processing, setting the foundation for subsequent discussions.

The survey then delves into the technical aspects and applications of medical imaging modalities, examining the strengths and limitations of X-ray, MRI, and CT in medical diagnostics. The subsequent section focuses on the application of AI technologies in medical imaging, specifically the integration of vision-language processing and deep learning techniques. This analysis highlights how AI-driven advancements enhance image reconstruction and quality, ultimately facilitating more accurate diagnoses and better patient outcomes. Additionally, it explores the utility of semi-structured representations of radiology reports, which streamline the identification of specific medical findings, and the role of explainable AI in enhancing human-AI collaboration, leading to improved task performance among medical professionals [20, 16].

The integration of AI with medical imaging is further explored, focusing on the potential and challenges of integrating AI technologies across various imaging modalities. This section examines synthetic data generation, the integration of diverse data sources, and presents case studies illustrating successful AI integration in clinical settings.

The survey concludes with a comprehensive discussion on the challenges faced in integrating AI with medical imaging, including issues related to data heterogeneity, the need for explainable AI to enhance human-AI collaboration, and the exploration of multimodal federated learning techniques. It outlines future research directions, emphasizing the importance of developing robust models that effectively utilize diverse data sources while improving the clarity and accessibility of radiology reports for both medical professionals and patients [16, 21, 13, 20, 19]. This includes addressing data quality and annotation challenges, computational and technical hurdles, integration and interoperability issues, and ethical and privacy concerns. The paper concludes by highlighting future research opportunities to address these challenges and reinforce the importance of AI integration in enhancing clinical decision support systems.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Definition and Significance of X-ray Imaging

X-ray imaging, a foundational diagnostic tool, uses electromagnetic radiation to visualize internal structures, crucial for detecting and managing respiratory diseases, including COVID-19. During the pandemic, chest X-ray (CXR) imaging facilitated the classification of images into healthy, COVID-19, or pneumonia categories, enabling timely diagnoses [1]. Its role in identifying pulmonary conditions underscores its diagnostic importance. However, challenges such as class imbalance in COVID-19 datasets complicate deep learning model training, necessitating innovative strategies for generating realistic X-ray images from limited datasets [5, 22]. Large datasets like NIH Chest X-Ray 14 enhance AI model training and validation, improving diagnostic accuracy [23].

Traditional image quality metrics for X-ray systems often do not correlate with diagnostic performance, indicating the need for improved evaluation methods [24]. Efforts to refine X-ray imaging include estimating the X-ray spectrum from raw data for accurate dose calculations and patient safety [4]. Datasets categorizing CXR images into severity levels—Normal-PCR+, Mild, Moderate, and Severe—highlight X-ray imaging's nuanced role in assessing disease severity and informing clinical decisions [2]. As technology and AI integration advance, X-ray imaging remains pivotal in diagnostics, enhancing patient care outcomes.

2.2 MRI and CT Imaging Modalities

Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are essential in modern diagnostics, each offering distinct advantages. MRI, using magnetic fields and radio waves, provides detailed soft tissue images without ionizing radiation, valuable in neurological, musculoskeletal, and cardiovascular imaging, facilitating targeted interventions [25, 16, 21, 7, 19]. Conversely, CT imaging, utilizing X-rays for cross-sectional images, offers rapid, high-resolution visualization of bones, organs, and blood vessels, crucial in emergencies like trauma and stroke.

CT imaging faces challenges such as reconstruction difficulties in limited-angle CT (LA-CT) due to the inverse problem's ill-posed nature [9]. Accurate calibration of X-ray CT systems is vital for reliable image reconstruction, as shown by advancements in calibration methodologies [26]. While statistical image reconstruction methods in CT could improve image quality and reduce doses, long reconstruction times limit practical use [27]. Artifacts like streaking from beam hardening affect diagnostic accuracy [28].

Deep learning innovations, such as deep-unrolling networks, enhance image reconstruction efficiency for large-scale tasks like X-ray CT [29]. These advancements address traditional technique limitations, enabling more accurate diagnostics. MRI and CT scans are vital in medical imaging, each contributing uniquely to clinical decision-making and patient care. MRI excels in soft tissue contrast, while CT provides rapid, detailed internal structure visualization, enabling swift diagnoses in emergencies. Together, these modalities empower healthcare professionals to make informed decisions tailored to individual patient needs [30, 13]. As technology and AI integration progress, these modalities promise even greater diagnostic precision and efficiency.

2.3 Multimodal Large Language Models (LLMs)

Multimodal Large Language Models (LLMs) enhance medical data analysis by integrating visual and textual information using advanced machine learning techniques. The Modality Imputation Network (MIN) exemplifies this by generating missing modalities in unimodal clients based on available data, addressing incomplete data integration challenges [13]. This integration overcomes unimodal approaches' limitations, often failing to capture the full information spectrum. The synthesis of high-fidelity COVID-19 images through unsupervised domain adaptation further illustrates Multimodal LLMs' potential in augmenting data quality and diversity, facilitating robust AI model development [5].

These models, including the DDMM, synthesize realistic X-ray images and segmentations using both labeled and unlabeled datasets, improving classifier training [22]. Their efficacy in clinical settings is underscored by successful AI model development for analyzing X-ray images [8]. As technologies like GPT-based frameworks for generating patient-friendly radiology reports evolve, Multimodal LLMs hold the potential to significantly improve diagnostic accuracy and patient outcomes [19, 1, 16]. These models represent a promising avenue for advancing medical imaging analysis, seamlessly integrating diverse data sources and enhancing AI interpretative capabilities.

2.4 Natural Language Processing in Medical Imaging

Natural Language Processing (NLP) enhances the interpretability and utility of medical imaging data by converting it into comprehensible formats. The CXR-CLIP approach, which aligns visual and textual information, exemplifies this by enhancing chest X-ray data interpretability [21]. NLP applications extend to automated semi-structured radiology report generation, crucial for extracting valuable medical research information [16]. By streamlining this process, NLP boosts research efficiency and accuracy.

The PRECISE framework exemplifies NLP's role in generating patient-friendly radiology reports, enhancing patient comprehension and supporting informed decisions [19]. NLP also addresses curriculum learning challenges in medical image classification, where the absence of objective measures for sample difficulty can introduce bias [31]. By systematically evaluating sample difficulty, NLP contributes to more robust learning models.

NLP is integral to frameworks like DeepDRR, which improve medical imaging data interpretability and application, enhancing diagnostic accuracy and patient care outcomes [25, 1]. These advancements highlight NLP's critical role in improving medical imaging data's interpretability, accessibility, and application, ultimately enhancing diagnostic accuracy and patient care outcomes.

