DEEP LEARNING APPLICATIONS IN MEDICAL IMAGE PROCESSING AND DIAGNOSTICS

Ankur Jain

IFTM University, Delhi Road Lodhipur Rajput Moradabad

ankur1101@gmail.com – ORCID ID: https://orcid.org/0000-0002-3246-7612

Deepankar Bharadwaj

IFTM University, Delhi Road Lodhipur Rajput Moradabad

deepankar.bharadwaj@gmail.com - ORCID ID: https://orcid.org/0009-0006-0035-680X

ABSTRACT

Medical imaging plays a crucial role in contemporary healthcare, facilitating early disease detection, treatment strategizing, and ongoing monitoring across diverse specialties, including radiology, oncology, ophthalmology, and cardiology. The evolution of modalities such as X-ray, computed tomography, magnetic resonance imaging, positron emission tomography, ultrasound, and digital pathology has resulted in the generation of extensive, intricate, and high-dimensional datasets. Manual interpretation of these images is inherently challenging due to their inherent variability, noise, and the escalating workload faced by clinicians. Deep learning has emerged as a potent methodology for analyzing medical image data, distinguished by its automated feature extraction capabilities and superior accuracy when compared to conventional machine learning techniques. This review scrutinizes the distinctive attributes of medical images, encompassing modality diversity, annotation complexities, and data imbalance issues. It further explores prominent deep learning architectures, such as convolutional neural networks, U-Nets, 3D networks, transformers, and generative models, elucidating their application in tasks like classification, segmentation, detection, and image reconstruction. Key clinical applications are discussed, alongside inherent limitations related to data scarcity, model generalization, interpretability, and regulatory considerations. Furthermore, the article outlines nascent research directions, including federated learning, foundation models, multimodal data integration, and explainable artificial intelligence. Collectively, these advancements underscore deep learning's transformative impact on medical imaging, thereby enabling more precise and efficient clinical decision-making.

Keywords : Medical Imaging, Deep Learning, Image Segmentation, Convolutional Neural Networks, Computer-Aided Diagnosis

Introduction

The integration of deep learning into medical imaging has heralded a transformative era, demonstrating considerable success across diverse applications and advancing the field into what is often termed the artificial intelligence era [1]. This paradigm shift is primarily driven by the ability of deep learning models, particularly neural networks, to discern intricate patterns and features within vast and complex medical image datasets, thereby reducing reliance on traditional manual interpretation [2]. This capability is particularly vital given the ever-increasing volume and complexity of medical imaging data generated from various modalities, including X-ray, CT, MRI, and ultrasound [3]. This enables deep learning algorithms to automate and enhance tasks such as disease classification, organ segmentation, anomaly

ISBN NR: 978-625-5694-60-7

detection, and image reconstruction with improved accuracy and efficiency [4] [2]. For instance, convolutional neural networks have shown remarkable proficiency in autonomously learning features from multidimensional medical images, obviating the need for laborious manual feature engineering [5]. This inherent capability of deep learning models to adapt and generalize from diverse datasets significantly augments their utility across various imaging modalities and clinical applications [4].

Background of Medical Imaging

The analysis of medical images is fundamental to modern healthcare, facilitating critical functions such as disease diagnosis, treatment planning, and patient monitoring [6]. Historically, this process relied heavily on manual interpretation by highly skilled medical professionals, which, while invaluable, was prone to inter-observer variability and human error [7]. The introduction of advanced computational techniques, particularly deep learning, has mitigated these challenges by offering automated and objective analytical capabilities that can process complex imaging data with unprecedented precision and consistency [8].

Traditional Medical Imaging Modalities

This shift toward automated analysis is revolutionizing medical imaging, leading to more efficient workflows and enhanced diagnostic accuracy across various specialties [9]. These deep learning models, trained on extensive datasets, can identify intricate patterns and features that might elude the human eye, offering a novel perspective on image features crucial for decision-making [10]. This advancement allows for a more quantitative approach to medical diagnostics, moving beyond subjective assessments [2]. Consequently, the integration of deep learning into medical image analysis has become indispensable, enabling real-time processing of vast and complex datasets to generate insights that improve healthcare outcomes and operational efficiency [11].

