Diffusion Models in Medical Imaging: A Survey

www.surveyx.cn

Abstract

Diffusion models have emerged as pivotal tools in medical imaging, leveraging artificial intelligence to enhance image synthesis, reconstruction, and interpretation, thereby improving diagnostic accuracy and efficiency. This survey explores the transformative role of diffusion models, highlighting their superiority over traditional methods like GANs, particularly in generating high-quality images from noisy data. These models address critical challenges in radiology by enhancing image quality, reducing MRI acquisition times, and facilitating synthetic CT image creation from MRI scans, thus optimizing diagnostic workflows. Additionally, diffusion models tackle data imbalance in medical datasets, improving machine learning algorithm robustness and accuracy. They also contribute significantly to image-to-image translation and realistic visual data creation for medical education. Despite their advantages, diffusion models face challenges such as high computational demands and reliance on quality training data, which can limit their scalability. Future research aims to optimize model architectures, enhance sampling efficiency, and explore hybrid approaches to overcome these limitations. The ongoing development of diffusion models promises to advance medical imaging technologies, contributing to more precise and efficient diagnostic practices and ultimately improving patient care outcomes.

1 Introduction

1.1 Significance of Diffusion Models in Medical Imaging

Diffusion models are pivotal in advancing medical imaging, enhancing image synthesis, reconstruction, and segmentation. These models excel in generating high-quality images from noisy data, crucial for improving diagnostic capabilities, particularly in MRI scans where noise reduction is essential for accurate evaluations [1, 2]. Additionally, diffusion models mitigate extended MRI acquisition times, reducing patient discomfort and motion artifacts, thus optimizing the imaging workflow [3].

In image generation, diffusion models outperform traditional generative adversarial networks (GANs), especially through score-based stochastic denoising methods [4]. This advantage is evident in their ability to synthesize CT images from MRI scans, addressing misalignment and high costs associated with dual imaging modalities, thereby facilitating comprehensive diagnostic assessments [5].

Moreover, diffusion models address data imbalance in medical imaging, particularly in pathology images with underrepresented nuclei classes, enhancing classification performance through synthetic data generation [6]. They also support image-to-image translation, improving the processing and interpretation of complex medical images [7].

The application of diffusion models further extends to creating realistic visual data for surgical simulations, enhancing medical education with high-fidelity visual aids [8]. Additionally, diffusion MRI (dMRI) exemplifies an advanced technique for characterizing tissue microstructure and white matter connectivity, driven by the demand for high-quality dMRI data to improve resolution and tissue contrast [9].

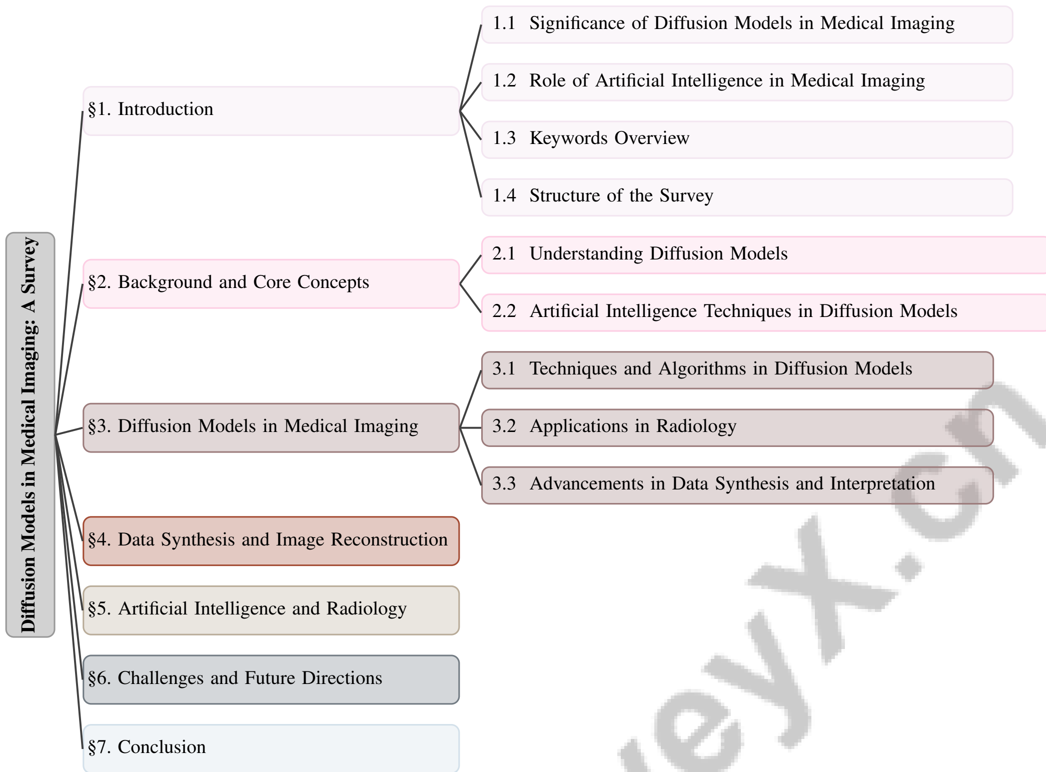


Figure 1: chapter structure

1.2 Role of Artificial Intelligence in Medical Imaging

Artificial intelligence (AI) significantly enhances medical imaging by integrating advanced techniques that improve image quality and diagnostic precision. Diffusion models, in particular, have emerged as essential tools, surpassing traditional methods like GANs in generating synthetic medical images. The Hybrid-fusion Network (Hi-Net) exemplifies this by synthesizing missing MRI modalities, thereby enhancing diagnostic and treatment outcomes [5].

These models effectively tackle data imbalance in medical imaging datasets through the DiffMix model, which employs a conditioned diffusion approach to generate synthetic data that balances nuclei class representation, thereby bolstering the robustness of training datasets and improving classification accuracy [6]. This capability is vital for training Convolutional Neural Networks (CNNs) across various medical image analysis tasks, necessitating large-scale synthetic datasets for high accuracy [5].

Furthermore, diffusion models have shown substantial potential in semantic segmentation tasks. By leveraging intermediate activations from pretrained Denoising Diffusion Probabilistic Models (DDPMs), they achieve effective segmentation with minimal labeled data, reducing reliance on extensive annotated datasets. This is complemented by a sophisticated data synthesis pipeline that utilizes 3D DDPMs to generate realistic metastatic volumes, enhancing the training of 3D U-Net segmentation models and improving performance in scenarios characterized by operator variability in manual segmentations [10, 11].