3 Medical Imaging Modalities

3.1 Technical Aspects and Applications of X-ray Imaging

X-ray imaging is essential in diagnostic radiology, providing non-invasive internal visualization through conventional radiography, fluoroscopy, and digital subtraction angiography, each tailored for specific clinical needs [32]. Conventional radiography is utilized for static imaging in diagnosing fractures, infections, and tumors, while fluoroscopy offers real-time imaging for dynamic assessments such as gastrointestinal evaluations. Digital subtraction angiography is pivotal for vascular imaging by subtracting pre-contrast images from post-contrast ones.

Technological advancements have significantly enhanced X-ray imaging's precision. The use of back-illuminated charge-coupled devices (CCDs) has improved positional resolution to below 2 μm, crucial for detailed imaging tasks [33]. Optimizing electric fields and light diffusion is critical for maintaining spatial resolution [32]. Evaluating X-ray system detectability through wavelet packet transformations applied to star-bar phantoms provides insights into resolving fine details [24].

Clinically, X-ray imaging is vital for rapid diagnosis. During the COVID-19 pandemic, chest X-ray (CXR) imaging was essential for classifying respiratory conditions, distinguishing between healthy individuals, COVID-19 patients, and those with other pneumonia types. Convolutional neural network (CNN) models have significantly improved CXR classification accuracy into binary and multi-class categories [34]. Bayesian Convolutional Neural Networks (BCNNs) enhance predictions by estimating uncertainty, providing radiologists insights into pixel-level contributions to uncertainty [3].

X-ray imaging remains a cornerstone of modern diagnostics, with advanced AI techniques, particularly CNNs and BCNNs, achieving up to 99.18

3.2 Technical Aspects and Applications of Computed Tomography (CT)

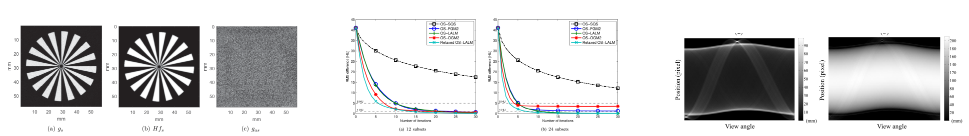
Computed Tomography (CT) is a crucial imaging modality, known for producing detailed cross-sectional images using ionizing radiation. CT imaging acquires multiple X-ray measurements from various angles, reconstructing them into a three-dimensional representation of the scanned area, vital for visualizing complex anatomical structures and diagnosing diverse conditions.

A significant challenge in CT imaging is managing scattered photons, which degrade image quality. Time-of-flight X-ray measurements have been proposed to mitigate this issue, enhancing image clarity by reducing scattered radiation effects [35]. Statistical image reconstruction (SIR) methods have been developed to maintain image quality while reducing X-ray doses, minimizing patient radiation exposure [27].

Innovative reconstruction techniques, including geometric relations and polynomial reproducing kernels, have improved accuracy in reconstructing three-dimensional convex bilevel polyhedrons from two-dimensional projections [26]. Stochastic primal-dual deep unrolling methods have enhanced image reconstruction efficiency in low-dose and sparse-view CT scenarios, significantly improving image quality while reducing computational demands [29].

Despite its benefits, CT imaging faces limitations, such as artifacts like streaking, often resulting from beam hardening effects when X-ray beams traverse dense materials. Theoretical models within nontrapping simple compact Riemannian manifolds framework have been utilized to evaluate and mitigate these artifacts, enhancing diagnostic reliability [28].

CT imaging is indispensable in emergency medicine for its rapid acquisition times and high-resolution capabilities, routinely employed for diagnosing traumatic injuries, tumors, and vascular conditions. Its ability to provide detailed representations of internal structures significantly enhances surgical precision and disease monitoring [19, 16].



(a) Optical Imaging of a Circular Object with a Circular Aperture[24]

(b) Comparison of RMS difference between different methods for 12 and 24 subsets[27]

(c) Optical Imaging of a Waveguide in a Waveguide Array[4]

Figure 2: Examples of Technical Aspects and Applications of Computed Tomography (CT)

As shown in Figure 2, exploring medical imaging modalities, particularly CT, reveals insights into technical aspects and practical applications. "Optical Imaging of a Circular Object with a Circular

Aperture" illustrates the detailed view of a circular object's surface and cross-section, emphasizing CT imaging precision. "Comparison of RMS difference between different methods for 12 and 24 subsets" quantitatively analyzes the efficiency and accuracy of iterative methods like OS-SQS and OS-FGM2. "Optical Imaging of a Waveguide in a Waveguide Array" showcases optical imaging's versatility within CT applications, enhancing our understanding of light intensity distribution. These examples encapsulate CT technology's multifaceted nature, from detailed imaging capabilities to computational advancements and diverse medical applications [24, 27, 4].

3.3 Challenges and Innovations in CT Imaging

Computed Tomography (CT) imaging faces challenges impacting image quality and diagnostic accuracy. Scattered photons contribute to image noise, degrading contrast-to-noise ratio and compromising diagnostic clarity [35]. Addressing this issue is essential for enhancing image quality and ensuring accurate diagnostics.

Recent advancements focus on reducing scattered photons' impact and improving reconstruction techniques. Time-of-flight X-ray measurements differentiate between scattered and primary photons, enhancing image clarity and reducing noise levels [35]. Innovations in statistical image reconstruction (SIR) methods allow for reduced X-ray doses while maintaining image quality, prioritizing patient safety [27].

Deep learning integration into CT imaging has advanced image reconstruction and artifact reduction. Stochastic primal-dual deep unrolling methods optimize reconstruction processes in low-dose and sparse-view scenarios, resulting in clearer images [29]. Challenges persist, particularly regarding artifact formation, such as streaking, often caused by beam hardening effects when X-ray beams encounter dense materials. Theoretical models and innovative reconstruction techniques are being developed to mitigate these artifacts, ensuring more reliable diagnostic outcomes. Ongoing research and innovation are crucial to address these limitations and enhance CT imaging capabilities, especially in the context of emerging health challenges like COVID-19, where improved imaging techniques are vital for accurately detecting and classifying pulmonary diseases. Frameworks such as PRECISE enhance radiology report clarity, employing deep learning for automatic disease classification from imaging data, and creating large-scale annotated datasets to support robust machine learning models, fostering a more effective and patient-centered approach to medical imaging [19, 1, 5, 16].