Challenges in Medical Image Analysis

However, despite the significant advancements, numerous inherent challenges persist within medical image analysis that necessitate further research and innovative solutions. These challenges include the scarcity of annotated data, the inherent variability in image acquisition protocols, and the critical need for model interpretability and robustness in clinical settings. Furthermore, addressing issues like data privacy, integrating deep learning tools into existing clinical workflows, and ensuring generalizability across diverse patient demographics and imaging equipment are paramount for successful clinical implementation [2] [12]. Addressing these hurdles will ensure the seamless and reliable integration of deep learning models into routine clinical practice, ultimately enhancing diagnostic accuracy and patient outcomes [4]. One crucial aspect for the success of deep learning in medical imaging is the careful consideration of data preprocessing, including normalization and standardization, which profoundly influences model performance [2].

Fundamentals of Deep Learning

This also encompasses the need for robust methods to handle missing data and correct for artifacts, ensuring the integrity and utility of the input for deep learning algorithms. Moreover, establishing standardized protocols for data curation and annotation is essential to mitigate biases and improve the generalizability of models across different clinical environments and patient populations [2]. The scalability and adaptability of deep learning algorithms allow their deployment across diverse clinical settings, potentially streamlining workflows and reducing interpretation times [4]. Such integration promises to augment the capabilities of healthcare professionals by providing accurate identification of pathological conditions and delineation of anatomical structures, thereby enhancing patient care and treatment planning [4] [2]. The development of enhanced interpretability techniques, such as those that provide visual explanations, will further build clinician trust and facilitate the widespread adoption of these systems within routine clinical workflows [2]. Future research must also focus on developing more robust models capable of handling heterogeneous data sources and exploring ethical considerations related to data privacy and deployment in clinical settings [2]. Moreover, exploring novel encryption methods for medical images could further bolster privacy and security measures, thereby increasing confidence in the adoption of these sophisticated AI systems in healthcare [13].

Neural Networks and Their Evolution

This increasing integration also necessitates the development of advanced deep learning architectures capable of handling multifaceted data, along with innovative transfer learning approaches to leverage pre-existing knowledge from large datasets [14]. Furthermore, advancements in model explainability are crucial for fostering trust among healthcare stakeholders by elucidating the rationale behind predictions, thereby facilitating clinical decision-making [15].

Key Deep Learning Architectures

The exploration of diverse deep learning architectures, such as Convolutional Neural Networks, Recurrent Neural Networks, and Transformers, has been pivotal in advancing medical image analysis, each offering unique strengths for different data types and diagnostic challenges. For instance, advancements in generative adversarial networks have shown promise in synthesizing realistic medical images, aiding in data augmentation and anonymization, which can be critical given the scarcity of labeled medical data. Moreover, the ongoing development of efficient optimization techniques aims to balance computational complexity with model accuracy, enabling the deployment of deep learning models on various hardware configurations, including edge devices, for real-time inference in point-of-care settings [16]. Addressing the limitations related to data privacy, security, and accessibility remains paramount for the broader adoption of these advanced models in clinical practice [17]. Additionally, future research should concentrate on enhancing model robustness against adversarial attacks and improving generalizability across diverse populations [2].

Training and Optimization of Deep Learning Models

The optimization of deep learning models in medical imaging involves meticulous hyperparameter tuning and sophisticated regularization techniques to prevent overfitting, which is particularly critical given the often-limited and imbalanced nature of medical datasets. Furthermore, the integration of multimodal data, combining medical images with genomics or electronic health records, necessitates advanced fusion techniques to enable more accurate diagnoses and personalized treatment planning [14]. This multifaceted approach, combining diverse data sources and advanced computational methods, is crucial for developing robust and clinically applicable AI solutions in healthcare [18]. Additionally, the increasing demand for interpretable AI models in medicine has led to the development of explainable artificial intelligence techniques, which provide insights into the decision-making processes of complex models, fostering greater trust and adoption among clinicians and regulatory authorities [19] [20].