In image-to-image translation, diffusion models facilitate the conversion of medical images across modalities, addressing modality mismatches and enhancing image synthesis. The integration of AI through diffusion models not only improves image quality and diagnostic accuracy but also optimizes the imaging workflow, leading to better patient outcomes. This is particularly important given the rising demand for radiological services, as diffusion models enable the generation of high-quality medical images—including CT, MRI, and PET scans—while maintaining patient privacy. By leveraging large-scale generative AI, these models enhance the efficiency of image interpretation and report generation, ultimately transforming clinical practices in medical imaging [12, 3, 13, 14].

1.3 Keywords Overview

Key terms are essential for understanding the impact of diffusion models in medical imaging. "Diffusion models" are generative models that iteratively refine noisy data to generate high-quality images, particularly advantageous for producing clear diagnostic visuals [1]. "Image synthesis" encompasses the creation of medical images from existing data, enhancing or reconstructing images to improve diagnostic accuracy and reduce the necessity for multiple imaging modalities [5]. "Image reconstruction" focuses on refining and rebuilding images from incomplete or noisy data, enhancing the clarity of medical scans [2]. The discipline of "radiology" greatly benefits from these advancements, leading to more accurate diagnoses and improved patient outcomes [3]. Additionally, "data synthesis" refers to generating synthetic data to augment existing datasets, addressing data imbalance and enhancing the performance of machine learning models in medical image analysis [6]. Collectively, these terms encapsulate the transformative influence of diffusion models in medical imaging, underscoring their role in advancing diagnostic technologies and practices.

1.4 Structure of the Survey

This survey is structured to provide a comprehensive examination of diffusion models, covering foundational principles, methodologies, and diverse applications within medical imaging, including high-quality synthetic image generation and data augmentation techniques [15, 16, 12]. The introduction outlines the significance of diffusion models in enhancing image quality and diagnostic accuracy through AI techniques.

Subsequent sections delve into the application of diffusion models in medical imaging, detailing pivotal techniques and algorithms that significantly improve image quality and diagnostic precision in radiology. Advancements in data synthesis and interpretation are highlighted, showcasing recent developments that propel the field forward.

A dedicated section discusses the role of diffusion models in data synthesis and image reconstruction, elucidating their impact on medical imaging practices. This is followed by a focus on AI integration in radiology through diffusion models, emphasizing improvements in diagnostic outcomes.

Finally, the survey addresses challenges and future directions for diffusion models in medical imaging, identifying current obstacles and exploring potential solutions, along with emerging trends and technologies shaping future research. The paper concludes with key findings and reflections on the future prospects of diffusion models in medical imaging.The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Understanding Diffusion Models

Diffusion models are a pivotal class of generative models in medical imaging, transforming noisy data into high-quality images through denoising diffusion probabilistic modeling (DDPM). This involves a forward diffusion phase that introduces noise and a reverse phase that systematically removes it, akin to a controlled autoencoding process, thereby enhancing image clarity and precision crucial for reliable medical applications [13, 17]. These models outperform traditional convolutional neural networks (CNNs) in addressing inverse problems, where unknown signals are reconstructed from noisy measurements, improving patient outcomes [18]. For instance, the DisC-Diff model employs a disentangled conditional diffusion approach for multi-contrast MRI super-resolution, integrating various contrasts to enhance image quality [2].

Latent Diffusion Models (LDMs) mitigate computational challenges by operating in a latent space, reducing computational demands while preserving statistical data integrity. This is especially beneficial in scenarios with limited datasets, such as generating synthetic chest X-ray images from text prompts and segmentation masks [7]. LDMs also improve the transformation of low-quality 3T dMRI data into high-quality 7T-like images, maintaining essential gradient information [9]. Additionally, diffusion models enhance low-resolution microscopy images, overcoming optical microscopy's diffraction limits [19], and facilitate conversions between imaging modalities, such as generating high-quality CT images from CBCT data using a Brownian Bridge Diffusion Model [3]. They also reconstruct images from limited photoacoustic tomography (PAT) measurements, employing a regularized maximum-likelihood objective to improve reconstruction quality [20].

Moreover, diffusion models address domain adaptation challenges, enabling consistent segmentation model performance across different domains without labeled data [6]. The ViT-DAE model exemplifies the integration of diffusion models with advanced architectures like vision transformers, synthesizing high-quality histopathology images through a semantic encoder [4]. Thus, diffusion models provide a robust framework for generating high-quality medical images while optimizing computational efficiency and managing large datasets. The integration of large-scale generative AI applications, such as MedDiT, into clinical workflows is expected to enhance diagnostic capabilities by improving medical image analysis and report generation, addressing the radiologist shortage and leading to better patient care [21, 22, 13, 17].

2.2 Artificial Intelligence Techniques in Diffusion Models

Artificial intelligence techniques have significantly enhanced diffusion models in medical imaging, improving image synthesis, reconstruction, and analysis. The iLGD framework exemplifies this by modifying the denoising process with attention injection and loss guidance, enhancing image layout control without additional training [23]. The Fourier Diffusion Models method employs convolutional operations to model the forward process, increasing image generation efficiency via a U-Net architecture [19]. Self-supervised learning frameworks, such as ASSCGD, use an adversarial mapper to enhance image sampling efficiency and quality, demonstrating the synergy between AI techniques and diffusion models [24]. This is particularly beneficial where acquiring ground-truth labels is challenging, reinforcing the robustness of diffusion models in practical applications.

In image translation, the Cascaded Multi-path Shortcut Diffusion Model (CMDM) merges prior information from GANs with iterative refinement through diffusion models, stabilizing the translation process and improving image quality [25]. The Progressive Growing AmbientGAN (ProAmGAN) employs advanced training strategies to enhance generative models' stability and performance, establishing stochastic object models (SOMs) from noisy imaging data [26]. Furthermore, integrating vision transformers as semantic encoders within diffusion autoencoder frameworks, as demonstrated in the ViT-DAE model, enhances the model's ability to capture intricate details of histopathology images [4].

Efforts to enhance training efficiency include a multi-stage framework that segments the training process into multiple phases with tailored multi-decoder U-Net architectures, optimizing computational resource allocation [18]. The incorporation of advanced AI techniques within diffusion models has broadened their applicability and effectiveness in medical imaging, paving the way for more precise diagnostic tools. Recent advancements, particularly through frameworks like MedDiT, underscore the transformative potential of AI-driven diffusion models, enabling the dynamic generation of realistic medical images tailored to simulated patient symptoms. This capability enhances medical education by providing diverse diagnostic training scenarios and addresses critical challenges such as the shortage of radiologists and the need for improved patient care through more accurate imaging interpretations. As large-scale generative AI continues to evolve, it is set to revolutionize clinical practices, enhancing patient outcomes and the overall healthcare experience [22, 13].