4 AI Technologies in Medical Imaging

Category	Feature	Method
Vision-Language Processing and Deep Learning	Reliability and Trust	m2d2[36], BCNN-F[3]
	Representation Learning	CXR-CLIP[21]
	Efficient Model Design	CMX[18]
Deep Learning Techniques for Image Analysis	Feature Extraction and Enhancement	SCC[37], DL-COVID[38], DO[9]
	Interpretability and Accessibility	PRECISE[19]
	Classification and Diagnostic Strategies	B3-X[15], DAD-COVID[39], MNv2[1]
Enhancements in Image Reconstruction and Quality	Efficiency and Speed Improvements	SESPA[26], RLALM[27]
	Frequency and Spectrum Methods	WPT-DA[24], ITM-Spectrum[4]
	Clarity and Noise Reduction	PI-2D-AXT[40], ToF-CT[35]
	Interpretability and Localization	PYLON[23]

Table 1: This table presents an overview of various AI methodologies applied in medical imaging, categorized into vision-language processing, deep learning techniques for image analysis, and enhancements in image reconstruction and quality. It highlights specific features and methods within each category, showcasing the diversity and application of AI technologies in improving diagnostic accuracy and patient care.

The integration of artificial intelligence (AI) technologies in medical imaging represents a significant advancement, enhancing diagnostic precision and improving patient outcomes. Vision-language processing and deep learning have emerged as transformative methodologies, enabling the fusion of visual data with textual information to bolster diagnostic accuracy. This section explores the methodologies and advancements in these areas, highlighting their role in automating image analysis and enhancing diagnostic interpretability. Table 2 provides a comprehensive summary of AI methodologies in medical imaging, detailing their categorization and specific applications in enhancing diagnostic processes. As illustrated in Figure 3, the hierarchy of AI technologies in medical imaging is depicted, focusing specifically on vision-language processing and deep learning. This

AI-generated, for reference only.

figure emphasizes deep learning techniques for image analysis, as well as enhancements in image reconstruction and quality. Furthermore, it highlights key techniques, models, and their applications, underscoring AI's transformative role in improving diagnostic accuracy and patient care.

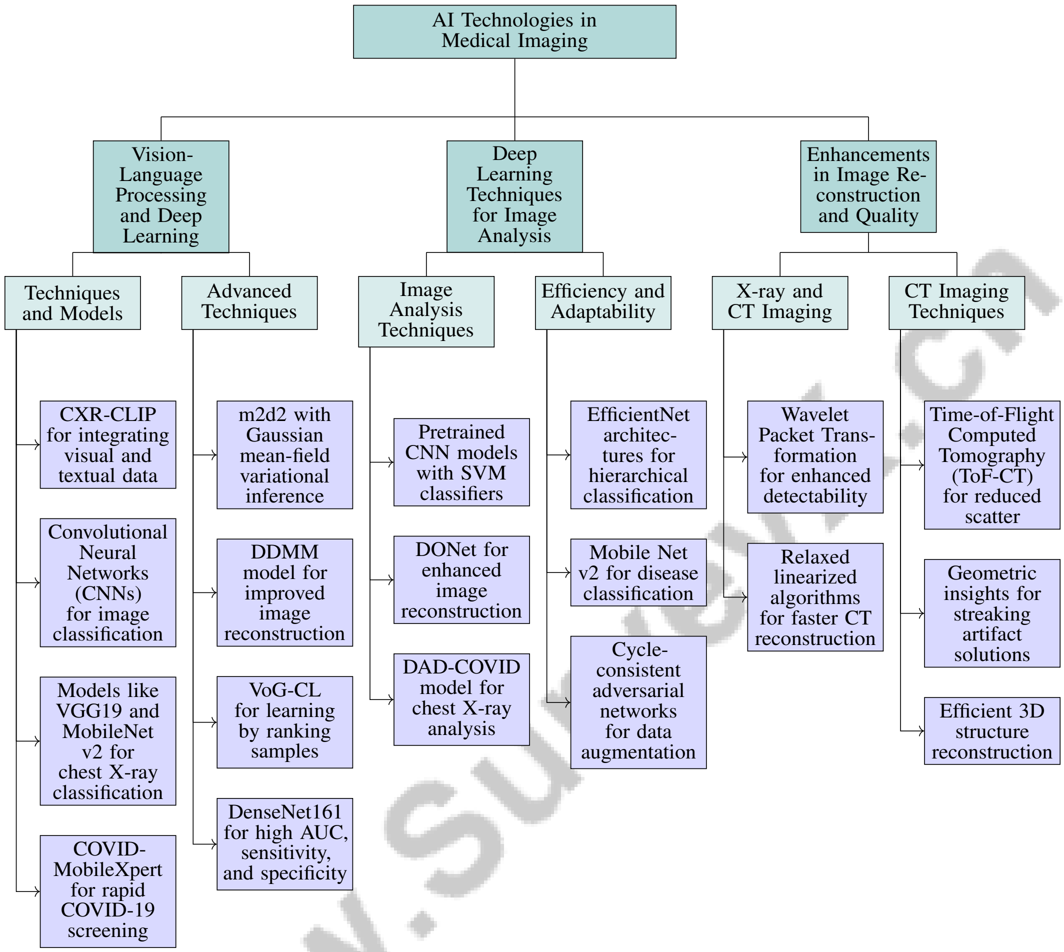


Figure 3: This figure illustrates the hierarchy of AI technologies in medical imaging, focusing on vision-language processing and deep learning, deep learning techniques for image analysis, and enhancements in image reconstruction and quality. It highlights key techniques, models, and their applications, emphasizing AI's transformative role in improving diagnostic accuracy and patient care.

4.1 Vision-Language Processing and Deep Learning

The fusion of vision-language processing with deep learning has markedly improved the diagnostic capabilities of medical imaging. Techniques like CXR-CLIP leverage large-scale chest X-ray datasets to integrate visual and textual data, enhancing interpretability [21]. Deep learning, especially through Convolutional Neural Networks (CNNs), automates image classification, significantly aiding radiologists. Models such as VGG19 and MobileNet v2 have been instrumental in classifying chest X-rays, improving diagnostic accuracy for conditions like COVID-19 and pneumonia. COVID-MobileXpert exemplifies the practical application of lightweight neural networks in clinical settings for rapid COVID-19 patient screening [18].

Advanced techniques like m2d2, utilizing Gaussian mean-field variational inference, enhance prediction reliability by improving uncertainty estimation [36]. The DDMM model, with its multi-branch architecture, improves image reconstruction quality, while VoG-CL enhances learning by ranking samples based on gradient variance [22, 31]. DenseNet161's high AUC, sensitivity, and specificity in diverse clinical environments underscore the robustness of deep learning models [6]. Benchmarking

AI-generated, for reference only.

models like COVID-SDNet demonstrate the significant potential of these technologies in enhancing diagnostic accuracy [2].