Applications of Deep Learning in Medical Imaging

Deep learning has revolutionized medical imaging by enabling automated and highly accurate analysis across a myriad of applications, from disease detection and diagnosis to treatment planning and prognosis. These applications encompass a broad spectrum of medical imaging modalities, including radiography, computed tomography, magnetic resonance imaging, and ultrasound [21]. This widespread applicability is further enhanced by the ability of deep learning models to identify subtle patterns often imperceptible to the human eye, thereby augmenting diagnostic capabilities [2]. This improved capability extends to areas such as early cancer detection, characterization of neurological disorders, and precise volumetric analysis of anatomical structures, significantly improving the precision of clinical assessments.

Image Classification

Image classification, a foundational task in medical imaging, involves categorizing an entire image into predefined classes, such as identifying the presence or absence of a disease [2]. Deep learning models, particularly Convolutional Neural Networks, have demonstrated exceptional performance in this domain, leveraging their hierarchical feature extraction capabilities to discern complex patterns indicative of various pathologies [22]. This has led to significant advancements in automated diagnostic systems, where models are trained on extensive datasets to classify medical images with high accuracy, often surpassing human expert performance [23].

Object Detection

Object detection further refines this capability by precisely localizing and identifying multiple anatomical structures or lesions within an image, providing bounding box predictions for each detected instance. This capability is crucial for tasks like tumor segmentation, organ localization, and counting specific cellular structures, offering more granular insights than simple image classification. The application of deep learning in object detection thus enables the automated identification and quantification of abnormalities, significantly streamlining clinical workflows and enhancing diagnostic efficiency [21].

Image Segmentation

Image segmentation, a more intricate task, precisely delineates the boundaries of specific regions or structures within medical images at a pixel level, which is indispensable for quantifying disease burden and planning interventions [24]. This fine-grained analysis is critical for accurate tumor volume measurement, delineation of organs-at-risk in radiotherapy, and detailed anatomical mapping for surgical planning [25].

Image Reconstruction and Enhancement

Beyond diagnostic applications, deep learning significantly contributes to image reconstruction and enhancement, optimizing the quality and interpretability of medical images by denois-ing, super-resolution, and artifact reduction. These advancements enable the generation of high-quality images from low-dose acquisitions or incomplete data, thereby minimizing patient exposure and acquisition time while maintaining diagnostic utility. Moreover, deep learning algorithms can reconstruct detailed 3D models from 2D slices, providing comprehensive anatomical context for complex procedures and educational purposes. The integration of deep learning in these reconstruction and enhancement processes not only improves image clarity but also allows for the extraction of more quantitative biomarkers, leading to a deeper understanding of disease progression and treatment response.

Image Generation and Synthesis

Deep learning models can also synthesize new medical images or augment existing datasets, which is particularly beneficial in scenarios with limited data availability for rare diseases or specific anatomical variations. This synthetic data generation can enhance the training of other deep learning models, improving their robustness and generalizability across various clinical presentations. Moreover, these generative models can facilitate the creation of realistic phantoms for training and validation, reducing the reliance on costly and time-consuming real patient data acquisition.

Deep Learning Across Different Medical Imaging Modalities

The diverse nature of medical imaging modalities, each with unique physical principles and data characteristics, presents distinct challenges and opportunities for deep learning applications. Consequently, specialized deep learning architectures and training methodologies are often tailored to effectively process and interpret data from modalities such as MRI, CT, and ultrasound, leveraging their inherent strengths while mitigating their limitations. For instance, deep learning significantly enhances Magnetic Resonance Imaging by improving image quality, accelerating scan times, and addressing data-related complexities through various network architectures, including end-to-end and generative models [26]. Deep learning has proven particularly useful in various steps of the clinical imaging workflow, including patient scheduling, data acquisition, and reconstruction [27]. Furthermore, deep neural networks have been widely adopted for enhancing existing images, generating features, and performing comprehensive analyses across different medical imaging modalities [28].