3 Diffusion Models in Medical Imaging

Diffusion models have revolutionized medical imaging by significantly enhancing image quality and diagnostic precision. This section delves into the methodologies and algorithms that underpin these models, highlighting their pivotal role in advancing imaging capabilities. As illustrated in **??**, the hierarchical structure of diffusion models in medical imaging is depicted, emphasizing key techniques and algorithms, as well as their applications in radiology. The figure further showcases advancements in data synthesis and interpretation, underscoring the critical role of diffusion models in enhancing image quality and diagnostic accuracy. Table 2 offers a comprehensive comparison of various diffusion models employed in medical imaging, underscoring their respective advantages and specific applications. Additionally, Table 1 presents a detailed summary of the various techniques, applications, and advancements associated with diffusion models in medical imaging, illustrating their significant impact on enhancing image quality and diagnostic accuracy. By addressing challenges such as data scarcity and patient privacy, these innovative models contribute to the broader implications

Category	Feature	Method
Techniques and Algorithms in Diffusion Models	Image Reconstruction Knowledge Transfer	ADIR[20] KDEDM[3]
Applications in Radiology	Image Generation Image Enhancement	PDM[27], LDM-dMRI[9], CAAT[28], ASSCGD[24], VD[4] FDM[19], DCD[2]
Advancements in Data Synthesis and Interpretation	Feature and Layout Integration Automated Annotation Efficiency and Optimization	DIFF[29], iLGD[23] SGDM[30] FDEM[31]

Table 1: This table provides a comprehensive overview of the key techniques, algorithms, and applications of diffusion models in medical imaging. It categorizes the methods into three main areas: Techniques and Algorithms in Diffusion Models, Applications in Radiology, and Advancements in Data Synthesis and Interpretation. Each category highlights specific features and the corresponding methods, demonstrating the diverse applications and innovations in this transformative field.

of diffusion models in medical imaging. We examine advanced architectures and self-training frameworks that have notably improved image synthesis and reconstruction, reinforcing the narrative of progress within this transformative field.

3.1 Techniques and Algorithms in Diffusion Models

Advanced techniques and algorithms in diffusion models have substantially progressed medical imaging, particularly in image synthesis and reconstruction. Latent Diffusion Models (LDM) have transformed high-quality diffusion MRI (dMRI) data generation, surpassing traditional methods by leveraging latent space for image synthesis, thereby optimizing computational efficiency while maintaining image fidelity [9]. The DisC-Diff model exemplifies the use of diffusion processes to generate high-resolution images from low-resolution multi-contrast MRI inputs, enhancing image quality through an integration of complementary information [2]. Such techniques are crucial for enhancing diagnostic accuracy in clinical environments.

In cone-beam computed tomography (CBCT) to pseudo-CT (pCT) image synthesis, self-training frameworks utilizing knowledge distillation have been developed to improve synthesized image quality, effectively reducing artifacts and enhancing clarity [3]. Adaptive diffusion models like ADIR highlight innovation by adapting the diffusion process with external images similar to degraded inputs, significantly boosting reconstruction quality [20]. Comparative analyses of various diffusion models reveal their strengths in effectiveness and computational efficiency across diverse tasks [1]. The ViT-DAE model, employing a two-stage training process with a vision transformer for semantic encoding followed by a conditional diffusion model for image generation, showcases the potential of integrating advanced architectures to enhance image synthesis [4].

These sophisticated techniques address challenges such as data scarcity and patient privacy, enabling the generation of high-quality synthetic images for training convolutional neural networks (CNNs) across various medical domains, including brain tumor MRI, leukemia, and COVID-19 imaging. These models enhance classification performance and facilitate the creation of realistic medical datasets, ultimately improving diagnostic accuracy while ensuring patient confidentiality [28, 5, 15, 32, 9]. By leveraging these innovations, diffusion models continue to improve the quality and reliability of medical imaging, contributing to better diagnostic outcomes and patient care.

As illustrated in Figure 2, diffusion models have garnered attention for their ability to enhance image quality and diagnostic accuracy. This figure categorizes diffusion models in medical imaging, highlighting their roles in image synthesis and reconstruction while addressing challenges such as data scarcity and patient privacy, which underscores their applications in anomaly detection. The "Effect of diffusion time" demonstrates how varying diffusion times influence model alignment with actual data, offering insights into optimization. The "Comparison of PSNR and Runtime for Different Deblurring Methods" evaluates the efficiency and effectiveness of various deblurring techniques, highlighting the superiority of certain methods in balancing speed and image clarity. Lastly, the "Comparison of MRI Image Restoration Techniques" underscores advancements in MRI image processing, comparing the realism and detail of images produced by different restoration techniques. Collectively, these examples underscore the transformative role of diffusion models in refining medical imaging processes, ultimately contributing to more accurate and reliable diagnostic tools [33, 31, 34].

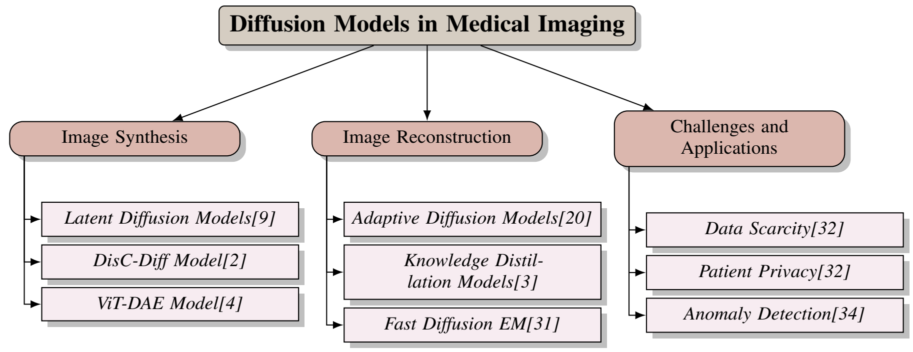


Figure 2: This figure illustrates the categorization of diffusion models in medical imaging, highlighting their roles in image synthesis and reconstruction. It also addresses challenges such as data scarcity and patient privacy, underscoring their applications in anomaly detection.

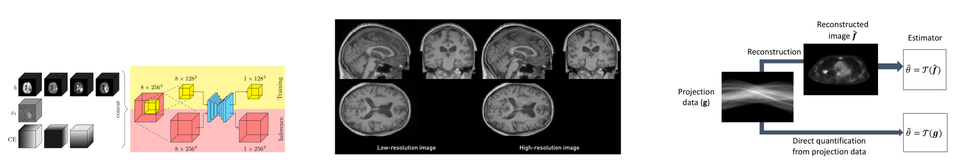
3.2 Applications in Radiology

Diffusion models have significantly advanced radiological practices by enhancing image quality and diagnostic accuracy through sophisticated computational techniques. These models excel in anomaly detection and segmentation, preserving healthy tissue integrity while enhancing pathological visibility. The DisC-Diff model, for instance, has demonstrated superior performance in multi-contrast MRI super-resolution, providing improved uncertainty estimation and image quality compared to traditional methods [2].