AI technologies, particularly vision-language processing and deep learning, promise substantial improvements in medical imaging capabilities, leading to enhanced diagnostic accuracy and patient care. The integration of visual and textual data enriches diagnostics and supports personalized healthcare solutions. Recent approaches to visualizing model prediction uncertainty further bolster trust in AI-assisted diagnostics, aiding healthcare practitioners in making informed decisions [3].

4.2 Deep Learning Techniques for Image Analysis

Deep learning techniques are pivotal in medical image analysis, offering enhanced diagnostic accuracy and efficiency. Pretrained CNN models for feature extraction, followed by SVM classifiers, improve classification accuracy, as evidenced in recent studies [38]. The DONet model, by learning convolutional filters tailored to inverse problems, significantly enhances image reconstruction quality [9]. The DAD-COVID model's dual approach for chest X-ray analysis exemplifies its utility in COVID-19 detection [39].

EfficientNet architectures, used in hierarchical classification strategies, optimize diagnostic accuracy and computational efficiency, particularly in large-scale applications [15]. Mobile Net v2's versatility in disease classification from X-ray images further underscores deep learning's adaptability [1]. Addressing data imbalance, techniques like cycle-consistent adversarial networks generate high-quality synthetic images, crucial for augmenting datasets and improving model training [5, 17].

Deep learning also enhances radiology report interpretation, as seen with the PRECISE framework using GPT-4 for generating readable summaries [19]. Techniques like dimensionality reduction through simple CNNs and phased training of DCNNs demonstrate model adaptability to specific tasks [7, 10]. These advancements are transforming medical image analysis, improving diagnostic accuracy and facilitating efficient handling of imbalanced datasets through data augmentation and generative modeling [17, 6, 1, 16].

(a) Distribution Shift Examples in Medical Imaging[37]

(b) A Diagram of a Complex Network[9]

Figure 4: Examples of Deep Learning Techniques for Image Analysis

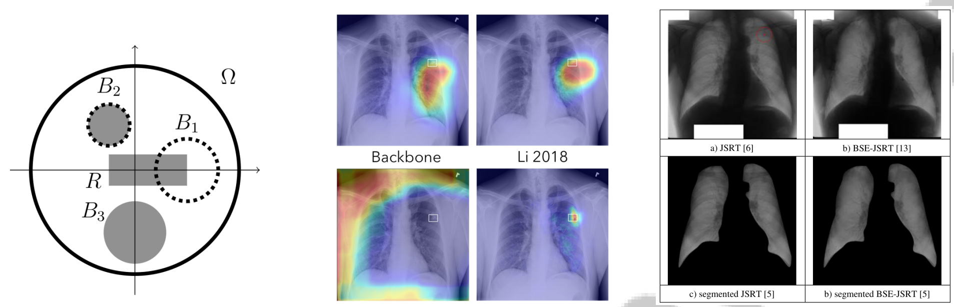
Figure 4 illustrates the transformative role of AI in medical imaging. The first image highlights distribution shifts in medical datasets, emphasizing the need for robust AI models. The second image showcases the complex architecture of deep learning networks, essential for processing intricate medical images. These examples underscore AI's role in enhancing image analysis, improving diagnostic accuracy and patient outcomes [37, 9].

4.3 Enhancements in Image Reconstruction and Quality

AI-driven advancements have significantly improved image reconstruction and quality in X-ray and CT imaging, enhancing resolution and reducing radiation doses [30]. In X-ray imaging, algorithms like Wavelet Packet Transformation enhance image detectability across frequency spaces, improving diagnostic utility [24]. Relaxed linearized algorithms for X-ray CT reconstruction have doubled convergence speed while maintaining quality [27].

In CT imaging, Time-of-Flight Computed Tomography (ToF-CT) reduces scattered photon contributions, enhancing clarity without traditional anti-scatter grids [35]. Geometric insights into streaking artifacts suggest extending solutions to complex manifolds beyond Euclidean space [28]. Efficient reconstruction of three-dimensional structures from minimal projections highlights potential advancements in image reconstruction [26]. Model spectra in spectrum estimation simplify inverse problems, ensuring stable estimation [4].

AI-driven enhancements in image reconstruction are pivotal for advancing medical imaging technologies, leading to accurate diagnostics and improved patient care. AI's integration into medical imaging continues to enhance image quality and diagnostic accuracy. Recent developments in semi-structured radiology report representations streamline medical findings extraction, improving data usability. Explainable AI enhances human-AI collaboration, significantly reducing error rates in chest X-ray assessments and improving diagnostic performance [20, 16].



(a) The image depicts a geometric figure with a central circle and three smaller shapes within it.[40]

(b) Comparison of Lung Cancer Detection Results Using Backbone and Li 2018[23]

(c) Comparison of Lung Segmentation Techniques in X-ray Images[7]

Figure 5: Examples of Enhancements in Image Reconstruction and Quality

Figure 5 showcases AI's impact on medical imaging, particularly in image reconstruction and quality enhancement. The first image symbolizes intricate reconstruction processes. The second compares lung cancer detection improvements with AI methodologies, while the third contrasts traditional and AI-enhanced lung segmentation techniques. These examples highlight AI's role in refining image quality and diagnostic accuracy, contributing to precise medical diagnoses [40, 23, 7].

Feature	**Vision-Language Processing and Deep Learning**	**Deep Learning Techniques for Image Analysis**	**Enhancements in Image Reconstruction and Quality**
Application Focus	Diagnostic Interpretability	Image Classification	Image Quality
Key Technique	Cxr-CLIP Integration	Pretrained Cnns	Wavelet Packet Transformation
Model Example	Densenet161	Efficientnet	Tof-CT

Table 2: This table presents a comparative analysis of various AI methodologies applied in medical imaging, specifically focusing on vision-language processing and deep learning techniques. It highlights the application focus, key techniques, and model examples for each category, illustrating their contributions to diagnostic interpretability, image classification, and image quality enhancement.

5 Integration of AI with Medical Imaging

5.1 Integration of AI in Medical Imaging Modalities

AI's integration across medical imaging modalities has revolutionized diagnostics, enhancing accuracy and efficiency. In X-ray imaging, CNNs have significantly improved pulmonary disease classification, including COVID-19, through techniques like transfer learning with pre-trained models, crucial during pandemics [18]. The COVID-MobileXpert app exemplifies this, streamlining COVID-19 patient triage using pre-trained networks.

CT imaging benefits from AI, with ToF-CT methods improving image quality by reducing photon scatter noise, enhancing diagnostic reliability [5]. Innovations like the LSPD approach offer computational efficiency, enabling faster image reconstruction without quality loss, crucial for clinical applications.