Deep Learning in Radiography (X-ray)

Deep learning techniques, such as convolutional neural networks, have significantly advanced radiography by automating tasks like fracture detection, pneumonia diagnosis, and tuberculosis screening, thereby augmenting diagnostic accuracy and efficiency [29]. These networks can effectively identify subtle pathological patterns that might be missed by human observers, leading to earlier and more reliable diagnoses in diverse radiographic applications [30].

Deep Learning in Computed Tomography (CT)

Deep learning in Computed Tomography has enabled breakthroughs in image reconstruction, dose reduction, and the automated detection and characterization of various pathologies, including lung nodules and vascular anomalies. It has also demonstrated considerable utility in artifact reduction and sparse-view reconstruction, enhancing image quality while minimizing radiation exposure [31].

Deep Learning in Magnetic Resonance Imaging (MRI)

Deep learning has revolutionized Magnetic Resonance Imaging by improving image quality, accelerating scan times, and addressing data-related challenges through advanced reconstruction algorithms and noise reduction techniques [32]. Specifically, deep learning methods have been applied to optimize acquisition protocols and enhance robustness against distribution shifts, addressing subtle biases inherent in MRI data acquisition [26].

Deep Learning in Ultrasound (US)

Deep learning applications in ultrasound imaging have focused on enhancing image quality through speckle noise reduction, automating fetal biometric measurements, and improving the accuracy of lesion detection and characterization [27]. These models not only refine diagnostic capabilities but also aid in real-time guidance for interventional procedures and the development of 3D/4D ultrasound reconstructions for comprehensive visualization [33].

Deep Learning in Histopathology

In histopathology, deep learning excels at analyzing high-resolution digital slides for tasks such as cancer detection, grading, and subtype classification, automating laborious manual processes

ISBN NR: 978-625-5694-60-7

and improving diagnostic consistency [34]. This approach allows for the quantitative assessment of complex tissue morphology and cellular characteristics, which is crucial for precision medicine and personalized treatment strategies [35]. Moreover, deep learning algorithms can identify intricate patterns within histopathological images that correlate with disease progression and therapeutic response, offering predictive insights beyond traditional visual inspection [13].

Challenges and Limitations

Despite the remarkable progress and extensive applications of deep learning in medical imaging, several critical challenges and limitations persist, impeding its widespread clinical adoption and necessitating further research. A primary concern revolves around the black-box nature of many deep learning models, making it difficult to interpret their decision-making processes, which is crucial for building trust and ensuring accountability in clinical settings. The limited availability of large, high-quality, and expertly annotated datasets further hinders the generalizability and robustness of these models, particularly for rare diseases or specific demographic groups [19] [1].

Data Availability and Annotation

This scarcity necessitates innovative approaches for data augmentation and synthetic data generation, though these methods introduce their own challenges related to fidelity and clinical relevance [36]. Furthermore, the process of obtaining expert annotations is often time-consuming and expensive, posing a significant bottleneck to dataset expansion [37]. This issue is compounded by inter-observer variability among annotators, which can introduce inconsistencies and biases into the training data [38].

Interpretability and Explainability of Models

Addressing the "black box problem" is paramount, as clinicians require transparent explanations for model predictions to integrate AI confidently into diagnostic workflows [39]. This necessitates the development of explainable AI techniques that can elucidate the rationale behind a model's output, thereby fostering clinical trust and facilitating regulatory approval [40].

Generalization and Robustness

Models must demonstrate robustness against adversarial attacks and the ability to generalize across diverse patient populations and varying acquisition protocols to ensure reliable performance in real-world clinical scenarios [41]. This includes mitigating biases that may arise from differences in imaging equipment or patient demographics across different centers [42].