In image reconstruction, diffusion models such as ViT-DAE have shown remarkable capabilities in synthesizing high-quality histopathology images, outperforming conventional GAN-based and vanilla DAE methods [4]. This advancement is crucial in radiology, where high-resolution images are essential for accurate diagnosis.

Diffusion models also excel in unsupervised domain adaptation, maintaining diagnostic consistency across clinical environments. Latent Diffusion Models have been employed to transform low-quality 3T dMRI data into high-quality 7T-like images while preserving critical gradient information necessary for detailed anatomical studies [9]. Furthermore, diffusion models enhance low-dose CT images. Fourier Diffusion Models have demonstrated superior performance over scalar diffusion models in low-dose CT image restoration, reducing radiation exposure while maintaining diagnostic accuracy [19].

In MRI, models like ASSCGD improve the quality of reconstructed images from undersampled data, enhancing diagnostic accuracy and efficiency [24]. These models are critical where full data acquisition is impractical, ensuring efficient and effective imaging workflows. Experiments with diffusion models, such as those conducted with CAAT using the CelebA-HQ dataset, demonstrate their broader applicability in radiological image enhancement [28]. Despite these advancements, challenges remain in achieving optimal uncertainty quantification alongside high image reconstruction accuracy. Ongoing research efforts continue to refine diffusion models for comprehensive diagnostic reliability, highlighting their transformative impact on radiology.



(a) Deep Learning for Brain Tumor Detection: A Comparative Study[27]

(b) Comparison of Low-Resolution and High-Resolution Brain MRI Images[35]

(c) Reconstruction and Estimation of Medical Images[21]

Figure 3: Examples of Applications in Radiology

AI-generated, for reference only.

As shown in Figure 3, diffusion models have emerged as powerful tools in medical imaging, particularly in radiology, offering innovative solutions for enhancing image quality and diagnostic accuracy. The first example, "Deep Learning for Brain Tumor Detection: A Comparative Study," showcases a comparative analysis of various deep learning models for detecting brain tumors, highlighting the efficacy of different training approaches on MRI datasets. The second example, "Comparison of Low-Resolution and High-Resolution Brain MRI Images," emphasizes the significant contrast in detail and clarity between low and high-resolution MRI images, showcasing the potential of diffusion models to enhance resolution and aid diagnosis. Lastly, the "Reconstruction and Estimation of Medical Images" example demonstrates reconstructing medical images from projection data, using an estimator for a more accurate representation of the original image. Collectively, these examples illustrate the transformative impact of diffusion models in radiology, paving the way for improved diagnostic capabilities and patient outcomes [27, 35, 21].

3.3 Advancements in Data Synthesis and Interpretation

Recent advancements in diffusion models have significantly enhanced data synthesis and interpretation in medical imaging, achieving state-of-the-art results across various applications. These models exhibit versatility, adapting to diverse imaging tasks while achieving superior image synthesis quality [16]. Their inherent ability to leverage rich, implicit knowledge facilitates the creation of generalized representations beneficial for performance enhancement in previously unseen domains [29].

As illustrated in Figure 4, the recent advancements in data synthesis and interpretation through diffusion models are highlighted, showcasing their applications in versatile modeling, blind deconvolution, and dataset augmentation. In blind deconvolution tasks, the Fast Diffusion EM algorithm exemplifies progress, providing superior image quality and reduced runtimes compared to traditional methods [31]. This advancement underscores the potential of diffusion models to enhance computational efficiency while maintaining high image fidelity. The ability of diffusion models to augment datasets is another critical development, addressing specific challenges within medical imaging and other domains. By generating synthetic data, these models contribute to more robust datasets, ultimately improving machine learning algorithm performance [12]. Self-guided approaches further enhance this capability, allowing for high-quality image generation without extensive manual annotation, making the process more scalable across diverse domains [30].

Innovations like the iLGD framework demonstrate advancements in image layout control, yielding higher image quality without the complexity associated with training-based methods [23]. These improvements are vital for optimizing the synthesis process and ensuring generated images meet high standards required in medical diagnostics. Despite these advancements, further optimization of diffusion models is needed, particularly regarding sampling efficiency. As powerful generative tools, diffusion models continue to evolve, with ongoing research focused on enhancing their applicability and effectiveness in medical imaging and beyond [1].

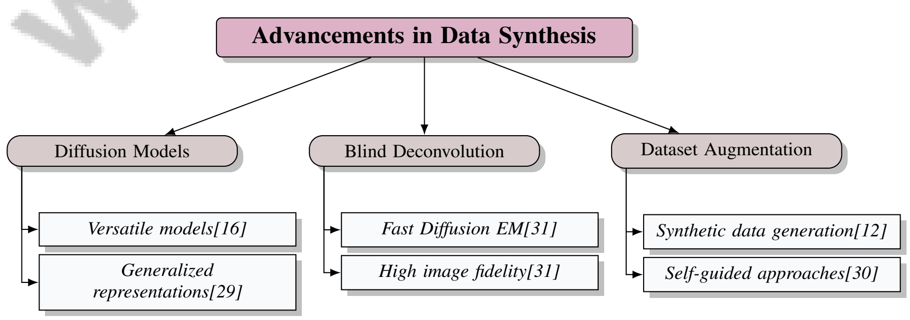


Figure 4: This figure illustrates the recent advancements in data synthesis and interpretation through diffusion models, highlighting their application in versatile modeling, blind deconvolution, and dataset augmentation.

Feature	Latent Diffusion Models (LDM)	DisC-Diff	Self-training Frameworks
Image Quality Enhancement	High-quality Dmri	High-resolution Enhancement	Artifact Reduction
Computational Efficiency	Optimized Synthesis	Complementary Integration	Knowledge Distillation
Application Domain	Mri	Multi-contrast Mri	Cbct TO Pct

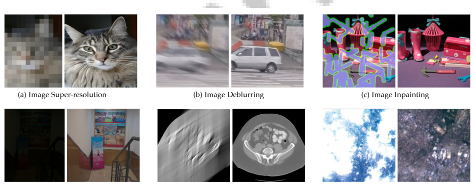
Table 2: This table provides a comparative overview of three advanced diffusion models used in medical imaging: Latent Diffusion Models (LDM), DisC-Diff, and self-training frameworks. It highlights key features such as image quality enhancement, computational efficiency, and application domains, illustrating their distinct contributions to improving imaging techniques and diagnostic accuracy.