In MRI, AI enhances predictive reliability and classification accuracy. The DDMM combines supervised and unsupervised loss components, improving data distribution coverage and image generation performance. EfficientNet-based models optimize processing of large-scale datasets, enhancing clinical workflows [10].

AI extends to multimodal approaches, combining image and text data to enhance diagnostic accuracy. The PRECISE framework exemplifies this by improving patient engagement through comprehensible radiology reports [19]. Modality imputation networks address modality incongruity, enhancing disease detection by filling in missing data.

AI addresses class imbalance in datasets, affecting model effectiveness. The PYLON architecture improves localization accuracy by redesigning network structures, enhancing robustness [6]. The COVID-SDNet methodology illustrates this by combining segmentation, data augmentation, and transformation techniques to boost performance [2].

These advancements highlight AI's transformative impact on medical imaging modalities, through semi-structured radiology report representations and explainable AI in clinical settings. Generating structured data from reports enhances medical findings identification, while explainable AI fosters human-AI collaboration by rendering predictions transparent. These innovations promise improved clinical outcomes and patient care, facilitating effective decision-making as AI evolves [20, 16].

5.2 Synthetic Data Generation and Augmentation

Synthetic data generation and augmentation are crucial strategies to enhance AI model performance in medical imaging, addressing class imbalance and limited datasets. DCGANs generate artificial chest X-ray images, augmenting datasets and improving deep learning training [17].

Class imbalance, especially in COVID-19 detection, necessitates innovative synthesis of positive examples. High-fidelity COVID-19 images generated through unsupervised domain adaptation illustrate synthetic data's potential to enhance quality and diversity [5]. Models like DDMM leverage labeled and unlabeled datasets, improving classifier training and diagnostic accuracy [22].

Synthetic data augmentation is vital for developing robust AI models that generalize across diverse systems. This standardizes benchmarks and enhances AI model reliability in varied clinical environments [2].

Integrating synthetic data generation and augmentation into AI-driven medical imaging overcomes data-related challenges, leading to accurate diagnostics. These techniques promise improved AI model training and performance, enhancing human-AI collaboration by providing clearer insights into AI decision-making. This evolution, demonstrated in studies where explainable AI reduced error rates in radiology assessments, enhances diagnoses and patient outcomes [21, 12, 20, 16].

5.3 Integration of Multimodal Data Sources

Integrating multimodal data sources in medical imaging enhances diagnostic accuracy and patient care. By combining diverse data types, such as visual and textual information, multimodal integration leverages each modality's strengths for comprehensive patient condition understanding, overcoming unimodal systems' limitations [23, 16, 13, 31, 19].

Modality Imputation Networks (MIN) address incomplete data integration by generating missing modalities from available data, crucial when certain modalities are unavailable [13].

Multimodal LLMs exemplify integrating visual and textual data to enhance diagnostic accuracy. Models like DDMM synthesize realistic X-ray images and segmentations, utilizing labeled and unlabeled datasets to improve classifier training and performance [22].

High-fidelity COVID-19 images through unsupervised domain adaptation enhance data diversity and quality, improving AI model robustness across systems and protocols [5]. Integrating multimodal data is crucial in medical imaging, where technique and equipment variations impact outcomes.

Multimodal integration supports personalized healthcare solutions. Frameworks like PRECISE enhance radiology report clarity and accessibility, aiding informed clinical decisions. This comprehensive approach improves complex medical information readability, fostering patient understanding and engagement. Informed decisions improve outcomes by ensuring interventions are based on

AI-generated, for reference only.

thorough patient understanding [36, 12, 16, 3, 19]. As AI evolves, integrating diverse data sources promises enhanced imaging capabilities, paving the way for accurate and efficient diagnostics.

5.4 Case Studies of AI Integration in Clinical Settings

AI integration in clinical settings enhances decision support systems and patient outcomes. Explainable AI improves decision-making by enhancing model transparency, as empirical studies show [20].

In medical imaging, AI-driven models expedite disease screening and diagnosis, such as COVID-19. The COVID-MobileXpert app streamlines triage, providing timely and accurate diagnoses crucial during pandemics [18]. This integration reduces healthcare professionals' workload, allowing focus on complex tasks.

Deep learning models enhance chest X-ray classification accuracy. Transfer learning with pre-trained models improves pulmonary disease detection, including pneumonia and COVID-19. AI and machine learning advancements enhance radiologists' capabilities, integrating frameworks like PRECISE for clearer report generation, semi-structured representation learning for data extraction, and AI-assisted systems like VinDr-CXR for abnormality detection. These technologies empower informed decisions by providing clear, accessible information and reliable second opinions, improving patient care [25, 41, 16, 21, 19].

AI integration with multimodal data advances diagnostic accuracy by combining visual and textual information for comprehensive patient understanding. Multimodal LLMs exemplify this, synthesizing diverse data types to enhance training and performance [22].

These case studies show AI's transformative impact on clinical environments, enhancing decision support systems and patient outcomes. Explainable AI increases task performance in human-AI collaboration, evidenced by a five-fold error rate reduction among radiologists supported by explainable AI. Advancements in semi-structured radiology report generation and frameworks like PRECISE improve medical information clarity and accessibility, facilitating informed decisions and patient engagement [12, 16, 21, 20, 19]. As AI evolves, its healthcare application promises advancements in diagnostic accuracy and efficiency, paving the way for effective and personalized care.

6 Challenges and Future Directions

Navigating the evolving landscape of artificial intelligence (AI) in medical imaging necessitates addressing multifaceted challenges, including data quality, annotation, computational, technical, integration, interoperability, ethical, and privacy concerns. The following subsections provide a comprehensive analysis of these challenges, starting with data quality and annotation.

6.1 Data Quality and Annotation Challenges

The efficacy of AI models in medical imaging is heavily contingent upon data quality and annotated datasets. A notable challenge is the domain gap between adult and pediatric chest X-ray (CXR) images due to anatomical and disease presentation variations [14]. This is compounded by the scarcity of labeled medical images, which is critical for distinguishing conditions like COVID-19 from similar lung diseases [18]. Variability in image quality and patient demographics further complicates this issue, as deep learning models require high-quality images for optimal performance [7]. Sparse photon density in certain imaging techniques can hinder the acquisition of clear images at the micro-meter scale [33].