Ethical Considerations and Regulatory Aspects

The integration of artificial intelligence into clinical practice raises profound ethical questions regarding patient privacy, data security, and the equitable distribution of AI-driven healthcare benefits [43]. These concerns underscore the urgent need for comprehensive regulatory frameworks and clear guidelines to ensure the responsible development and deployment of AI in medical imaging [44] [45].

Computational Resources

The substantial computational demands of training and deploying complex deep learning models, particularly foundation models with vast parameter counts, present significant infrastructural and financial barriers [46]. These resource limitations can restrict access to advanced AI tools for institutions with fewer resources, potentially widening healthcare disparities [47].

Future Directions and Emerging Trends

Emerging trends indicate a shift towards more generalized and adaptable AI solutions, such as foundation models, which are pre-trained on extensive datasets and can be fine-tuned for various downstream tasks, significantly reducing the need for extensive de novo annotation [48]. This paradigm promises to accelerate the development of AI applications in medical imaging by leveraging transferable knowledge, thereby improving efficiency and broadening applicability across diverse clinical scenarios [49].

Federated Learning and Privacy-Preserving AI

Federated learning offers a solution to data privacy concerns by enabling collaborative model training across multiple institutions without centralizing sensitive patient data [50]. This approach allows for the aggregation of insights from diverse datasets while maintaining data locality and confidentiality, a critical factor for sensitive medical information [51].

Self-supervised and Unsupervised Learning

These methodologies are particularly valuable in medical imaging, where labeled data is scarce, as they can learn meaningful representations directly from unlabeled data, thereby reducing the dependency on laborious manual annotation processes. Furthermore, advancements in self-supervised learning, such as contrastive learning and masked image modeling, enable the extraction of robust features from vast quantities of unlabeled medical images, paving the way for more data-efficient and scalable AI model development [52]. This approach is particularly beneficial for foundational models, which are characterized by large deep neural networks trained on extensive data through self-supervised learning, enabling efficient adaptation across various medical imaging tasks while reducing dependency on labeled data [53] [46].

Multimodal Learning

Integrating information from diverse data sources, such as medical images, electronic health records, and genomic data, promises a more comprehensive understanding of disease, leading to more accurate diagnoses and personalized treatment plans. This holistic approach leverages the synergistic power of different data types to construct richer patient profiles, moving beyond single-modality limitations [48].

Integration with Clinical Decision Support Systems

The seamless integration of AI-driven insights directly into clinical workflows can empower healthcare professionals with real-time diagnostic assistance and predictive analytics, thereby enhancing the efficiency and effectiveness of medical interventions. This integration can also facilitate proactive patient management by identifying individuals at high risk for certain conditions, allowing for earlier interventions and improved patient outcomes. Such advancements position AI as a transformative force, enabling clinicians to make more informed decisions, streamline operational processes, and ultimately elevate the standard of patient care [54].

Advancements in Hardware and Software

Continuous innovation in computing power, driven by specialized processors like GPUs and TPUs, along with the development of optimized deep learning frameworks, is crucial for supporting the increasing complexity and scale of medical AI models. These technological leaps enable faster training times and more efficient inference, which are vital for deploying real-time AI solutions in demanding clinical environments [55]. Moreover, the evolution of distributed computing architectures and cloud-based platforms is increasingly democratizing access to these powerful resources, fostering broader participation in AI research and development within the medical domain. This ongoing progress is pivotal for facilitating the adoption of advanced AI techniques, such as foundation models for 3D medical imaging, which require substantial computational resources for both training and deployment [56].