4 Data Synthesis and Image Reconstruction

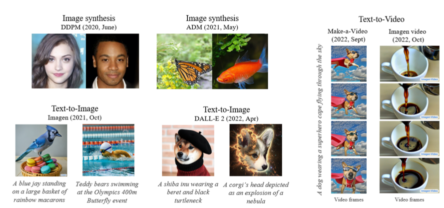
4.1 Applications in Image Synthesis and Reconstruction

Diffusion models have emerged as pivotal in advancing medical image synthesis and reconstruction, significantly enhancing image quality and diagnostic accuracy. The DisC-Diff model exemplifies this by effectively utilizing multi-contrast information, leading to superior restoration quality and uncertainty estimation, crucial for maintaining structural integrity in MRI scans [2]. In adaptive radiation therapy, these models synthesize high-quality pseudo-CT (pCT) images from daily cone-beam computed tomography (CBCT) scans, addressing challenges posed by artifacts and quality variations inherent in CBCT [3]. This capability improves treatment planning and delivery accuracy.

The ADIR method further showcases the adaptability of diffusion models by reconstructing clean images from degraded versions using similar external images, thereby enhancing overall image quality and reliability [20]. Such methodologies are particularly beneficial when high-quality data acquisition is limited. Diffusion models are revolutionizing medical imaging by introducing innovative techniques for image synthesis and reconstruction that address critical challenges like data scarcity and privacy concerns. They generate high-quality synthetic medical images, facilitating the training of convolutional neural networks (CNNs) in applications such as Brain Tumor MRI, Acute Lymphoblastic Leukemia (ALL), and SARS-CoV-2 CT scans. Furthermore, diffusion probabilistic models have demonstrated the ability to produce realistic three-dimensional imaging data, improving performance in tasks like breast segmentation, especially in scenarios with limited datasets. Advancements such as AutoDDPM enhance the robustness and generalizability of anomaly detection, allowing for more effective image reconstruction while preserving healthy tissue integrity. Collectively, these developments underscore the potential of diffusion models to augment existing medical imaging techniques and contribute to the creation of autonomous clinical decision systems with enhanced interpretability and accuracy [15, 5, 36].



(a) Image Super-resolution, Image Deblurring, Image Inpainting, Low-light Image Enhancement, Limited-angle CT Reconstruction, Cloud Removal[37]



(b) Recent Advances in Image and Text Generation Techniques[38]

Figure 5: Examples of Applications in Image Synthesis and Reconstruction

As illustrated in Figure 5, substantial advancements in data synthesis and image reconstruction have been achieved through various advanced techniques. The examples provided highlight diverse applications in this field, showcasing the effectiveness of modern image processing methods in enhancing or correcting original images. Techniques such as image super-resolution, deblurring, inpainting, low-light enhancement, limited-angle CT reconstruction, and cloud removal address specific challenges within image synthesis and reconstruction. Furthermore, recent advances in image and text generation techniques, including DDPM, ADM, and Imagen, represent milestones in the evolution of image synthesis technologies. These innovations not only demonstrate the development of new methodologies but also emphasize their significant impact on generating high-quality images for a wide range of applications, from medical imaging to artistic creation [37, 38].

4.2 Challenges and Solutions in Image Reconstruction

Despite the promise of diffusion models in medical imaging, several challenges persist, particularly in image reconstruction. A primary concern is the accuracy of AI-generated reconstructions relative to human radiologist interpretations, raising questions about the reliability and clinical applicability of these models, which must meet stringent diagnostic standards [13]. Addressing this issue requires advanced validation techniques and the integration of expert feedback into model training to enhance image fidelity.

Another challenge involves the integration of AI-driven diffusion models into existing clinical workflows. The complexity and computational demands of these models can hinder seamless integration, potentially disrupting established diagnostic processes. Solutions include developing more efficient algorithms that minimize computational overhead and creating user-friendly interfaces to facilitate adoption by clinical practitioners [13].

Data privacy and model reliability are also significant challenges in deploying diffusion models for image reconstruction. Ensuring patient data confidentiality while maintaining model robustness is essential for gaining trust within the medical community. Implementing secure data handling protocols and developing models resilient to data variability are crucial steps in overcoming these challenges [13].

To address the challenges associated with diffusion models in generative AI, exploring hybrid approaches that integrate diffusion models with complementary AI techniques, such as convolutional neural networks (CNNs) and transformers, is essential. This integration aims to enhance model performance and reliability by leveraging the strengths of each method, including improved data augmentation, semantic manipulation, and resilience to adversarial attacks, ultimately leading to more effective and secure generative modeling across various applications [12, 28]. Additionally, ongoing research into self-supervised and semi-supervised learning methods shows promise in reducing dependency on large annotated datasets, thereby enhancing the scalability and adaptability of diffusion models in diverse clinical settings.

While diffusion models hold significant potential for improving medical imaging—particularly in generating synthetic data to address issues like data scarcity and privacy concerns—realizing their full clinical potential will require innovative solutions to current challenges, such as ensuring data quality and safeguarding patient privacy, alongside collaborative efforts between the medical and AI research communities [13, 5, 14, 32, 9].

5 Artificial Intelligence and Radiology

The intersection of artificial intelligence (AI) and radiology is reshaping traditional practices through cutting-edge methodologies. This section explores the integration of AI with diffusion models, which have significantly enhanced radiological imaging. By examining specific applications and advancements, we highlight improvements in image quality, diagnostic precision, and clinical efficacy. The following subsection details the mechanisms and frameworks facilitating this integration, beginning with AI incorporation into radiological practices.

5.1 Integration with Artificial Intelligence

Integrating diffusion models with AI has revolutionized radiological practices by enhancing image quality and diagnostic precision. The HiDiff framework exemplifies this synergy, combining existing segmentors' discriminative abilities with a binary Bernoulli diffusion model's generative capabilities to refine segmentation masks effectively [39]. This hybrid approach enhances segmentation accuracy and demonstrates the potential of model integration in medical imaging.

The BGDM framework showcases AI's integration into radiology through diffusion models, significantly improving image quality and sampling efficiency compared to traditional methods [40]. By optimizing the generative process, BGDM enhances the fidelity of reconstructed images, crucial for accurate diagnostics. Additionally, merging diffusion models with deep learning has advanced medical image synthesis, particularly in CT to MRI conversion, facilitating better diagnostic outcomes through high-quality synthetic images [41].

In image denoising, the R2D2+ method highlights the benefits of AI-diffusion model integration, improving denoising performance and robustness against complex noise distributions [42]. This is crucial where noise may obscure vital diagnostic information. Diffusion models also excel in generating realistic synthetic data, as seen in synthesizing rare cataract surgery datasets, addressing data sparsity and enhancing classifier performance [43].