Annotated datasets are crucial for AI model training and validation, yet their availability is limited. The lack of sufficient clinical data and variability from different surgical tools and imaging protocols complicates data collection and annotation [13]. This scarcity is particularly evident in emerging diseases like COVID-19, where limited training dataset sizes can affect model generalizability [42]. Existing benchmarks often evaluate AI systems on retrospective datasets that may not reflect real clinical scenarios, leading to overestimated performance [6]. This discrepancy underscores the need for ongoing validation and adaptation of AI models in dynamic clinical environments.

AI-generated, for reference only.

The demand for annotated datasets extends to the classification of specific medical conditions, such as fractures, where underrepresented classes limit the performance of weakly-supervised methods [11]. While techniques like PYLON improve localization accuracy, further investigation is required to understand performance-affecting factors, such as the impact of Group Normalization [23].

Addressing data quality and annotation challenges is crucial for advancing AI technologies in medical imaging. Efforts to bridge domain gaps, enhance data quality, and expand annotated datasets will significantly improve the reliability and applicability of AI models across diverse clinical settings. Future research should also focus on optimizing techniques like LSPD in small minibatch scenarios and exploring additional applications in various imaging modalities [29].

6.2 Computational and Technical Challenges

AI integration with medical imaging modalities faces significant computational and technical challenges. A primary issue is the reliance on high-quality training data, essential for deep learning model performance. The scarcity and imbalance of datasets, particularly for accurately classifying diseases like COVID-19, present barriers to model generalizability and robustness. The absence of comprehensive benchmark datasets with diverse COVID-19 cases complicates model validation, affecting reliability across clinical settings [3].

The computational complexity of training deep neural networks, such as DONet, requires substantial resources, challenging their practical implementation in real-world settings, especially given limited annotated data availability [21, 16]. This necessitates developing more efficient algorithms for clinical application.

Technical challenges also arise from methods' sensitivity to gradient approximation errors, affecting stability when using numerous subsets for acceleration [27]. Noise presence and sample quality significantly impact AI model performance, particularly with fewer projections or complex structures [26]. The propagation of conormal singularities along strictly convex metal regions further complicates image reconstruction, underscoring the need for robust optimization techniques [28].

Moreover, dark counts and careful calibration of measurement thresholds in Time-of-Flight Computed Tomography (ToF-CT) complicate timing distributions, affecting image quality [35]. The complexity of scaling uncertainty quantification in real-time clinical systems presents another challenge, as data shifts can adversely impact predictive performance, necessitating ongoing validation and adaptation [36].

The reliance on initial manual annotation quality poses limitations, affecting AI model generalizability to different datasets or reporting styles [16]. Addressing these computational and technical challenges is essential for advancing AI integration with medical imaging modalities, ultimately improving diagnostic accuracy and patient care outcomes. Continued research should focus on developing more efficient algorithms and robust data annotation techniques to overcome these hurdles.

6.3 Integration and Interoperability Issues

AI integration with medical imaging modalities presents challenges related to interoperability and data exchange. Heterogeneity of data sources and formats complicates AI model integration across clinical environments, necessitating standardized protocols and interfaces for compatibility with existing healthcare infrastructure [13]. Variability in imaging techniques and equipment further affects AI model performance and reliability. The lack of standardized benchmarks for evaluating AI systems across diverse imaging modalities hampers performance assessment and comparison in real-world clinical settings [6]. This variability underscores the need for robust validation frameworks accommodating diverse imaging protocols and equipment.

Integrating AI with multimodal data sources, such as visual and textual information, also presents interoperability challenges. Synthesizing diverse data types requires sophisticated algorithms capable of harmonizing disparate data streams to provide coherent diagnostic outputs. This complexity necessitates the development of advanced data fusion techniques and machine learning models for seamless multimodal data integration [22].

Scalability of AI systems is critical for ensuring interoperability in clinical settings. AI model deployment must account for healthcare facilities' computational and technical constraints, which may limit advanced AI technologies' effective integration. Addressing scalability issues is essential for facilitating widespread AI system adoption in medical imaging and ensuring practical applicability across clinical environments [15].

Overcoming integration and interoperability issues is crucial for realizing AI's full potential in medical imaging. Efforts to standardize data formats, implement comprehensive validation frameworks, and enhance AI system scalability are vital for seamless integration with medical imaging modalities. These initiatives will improve radiology report clarity and accessibility, as demonstrated by the PRECISE framework, and enable the development of semi-structured representations of medical findings. Addressing modality incongruity through multimodal federated learning can enhance AI model effectiveness in diagnostics, while large-scale image-text datasets can bolster vision-language pre-training model performance in interpreting chest X-rays. Collectively, these advancements will contribute to more reliable and informative medical imaging practices, ultimately improving patient outcomes and engagement [21, 19, 13, 16].

6.4 Ethical and Privacy Concerns

AI integration into medical imaging and clinical decision support systems raises significant ethical and privacy concerns. Safeguarding patient privacy is critical, particularly when managing sensitive medical data, ensuring compliance with regulations and fostering trust in AI technologies [19, 1, 20]. Stringent data protection measures are necessary to prevent unauthorized access and misuse, with compliance with regulations like the GDPR vital for maintaining patient trust and confidentiality.

Ethical considerations include the need for transparency and accountability in decision-making processes. A study approved by the Ethics Commission of ETH Zurich emphasizes the importance of informed consent and ethical oversight in AI research, highlighting the necessity for ethical frameworks guiding AI technology development and deployment [20]. Such frameworks ensure AI systems respect patient autonomy and promote fair, equitable healthcare outcomes.

Ethical considerations also extend to improving patient understanding and engagement in healthcare decision-making. The PRECISE framework exemplifies this by utilizing AI to generate patient-friendly summaries of radiology reports, enhancing communication and empowering patients to make informed healthcare decisions [19]. This approach improves patient comprehension and fosters greater involvement in their care, aligning with ethical principles of patient-centered care.

Effectively addressing ethical and privacy concerns is essential for AI technologies' successful integration in medical imaging and clinical environments, as these issues directly impact AI-driven diagnostic tools' reliability, AI decision-making transparency, and medical information accessibility to patients, ultimately influencing patient care quality and trust in AI applications [16, 21, 20, 19, 1]. Ongoing dialogue and collaboration among stakeholders, including ethicists, healthcare professionals, and policymakers, will be essential to ensure AI applications align with ethical standards and protect patient rights.

6.5 Future Directions and Research Opportunities

Future research in AI integration with medical imaging modalities will address pivotal challenges and explore promising advancement avenues. A key focus will be developing low-dose imaging techniques to minimize patient exposure to ionizing radiation while maintaining diagnostic efficacy. Enhancing image processing algorithms and exploring novel materials for X-ray generation and detection will improve image clarity and diagnostic precision. Future research will focus on optimizing detection systems, managing dark counts, and improving energy calibration accuracy for better clinical performance [35].