Conclusion

The rapid advancements in AI, particularly within medical data analysis, have significantly enhanced diagnostic precision and therapeutic planning, underscoring its role in precision medicine [57] [58]. However, despite substantial progress, several challenges remain, including the need for robust generalization across diverse patient populations and the development of ethical frameworks to govern AI's increasing autonomy in clinical decision-making [59]. Future efforts must therefore focus on improving AI interpretability and transparency to foster trust among clinicians, while also addressing issues of algorithmic bias and data security to ensure equitable and safe implementation [60]. Addressing these challenges will be paramount to realizing the full potential of AI in revolutionizing healthcare delivery and improving patient outcomes globally [61] [62]. The widespread implementation of AI in healthcare, while promising, necessitates overcoming fundamental concerns related to data quality, privacy, and algorithmic biases to fully unlock its transformative potential [63] [64]. The integration of machine learning and deep neural networks in medical imaging interpretation, pathology analysis, and complex pattern recognition has demonstrated remarkable accuracy across diverse datasets, facilitating earlier disease detection and more precise treatment selection [65]. Furthermore, AI's capacity to process extensive datasets more rapidly and accurately than human counterparts is improving clinical decision-making and patient prognoses [66]. This predictive capability extends to identifying subtle patterns indicative of disease progression, thereby enabling proactive interventions and personalized treatment regimens [67].

References

[1] S. K. Zhou *et al.* , “A Review of Deep Learning in Medical Imaging: Imaging Traits, Technology Trends, Case Studies With Progress Highlights, and Future Promises,” *Proceedings of the IEEE* , vol. 109, no. 5. Institute of Electrical and Electronics Engineers, p. 820, Feb. 26, 2021. doi: 10.1109/jproc.2021.3054390.

[2] F. Olaoye, A. Egon, and L. Doris, “Deep Learning Techniques for Medical Image Analysis and Diagnosis,” *Research Square (Research Square)* , Oct. 2024, doi: 10.21203/rs.3.rs-5339461/v1.

[3] Y. Bian, J. Li, C. Ye, X. Jia, and Q. Yang, “Artificial intelligence in medical imaging: From task-specific models to large-scale foundation models,” *Chinese Medical Journal* . Lippincott Williams & Wilkins, Feb. 26, 2025. doi: 10.1097/cm9.0000000000003489.

[4] G. K. Thakur, A. Thakur, S. Kulkarni, N. Khan, and S. Khan, “Deep Learning Approaches for Medical Image Analysis and Diagnosis,” *Cureus* , May 2024, doi: 10.7759/cureus.59507.

[5] A. A. Eli and A. Ali, “Deep Learning Applications in Medical Image Analysis: Advancements, Challenges, and Future Directions,” 2024, doi: 10.48550/ARXIV.2410.14131.

[6] X. Li, L. Zhang, J. Yang, and F. Teng, “Role of Artificial Intelligence in Medical Image Analysis: A Review of Current Trends and Future Directions,” *Journal of Medical and*

Biological Engineering , vol. 44, no. 2. Springer Science+Business Media, p. 231, Apr. 01, 2024. doi: 10.1007/s40846-024-00863-x.

[7] R. Haripriya, N. Khare, and M. Pandey, "Privacy-preserving federated learning for collaborative medical data mining in multi-institutional settings," *Scientific Reports* , vol. 15, no. 1, Apr. 2025, doi: 10.1038/s41598-025-97565-4.

[8] D. Koh *et al.* , "Artificial intelligence and machine learning in cancer imaging," *Communications Medicine* , vol. 2, no. 1. Nature Portfolio, Oct. 27, 2022. doi: 10.1038/s43856-022-00199-0.

[9] D. Giansanti, "Revolutionizing Medical Imaging: The Transformative Role of Artificial Intelligence in Diagnostics and Treatment," *Diagnostics* , vol. 15, no. 12, p. 1557, Jun. 2025, doi: 10.3390/diagnostics15121557.

[10] L. Coelho, "How Artificial Intelligence Is Shaping Medical Imaging Technology: A Survey of Innovations and Applications," *Bioengineering* , vol. 10, no. 12, p. 1435, Dec. 2023, doi: 10.3390/bioengineering10121435.