The ProAmGAN approach demonstrates the efficacy of AI and diffusion model integration in mitigating measurement noise and reconstruction artifacts, producing high-quality images closely resembling ground truth [26]. This integration is vital for ensuring medical imaging accuracy and reliability. In surgical training, diffusion models enhance laparoscopic video realism and interactivity, improving the training experience [8].

Latent diffusion models significantly boost diagnostic task performance, especially in data-scarce environments, addressing data scarcity and enhancing CNN model generalizability [7, 5]. Generating high-quality diffusion MRI images while preserving essential features is another critical advantage, vital for maintaining diagnostic image integrity [9].

AI and diffusion model integration has transformed radiological practices, enabling high-quality synthetic image generation, enhancing reconstruction processes, and improving analytical accuracy. This synergy addresses data scarcity and privacy concerns in medical imaging while optimizing training datasets for machine learning models, leading to more robust diagnostic capabilities. The application of diffusion models alongside innovative methodologies, like knowledge distillation, demonstrates superiority over traditional image processing methods, paving the way for precise and context-aware imaging solutions in clinical settings [3, 13, 5, 12, 23]. These advancements underscore AI-driven diffusion models' transformative potential in enhancing diagnostic outcomes and advancing medical imaging technologies.

5.2 Improving Diagnostic Outcomes

AI-driven diffusion models have notably improved diagnostic outcomes in medical imaging by enhancing image quality, diversity, and fidelity, essential for accurate diagnosis and treatment planning. The Medfusion benchmark highlights diffusion models' strengths in generating high-quality medical images, enriching diagnostic processes' diversity and fidelity [44]. This capability is crucial for addressing data limitations and ensuring comprehensive diagnostic evaluations.

Integrating diffusion models with deep learning has substantially improved diagnostic accuracy. The Physics-Informed Deep Diffusion MRI (PIDD) model, validated by clinicians, demonstrates high diagnostic value and improved outcomes [45]. Such advancements emphasize diffusion models' potential to enhance diagnostic precision and reliability.

Latent Diffusion Models effectively generate synthetic brain images replicating real images' properties while allowing covariate conditioning [46]. This approach addresses significant limitations in medical imaging datasets, offering viable alternatives for training and improving segmentation network performance [47]. By enhancing dataset quality and diversity, diffusion models contribute to more accurate and efficient diagnostic processes.

The Diffuse-UDA model marks a significant advancement in unsupervised domain adaptation for medical image segmentation, achieving superior performance metrics [48]. Improved segmentation accuracy directly translates to better diagnostic outcomes, as precise segmentation is crucial for identifying pathological regions.

Diffusion models also reduce aleatoric uncertainty in tumor segmentation, providing a more reliable alternative to standard augmentation techniques [49]. This uncertainty reduction enhances diagnostic model robustness, ensuring consistent performance across various clinical scenarios.

Proposed methods utilizing diffusion models improve image quality and accurate anatomical representation, essential for effective treatment planning and monitoring in radiology [3]. By optimizing training efficiency, reducing computational demands, and enhancing sampling quality, diffusion models offer a comprehensive approach to improving diagnostic outcomes [18].

AI-driven diffusion models have transformed medical imaging by introducing sophisticated techniques for generating, reconstructing, and analyzing images. These models address critical issues like data scarcity and privacy concerns by producing high-quality synthetic medical images, enhancing CNN training across domains like brain tumor MRI, acute lymphoblastic leukemia (ALL), and SARS-CoV-2 CT scans. Studies indicate CNNs trained on synthetic datasets achieve classification performances comparable to those trained on original datasets, reducing reliance on patient-specific data. Moreover, diffusion models create realistic three-dimensional medical images, preserving privacy while augmenting limited datasets. This advancement leads to improved diagnostic accuracy and better patient care outcomes, as evidenced by enhanced performance in tasks like breast segmentation [15].

6 Challenges and Future Directions

6.1 Challenges in Diffusion Models

The application of diffusion models in medical imaging faces several challenges, primarily due to the computational intensity of the generation process, which results in low sampling speeds and restricts practical use [1]. This is compounded by the high resource demands of diffusion models and associated techniques like convolutional neural networks (CNNs), which necessitate optimized hyperparameters for efficient functionality [5]. The scarcity of high-quality training data, such as 7T MRI, further impedes model generalizability [9]. Additionally, diffusion models can be sensitive to noise in multi-contrast MRI applications, potentially degrading performance if not properly managed [2].

Generative artifacts, particularly in reconstructing small anatomical structures, pose another challenge, with performance variability observed across different clinical settings [3]. This necessitates robust models capable of consistent performance in diverse scenarios and underscores the importance of thorough validation to ensure diagnostic accuracy. While models like ViT-DAE improve stability and representation of complex spatial structures, achieving efficient execution times without compromising image quality remains a challenge [4]. Addressing these issues through innovative research is crucial for enhancing the effectiveness of diffusion models in medical imaging.

6.2 Future Directions and Emerging Trends

Future research on diffusion models in medical imaging aims to enhance model robustness, efficiency, and applicability. Optimizing diffusion processes within compact latent spaces to reduce memory consumption and improve training efficiency is a promising direction [2]. Hybrid approaches that integrate diffusion models with other generative techniques may also enhance sampling efficiency [1]. Augmenting training data and applying diffusion models to various imaging modalities are anticipated to improve model robustness and extend applicability across diverse clinical scenarios [9]. Refining adaptation mechanisms and exploring external data sources could significantly enhance image reconstruction processes, providing more reliable diagnostic tools [20].

Ensuring generalizability across diverse patient populations and imaging modalities is a priority, with future studies likely to explore advanced data normalization techniques [3]. Advanced model architectures, such as vision transformers, could enhance image synthesis and reconstruction capabilities, addressing current limitations and allowing application to additional datasets [4]. The future of diffusion models in medical imaging is poised for substantial advancements, driven by ongoing research focused on optimizing model architectures, enhancing data robustness, and broadening applicability across diverse clinical contexts. Large-scale generative AI applications are being explored to alleviate the shortage of radiologists and improve report generation and image interpretation efficiency. Diffusion models are effective in image data augmentation, generating high-quality, diverse images that enhance machine learning model performance. Recent developments in deep generative modeling for diffusion MRI have shown promise in improving image quality and resolution, potentially transforming medical imaging practices [12, 9, 13]. These efforts will contribute to developing more precise and efficient diagnostic tools, improving patient care and outcomes.