The application of self-supervised learning techniques, such as the SCC method, to multi-label tasks represents a promising direction. This approach can significantly enhance AI models' robustness and accuracy in pediatric imaging, where data scarcity and variability present substantial challenges. Expanding datasets and exploring additional deep learning architectures will be crucial for improving diagnostic accuracy and generalizability across diverse clinical settings [1].

Optimizing detector configurations and exploring new applications of advanced detectors, such as the Micromegas detector, can further improve imaging quality and broaden medical imaging applications. Future research should focus on collecting more diverse datasets, developing deeper

CNN architectures, and creating user-friendly interfaces for radiologists to facilitate AI technology integration in clinical practice. Research could explore alternative normalization techniques and further refine architectures to enhance localization performance [23].

Advancements in photon density and readout speeds will be essential for enhancing imaging clarity and resolution, particularly in direct X-ray imaging applications. Improving lesion detector accuracy and exploring continuous learning mechanisms for AI systems will be vital for maintaining high diagnostic performance in dynamic clinical environments. Future research could focus on expanding the application of the KTD framework to other medical imaging tasks beyond COVID-19 [18].

The application of advanced deep learning models, such as DONet, to real-world data and exploring enhancements to the learning process and network architecture will improve efficiency and accuracy in medical imaging. Future research may focus on improving DDMM robustness, exploring its application in other imaging domains, and enhancing the integration of additional modalities for comprehensive image analysis [22]. Future directions should also include optimizing the balance between classification and retrieval performance in AI models and enhancing the diversity of generated text to improve model training. Research could explore enhancements to the modality imputation process and its application in other multimodal contexts, addressing current challenges in AI integration with medical imaging [13].

Finally, enhancing volumetric segmentation processes and increasing training set sizes will improve scatter estimation and overall image quality, facilitating more accurate diagnostics and better patient outcomes. Future research will focus on improving the method's robustness against scattered radiation and exploring its application in estimating effective spectra for CT scans with tube potential modulation [4]. As research progresses, these future directions will be crucial in overcoming current challenges and advancing AI technologies' integration with medical imaging modalities, ultimately leading to improved clinical decision support and patient care.

7 Conclusion

This survey illustrates the transformative impact of integrating artificial intelligence (AI) technologies with medical imaging modalities, including X-ray, MRI, and CT, to enhance clinical decision support systems. The application of AI, particularly through deep learning techniques, has significantly improved diagnostic speed and accuracy, as demonstrated by studies on AI's efficacy in detecting COVID-19 from chest X-ray images [43]. Additionally, AI-driven models, such as vision-language pre-training (VLP) models, show promise in enhancing diagnostic accuracy and tailoring treatment strategies for conditions like osteoarthritis [12].

The survey emphasizes AI's vital role in overcoming challenges related to data quality, computational complexity, and interoperability in medical imaging. Bayesian Convolutional Neural Networks (BCNNs) have proven essential in interpreting uncertainty in model predictions, thereby fostering trust in computer-aided diagnosis and offering valuable insights to radiologists [3]. These advancements not only enhance diagnostic precision but also facilitate more personalized and effective healthcare solutions.

As AI technologies advance, their integration with medical imaging is expected to yield further improvements in diagnostic accuracy and patient care outcomes. By harnessing AI's capabilities, healthcare systems can achieve more efficient and precise clinical decision-making, ultimately leading to better patient outcomes and a strengthened healthcare infrastructure.

References

[1] Ioannis D Apostolopoulos, Sokratis I Aznaouridis, and Mpesiana A Tzani. Extracting possibly representative covid-19 biomarkers from x-ray images with deep learning approach and image data related to pulmonary diseases. *Journal of Medical and Biological Engineering*, 40:462–469, 2020.

[2] Siham Tabik, Anabel Gómez-Ríos, José Luis Martín-Rodríguez, Iván Sevillano-García, Manuel Rey-Area, David Charte, Emilio Guirado, Juan-Luis Suárez, Julián Luengo, MA Valero-González, et al. Covidgr dataset and covid-sdnet methodology for predicting covid-19 based on chest x-ray images. *IEEE journal of biomedical and health informatics*, 24(12):3595–3605, 2020.

[3] Gayathiri Murugamoorthy and Naimul Khan. Interpreting uncertainty in model predictions for covid-19 diagnosis, 2020.

[4] Wei Zhao, Kai Niu, Sebastian Schafer, and Kevin Royalty. An indirect transmission measurement-based spectrum estimation method for computed tomography, 2015.

[5] Hasib Zunair and A. Ben Hamza. Synthesis of covid-19 chest x-rays using unpaired image-to-image translation, 2020.

[6] Manu Goyal, Judith Austin-Strohbehn, Sean J. Sun, Karen Rodriguez, Jessica M. Sin, Yvonne Y. Cheung, and Saeed Hassanpour. Sensitivity and specificity evaluation of deep learning models for detection of pneumoperitoneum on chest radiographs, 2020.

[7] Yu. Gordienko, Yu. Kochura, O. Alienin, O. Rokovyi, S. Stirenko, Peng Gang, Jiang Hui, and Wei Zeng. Dimensionality reduction in deep learning for chest x-ray analysis of lung cancer, 2018.

[8] Soumya Ranjan Nayak, Deepak Ranjan Nayak, Utkarsh Sinha, Vaibhav Arora, and Ram Bilas Pachori. Application of deep learning techniques for detection of covid-19 cases using chest x-ray images: A comprehensive study. *Biomedical Signal Processing and Control*, 64:102365, 2021.

[9] Tatiana A. Bubba, Mathilde Galinier, Matti Lassas, Marco Prato, Luca Ratti, and Samuli Siltanen. Deep neural networks for inverse problems with pseudodifferential operators: an application to limited-angle tomography, 2020.

[10] Aiga Suzuki, Hidenori Sakanashi, Shoji Kido, and Hayaru Shouno. Feature representation analysis of deep convolutional neural network using two-stage feature transfer -an application for diffuse lung disease classification-, 2018.

[11] Amelia Jiménez-Sánchez, Anees Kazi, Shadi Albarqouni, Sonja Kirchhoff, Alexandra Sträter, Peter Biberthaler, Diana Mateus, and Nassir Navab. Weakly-supervised localization and classification of proximal femur fractures, 2018.

[12] Banafshe Felfeliyan, Yuyue Zhou, Shrimanti Ghosh, Jessica Kupper, Shaobo Liu, Abhilash Hareendranathan, and Jacob L. Jaremko. Application of vision-language models for assessing osteoarthritis disease severity, 2024.