[11] M. Li, Y. Jiang, Y. Zhang, and Z. Haisheng, "Medical image analysis using deep learning algorithms," *Frontiers in Public Health* , vol. 11. Frontiers Media, Nov. 07, 2023. doi: 10.3389/fpubh.2023.1273253.

[12] G. Ayana, K. Dese, A. M. Abagaro, K. C. Jeong, S. Yoon, and S. Choe, "Multistage transfer learning for medical images," *Artificial Intelligence Review* , vol. 57, no. 9, Aug. 2024, doi: 10.1007/s10462-024-10855-7.

[13] V. K. Prasad *et al.* , "Revolutionizing healthcare: a comparative insight into deep learning's role in medical imaging," *Scientific Reports* , vol. 14, no. 1, Dec. 2024, doi: 10.1038/s41598-024-71358-7.

[14] V. Berezovsky and N. V. Vygovskaya, "An overview of neural networks for medical image recognition," *E3S Web of Conferences* , vol. 460, p. 4028, Jan. 2023, doi: 10.1051/e3sconf/202346004028.

[15] Y. Brima and M. Atemkeng, "Saliency-driven explainable deep learning in medical imaging: bridging visual explainability and statistical quantitative analysis," *BioData Mining* , vol. 17, no. 1, Jun. 2024, doi: 10.1186/s13040-024-00370-4.

[16] M. Zubair *et al.* , "An Interpretable Framework for Gastric Cancer Classification Using Multi-Channel Attention Mechanisms and Transfer Learning Approach on Histopathology Images," *Research Square (Research Square)* , Nov. 2024, doi: 10.21203/rs.3.rs-5316440/v1.

[17] L. Dao and N. Q. Ly, "Recent Advances in Medical Image Classification," *International Journal of Advanced Computer Science and Applications* , vol. 15, no. 7, Jan. 2024, doi: 10.14569/ijacsa.2024.0150727.

[18] T. M. Fagbola and I. Success, "Leveraging Pretrained Models for Multimodal Medical Image Interpretation: An Exhaustive Experimental Analysis," *medRxiv (Cold Spring Harbor Laboratory)* , Aug. 2024, doi: 10.1101/2024.08.09.24311762.

[19] C. Jiménez-Mesa, J. E. Arco, F. J. Martínez-Murcia, J. Suckling, J. Ramírez, and J. M. Górriz, "Applications of machine learning and deep learning in SPECT and PET imaging: General overview, challenges and future prospects," *Pharmacological Research* , vol. 197. Elsevier BV, p. 106984, Nov. 01, 2023. doi: 10.1016/j.phrs.2023.106984.

[20] M. Rahmani, A. Kazemi, M. J. Aziz, E. Najafzadeh, P. Farnia, and A. Ahmadian, "A Systematic Review on Medical Image Segmentation using Deep Learning," *Scientia Iranica* , vol., no. Sharif University of Technology, p. 0, Jul. 22, 2024. doi: 10.24200/sci.2024.61686.7441.

[21] H. H. Zhang and Y. Qie, "Applying Deep Learning to Medical Imaging: A Review," *Applied Sciences* , vol. 13, no. 18. Multidisciplinary Digital Publishing Institute, p. 10521, Sep. 21, 2023. doi: 10.3390/app131810521.

[22] S. S.K.B *et al.* , "An enhanced multimodal fusion deep learning neural network for lung cancer classification," *Systems and Soft Computing* , vol. 6, p. 200068, Dec. 2023, doi: 10.1016/j.sasc.2023.200068.

[23] A. Rasekh *et al.* , "Towards Precision Healthcare: Robust Fusion of Time Series and Image Data," *arXiv (Cornell University)* , May 2024, doi: 10.48550/arxiv.2405.15442.

[24] Md. E. Rayed, S. M. S. Islam, S. I. Niha, J. R. Jim, Md. M. Kabir, and M. F. Mridha, "Deep learning for medical image segmentation: State-of-the-art advancements and challenges," *Informatics in Medicine Unlocked* , vol. 47, p. 101504, Jan. 2024, doi: 10.1016/j.imu.2024.101504.