7 Conclusion

Diffusion models have emerged as pivotal tools in the realm of medical imaging, showcasing their capacity to significantly elevate image quality and diagnostic precision. By leveraging sophisticated generative algorithms, these models surpass traditional techniques, such as GANs, in producing high-fidelity images from noisy inputs. The integration of artificial intelligence within diffusion models has further amplified their efficacy in tasks encompassing image synthesis, reconstruction, and analysis, offering comprehensive solutions across diverse medical imaging challenges.

In radiology, diffusion models play a crucial role in refining the quality and dependability of diagnostic imagery, directly contributing to improved patient outcomes. They also address data imbalance by creating synthetic datasets that enhance the performance of machine learning models in medical diagnostics. Despite their promise, diffusion models face hurdles, such as high computational requirements and the need for superior training datasets, which may limit their scalability and generalizability.

Future research endeavors will likely concentrate on overcoming these challenges by optimizing model architectures, improving training efficiency, and exploring hybrid methodologies that integrate diffusion models with other generative frameworks. The continued evolution of diffusion models is expected to drive significant advancements in medical imaging technologies, enhancing their applicability and effectiveness in clinical environments. These developments are anticipated to foster the creation of more precise, efficient, and reliable diagnostic tools, ultimately advancing patient care and outcomes.

AI-generated, for reference only.

References

[1] Florinel-Alin Croitoru, Vlad Hondru, Radu Tudor Ionescu, and Mubarak Shah. Diffusion models in vision: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(9):10850–10869, 2023.

[2] Ye Mao, Lan Jiang, Xi Chen, and Chao Li. Disc-diff: Disentangled conditional diffusion model for multi-contrast mri super-resolution, 2023.

[3] Joonil Hwang, Sangjoon Park, NaHyeon Park, Seungryong Cho, and Jin Sung Kim. Improving cone-beam ct image quality with knowledge distillation-enhanced diffusion model in imbalanced data settings, 2024.

[4] Xuan Xu, Saarthak Kapse, Rajarsi Gupta, and Prateek Prasanna. Vit-dae: Transformer-driven diffusion autoencoder for histopathology image analysis, 2023.

[5] Abdullah al Nomaan Nafi, Md. Alamgir Hossain, Rakib Hossain Rifat, Md Mahabub Uz Zaman, Md Manjurul Ahsan, and Shivakumar Raman. Diffusion-based approaches in medical image generation and analysis, 2024.

[6] Hyun-Jic Oh and Won-Ki Jeong. Diffmix: Diffusion model-based data synthesis for nuclei segmentation and classification in imbalanced pathology image datasets, 2023.

[7] Eva Prakash, Jeya Maria Jose Valanarasu, Zhihong Chen, Eduardo Pontes Reis, Andrew Johnston, Anuj Pareek, Christian Bluethgen, Sergios Gatidis, Cameron Olsen, Akshay Chaudhari, Andrew Ng, and Curtis Langlotz. Evaluating and improving the effectiveness of synthetic chest x-rays for medical image analysis, 2024.

[8] Ivan Iliash, Simeon Allmendinger, Felix Meissen, Niklas Kühl, and Daniel Rückert. Interactive generation of laparoscopic videos with diffusion models, 2024.

[9] Xi Zhu, Wei Zhang, Yijie Li, Lauren J. O'Donnell, and Fan Zhang. When diffusion mri meets diffusion model: A novel deep generative model for diffusion mri generation, 2024.

[10] Emile Saillard, Aurélie Levillain, David Mitton, Jean-Baptiste Pialat, Cyrille Confavreux, Hélène Follet, and Thomas Grenier. Enhanced segmentation of femoral bone metastasis in ct scans of patients using synthetic data generation with 3d diffusion models, 2024.

[11] Yanwu Xu, Li Sun, Wei Peng, Shuyue Jia, Katelyn Morrison, Adam Perer, Afrooz Zandifar, Shyam Visweswaran, Motahhare Eslami, and Kayhan Batmanghelich. Medsyn: Text-guided anatomy-aware synthesis of high-fidelity 3d ct images, 2024.

[12] Panagiotis Alimisis, Ioannis Mademlis, Panagiotis Radoglou-Grammatikis, Panagiotis Sarigiannidis, and Georgios Th. Papadopoulos. Advances in diffusion models for image data augmentation: A review of methods, models, evaluation metrics and future research directions, 2025.

[13] Inwoo Seo, Eunkyoung Bae, Joo-Young Jeon, Young-Sang Yoon, and Jiho Cha. The era of foundation models in medical imaging is approaching : A scoping review of the clinical value of large-scale generative ai applications in radiology, 2024.

[14] Yongyi Shi, Wenjun Xia, Chuang Niu, Christopher Wiedeman, and Ge Wang. Enabling competitive performance of medical imaging with diffusion model-generated images without privacy leakage, 2024.

[15] Firas Khader, Gustav Mueller-Franzes, Soroosh Tayebi Arasteh, Tianyu Han, Christoph Haarburger, Maximilian Schulze-Hagen, Philipp Schad, Sandy Engelhardt, Bettina Baessler, Sebastian Foersch, Johannes Stegmaier, Christiane Kuhl, Sven Nebelung, Jakob Nikolas Kather, and Daniel Truhn. Medical diffusion: Denoising diffusion probabilistic models for 3d medical image generation, 2023.

[16] Ling Yang, Zhilong Zhang, Yang Song, Shenda Hong, Runsheng Xu, Yue Zhao, Wentao Zhang, Bin Cui, and Ming-Hsuan Yang. Diffusion models: A comprehensive survey of methods and applications. *ACM Computing Surveys*, 56(4):1–39, 2023.

[17] Sonja Kunzmann, Mathias Öttl, Prathmesh Madhu, Felix Denzinger, and Andreas Maier. An unobtrusive quality supervision approach for medical image annotation, 2022.

[18] Huijie Zhang, Yifu Lu, Ismail Alkhouri, Saiprasad Ravishankar, Dogyoon Song, and Qing Qu. Improving efficiency of diffusion models via multi-stage framework and tailored multi-decoder architectures, 2024.

[19] Matthew Tivnan, Jacopo Teneggi, Tzu-Cheng Lee, Ruoqiao Zhang, Kirsten Boedeker, Liang Cai, Grace J. Gang, Jeremias Sulam, and J. Webster Stayman. Fourier diffusion models: A method to control mtf and nps in score-based stochastic image generation, 2023.

[20] Shady Abu-Hussein, Tom Tirer, and Raja Giryes. Adir: Adaptive diffusion for image reconstruction, 2022.

[21] Abhinav K. Jha, Kyle J. Myers, Nancy A. Obuchowski, Ziping Liu, Md Ashequr Rahman, Babak Saboury, Arman Rahmim, and Barry A. Siegel. Objective task-based evaluation of artificial intelligence-based medical imaging methods: Framework, strategies and role of the physician, 2021.