[13] Pramit Saha, Divyanshu Mishra, Felix Wagner, Konstantinos Kamnitsas, and J. Alison Noble. Examining modality incongruity in multimodal federated learning for medical vision and language-based disease detection, 2024.

[14] Weiwei Tian, Xinyu Huang, Tianhao Cheng, Wen He, Jinwu Fang, Rui Feng, Daoying Geng, and Xiaobo Zhang. A medical multimodal large language model for pediatric pneumonia, 2024.

[15] Eduardo Luz, Pedro Silva, Rodrigo Silva, Ludmila Silva, João Guimarães, Gustavo Miozzo, Gladston Moreira, and David Menotti. Towards an effective and efficient deep learning model for covid-19 patterns detection in x-ray images. *Research on Biomedical Engineering*, pages 1–14, 2021.

[16] Tamara Katic, Martin Pavlovski, Danijela Sekulic, and Slobodan Vucetic. Learning semi-structured representations of radiology reports, 2021.

[17] Sagar Kora Venu. Evaluation of deep convolutional generative adversarial networks for data augmentation of chest x-ray images, 2020.

[18] Xin Li, Chengyin Li, and Dongxiao Zhu. Covid-mobilexpert: On-device covid-19 patient triage and follow-up using chest x-rays, 2020.

[19] Satvik Tripathi, Liam Mutter, Meghana Muppuri, Suhani Dheer, Emiliano Garza-Frias, Komal Awan, Aakash Jha, Michael Dezube, Azadeh Tabari, Christopher P. Bridge, and Dania Daye. Precise framework: Gpt-based text for improved readability, reliability, and understandability of radiology reports for patient-centered care, 2024.

[20] Julian Senoner, Simon Schallmoser, Bernhard Kratzwald, Stefan Feuerriegel, and Torbjørn Netland. Explainable ai improves task performance in human-ai collaboration, 2024.

[21] Kihyun You, Jawook Gu, Jiyeon Ham, Beomhee Park, Jiho Kim, Eun Kyoung Hong, Woonhyunk Baek, and Byungseok Roh. Cxr-clip: Toward large scale chest x-ray language-image pre-training, 2023.

[22] Pham Ngoc Huy and Tran Minh Quan. Denoising diffusion medical models, 2023.

[23] Konpat Preechakul, Sira Sriswasdi, Boonserm Kijsirikul, and Ekapol Chuangsuwanich. High resolution weakly supervised localization architectures for medical images, 2020.

[24] Antonio González-López. Detectability assessment of an x-ray imaging system using the nodes in a wavelet packet decomposition of a star-bar object, 2020.

[25] Mathias Unberath, Jan-Nico Zaech, Sing Chun Lee, Bastian Bier, Javad Fotouhi, Mehran Armand, and Nassir Navab. Deepdrr – a catalyst for machine learning in fluoroscopy-guided procedures, 2018.

[26] Renke Wang, Francien G. Bossema, Thierry Blu, and Pier Luigi Dragotti. Reconstructing classes of 3d fri signals from sampled tomographic projections at unknown angles, 2024.

[27] Hung Nien and Jeffrey A. Fessler. Relaxed linearized algorithms for faster x-ray ct image reconstruction, 2015.

[28] Hiroyuki Chihara. Geodesic x-ray transform and streaking artifacts on simple surfaces or on spaces of constant curvature, 2024.

[29] Junqi Tang, Subhadip Mukherjee, and Carola-Bibiane Schönlieb. Stochastic primal-dual deep unrolling, 2022.

[30] Martin Berger, Qiao Yang, and Andreas Maier. X-ray imaging. *Medical Imaging Systems: An Introductory Guide*, pages 119–145, 2018.

[31] Zhengbo Zhou, Jun Luo, Dooman Arefan, Gene Kitamura, and Shandong Wu. Human not in the loop: objective sample difficulty measures for curriculum learning, 2023.

[32] A. Cools, S. Aune, F. Beau, F. M. Brunbauer, T. Benoit, D. Desforge, E. Ferrer-Ribas, A. Kallitsopoulou, C. Malgorn, E. Oliveri, T. Papaevangelou, E. C. Pollacco, L. Ropelewski, A. Sari, and F. J. Iguaz. X-ray imaging with micromegas detectors with optical readout, 2023.

[33] E. Miyata, M. Miki, H. Tsunemi, J. Hiraga, H. Kouno, and K. Miyaguchi. Direct x-ray imaging of μm precision using back-illuminated ccd, 2002.

[34] Ali Narin, Ceren Kaya, and Ziynet Pamuk. Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks, 2020.

[35] Gaëtan Lemaire, Romain Espagnet, Julien Rossignol, Louis-Daniel Gaulin, Edouard Villemure, Audrey Corbeil Therrien, Yves Bérubé-Lauzière, Marc-André Tétrault, and Réjean Fontaine. Time-of-flight x-ray measurements for computed tomography, 2023.

[36] L. Julian Lechuga Lopez, Tim G. J. Rudner, and Farah E. Shamout. Informative priors improve the reliability of multimodal clinical data classification, 2023.

[37] Sheng Cheng, Zbigniew A. Starosolski, and Devika Subramanian. Self-supervised learning for building robust pediatric chest x-ray classification models, 2024.

[38] Aras M Ismael and Abdulkadir Şengür. Deep learning approaches for covid-19 detection based on chest x-ray images. *Expert Systems with Applications*, 164:114054, 2021.

[39] Jianpeng Zhang, Yutong Xie, Yi Li, Chunhua Shen, and Yong Xia. Covid-19 screening on chest x-ray images using deep learning based anomaly detection. *arXiv preprint arXiv:2003.12338*, 27(10.48550), 2020.

[40] Hiroshi Fujiwara, Kamran Sadiq, and Alexandru Tamasan. Partial inversion of the 2d attenuated x-ray transform with data on an arc, 2021.

[41] Ngoc Huy Nguyen, Ha Quy Nguyen, Nghia Trung Nguyen, Thang Viet Nguyen, Hieu Huy Pham, and Tuan Ngoc-Minh Nguyen. A clinical validation of vindr-cxr, an ai system for detecting abnormal chest radiographs, 2021.

[42] Asif Iqbal Khan, Junaid Latief Shah, and Mohammad Mudasir Bhat. Coronet: A deep neural network for detection and diagnosis of covid-19 from chest x-ray images. *Computer methods and programs in biomedicine*, 196:105581, 2020.

[43] Ali Narin, Ceren Kaya, and Ziynet Pamuk. Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. *Pattern Analysis and Applications*, 24:1207–1220, 2021.

Disclaimer:

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

AI-generated, for reference only.