[22] Yanzeng Li, Cheng Zeng, Jinchao Zhang, Jie Zhou, and Lei Zou. Meddit: A knowledge-controlled diffusion transformer framework for dynamic medical image generation in virtual simulated patient, 2024.

[23] Zakaria Patel and Kirill Serkh. Enhancing image layout control with loss-guided diffusion models, 2024.

[24] Mojtaba Safari, Zach Eidex, Shaoyan Pan, Richard L. J. Qiu, and Xiaofeng Yang. Self-supervised adversarial diffusion models for fast mri reconstruction, 2024.

[25] Yinchi Zhou, Tianqi Chen, Jun Hou, Huidong Xie, Nicha C. Dvornek, S. Kevin Zhou, David L. Wilson, James S. Duncan, Chi Liu, and Bo Zhou. Cascaded multi-path shortcut diffusion model for medical image translation, 2024.

[26] Weimin Zhou, Sayantan Bhadra, Frank J. Brooks, Hua Li, and Mark A. Anastasio. Learning stochastic object models from medical imaging measurements using progressively-growing ambientgans, 2020.

[27] Florentin Bieder, Julia Wolleb, Alicia Durrer, Robin Sandkühler, and Philippe C. Cattin. Memory-efficient 3d denoising diffusion models for medical image processing, 2024.

[28] Jingyao Xu, Yuetong Lu, Yandong Li, Siyang Lu, Dongdong Wang, and Xiang Wei. Perturbing attention gives you more bang for the buck: Subtle imaging perturbations that efficiently fool customized diffusion models, 2024.

[29] Yuxiang Ji, Boyong He, Chenyuan Qu, Zhuoyue Tan, Chuan Qin, and Liaoni Wu. Diffusion features to bridge domain gap for semantic segmentation, 2024.

[30] Vincent Tao Hu, David W Zhang, Yuki M. Asano, Gertjan J. Burghouts, and Cees G. M. Snoek. Self-guided diffusion models, 2023.

[31] Charles Laroche, Andrés Almansa, and Eva Coupete. Fast diffusion em: a diffusion model for blind inverse problems with application to deconvolution, 2023.

[32] Salman Ul Hassan Dar, Marvin Seyfarth, Isabelle Ayx, Theano Papavassiliu, Stefan O. Schoenberg, Robert Malte Siepmann, Fabian Christopher Laqua, Jannik Kahmann, Norbert Frey, Bettina Baeßler, Sebastian Foersch, Daniel Truhn, Jakob Nikolas Kather, and Sandy Engelhardt. Unconditional latent diffusion models memorize patient imaging data: Implications for openly sharing synthetic data, 2025.

[33] Giulio Franzese, Simone Rossi, Lixuan Yang, Alessandro Finamore, Dario Rossi, Maurizio Filippone, and Pietro Michiardi. How much is enough? a study on diffusion times in score-based generative models, 2022.

[34] Julia Wolleb, Florentin Bieder, Robin Sandkühler, and Philippe C. Cattin. Diffusion models for medical anomaly detection, 2022.

[35] Walter H. L. Pinaya, Mark S. Graham, Eric Kerfoot, Petru-Daniel Tudosiu, Jessica Dafflon, Virginia Fernandez, Pedro Sanchez, Julia Wolleb, Pedro F. da Costa, Ashay Patel, Hyungjin Chung, Can Zhao, Wei Peng, Zelong Liu, Xueyan Mei, Oeslle Lucena, Jong Chul Ye, Sotirios A. Tsaftaris, Prerna Dogra, Andrew Feng, Marc Modat, Parashkev Nachev, Sebastien Ourselin, and M. Jorge Cardoso. Generative ai for medical imaging: extending the monai framework, 2023.

[36] Cosmin I. Bercea, Michael Neumayr, Daniel Rueckert, and Julia A. Schnabel. Mask, stitch, and re-sample: Enhancing robustness and generalizability in anomaly detection through automatic diffusion models, 2023.

[37] Chunming He, Yuqi Shen, Chengyu Fang, Fengyang Xiao, Longxiang Tang, Yulun Zhang, Wangmeng Zuo, Zhenhua Guo, and Xiu Li. Diffusion models in low-level vision: A survey, 2025.

[38] Anwaar Ulhaq and Naveed Akhtar. Efficient diffusion models for vision: A survey, 2024.

[39] Tao Chen, Chenhui Wang, Zhihao Chen, Yiming Lei, and Hongming Shan. Hidiff: Hybrid diffusion framework for medical image segmentation, 2024.

[40] Hossein Askari, Fred Roosta, and Hongfu Sun. Bi-level guided diffusion models for zero-shot medical imaging inverse problems, 2024.

[41] Qing Lyu and Ge Wang. Conversion between ct and mri images using diffusion and score-matching models, 2022.

[42] Hyungjin Chung, Eun Sun Lee, and Jong Chul Ye. Mr image denoising and super-resolution using regularized reverse diffusion, 2022.

[43] Yannik Frisch, Moritz Fuchs, Antoine Sanner, Felix Anton Ucar, Marius Frenzel, Joana Wasielica-Poslednik, Adrian Gericke, Felix Mathias Wagner, Thomas Dratsch, and Anirban Mukhopadhyay. Synthesising rare cataract surgery samples with guided diffusion models, 2023.

[44] scientific reports.

[45] Chen Qian, Yuncheng Gao, Mingyang Han, Zi Wang, Dan Ruan, Yu Shen, Yaping Wu, Yirong Zhou, Chengyan Wang, Boyu Jiang, Ran Tao, Zhigang Wu, Jiazheng Wang, Liuhong Zhu, Yi Guo, Taishan Kang, Jianzhong Lin, Tao Gong, Chen Yang, Guoqiang Fei, Meijin Lin, Di Guo, Jianjun Zhou, Meiyun Wang, and Xiaobo Qu. Physics-informed deep diffusion mri reconstruction with synthetic data: Break training data bottleneck in artificial intelligence, 2024.

[46] Brain imaging generation with la.

[47] Muhammad Usman Akbar, Måns Larsson, and Anders Eklund. Brain tumor segmentation using synthetic mr images – a comparison of gans and diffusion models, 2024.

[48] Haifan Gong, Yitao Wang, Yihan Wang, Jiashun Xiao, Xiang Wan, and Haofeng Li. Diffuse-uda: Addressing unsupervised domain adaptation in medical image segmentation with appearance and structure aligned diffusion models, 2024.

[49] Abhishek Singh Sambyal, Narayanan C. Krishnan, and Deepti R. Bathula. Towards reducing aleatoric uncertainty for medical imaging tasks, 2022.

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.