[25] Z. Jian *et al.* , "Deep learning method for detecting fluorescence spots in cancer diagnostics via fluorescence in situ hybridization," *Scientific Reports* , vol. 14, no. 1, Nov. 2024, doi: 10.1038/s41598-024-78571-4.

[26] R. Heckel, M. Jacob, A. Chaudhari, O. Perlman, and E. Shimron, "Deep Learning for Accelerated and Robust MRI Reconstruction: a Review," *arXiv (Cornell University)* . Cornell University, Apr. 24, 2024. doi: 10.48550/arxiv.2404.15692.

[27] Z. Chen, K. Pawar, M. Ekanayake, C. D. Pain, S. Zhong, and G. F. Egan, "Deep Learning for Image Enhancement and Correction in Magnetic Resonance Imaging—State-of-the-Art and Challenges," *Journal of Digital Imaging* , vol. 36, no. 1. Springer Science+Business Media, p. 204, Nov. 02, 2022. doi: 10.1007/s10278-022-00721-9.

[28] M. Yaqub *et al.* , "Deep Learning-Based Image Reconstruction for Different Medical Imaging Modalities," *Computational and Mathematical Methods in Medicine* , vol. 2022. Hindawi Publishing Corporation, p. 1, Jun. 16, 2022. doi: 10.1155/2022/8750648.

[29] A. B. Pawar, C. Priya, V. V. J. R. Krishnaiah, V. A. A. Daniel, Y. A. B. El–Ebiary, and A. I. Taloba, "Multi-Scale Deep Learning-based Recurrent Neural Network for Improved Medical Image Restoration and Enhancement," *International Journal of Advanced Computer Science and Applications* , vol. 14, no. 10, Jan. 2023, doi: 10.14569/ijacsa.2023.0141088.

[30] P. K. Mall *et al.* , "A comprehensive review of deep neural networks for medical image processing: Recent developments and future opportunities," *Healthcare Analytics* , vol. 4. Elsevier BV, p. 100216, Jul. 11, 2023. doi: 10.1016/j.health.2023.100216.

[31] M. Feigin, D. Z. Freedman, and B. Anthony, "A Deep Learning Framework for Single-Sided Sound Speed Inversion in Medical Ultrasound," *IEEE Transactions on Biomedical Engineering* , vol. 67, no. 4, p. 1142, Jul. 2019, doi: 10.1109/tbme.2019.2931195.

[32] R. Heckel, M. Jacob, A. Chaudhari, O. Perlman, and E. Shimron, "Deep learning for accelerated and robust MRI reconstruction," *Magnetic Resonance Materials in Physics Biology and Medicine* , vol. 37, no. 3. Springer Science+Business Media, p. 335, Jul. 23, 2024. doi: 10.1007/s10334-024-01173-8.

[33] K. Song, J. Feng, and D. Chen, "A survey on deep learning in medical ultrasound imaging," *Frontiers in Physics* , vol. 12, Jul. 2024, doi: 10.3389/fphy.2024.1398393.

[34] C. Albuquerque, R. Henriques, and M. Castelli, "Deep learning-based object detection algorithms in medical imaging: Systematic review," *Heliyon* , vol. 11, no. 1. Elsevier BV, Dec. 11, 2024. doi: 10.1016/j.heliyon.2024.e41137.

[35] F. Zartashea, "Revolutionizing disease diagnosis: The role of deep learning in medical imaging and radiology," *International Journal of Science and Research Archive* , vol. 10, no. 1, p. 1175, Oct. 2023, doi: 10.30574/ijsra.2023.10.1.0707.

[36] Y. Hong, X. Zhang, X. Zhang, and J. T. Zhou, "Evolution-aware VAriance (EVA) Coreset Selection for Medical Image Classification," *arXiv (Cornell University)* , Jun. 2024, doi: 10.1145/3664647.3681592.

[37] S. Reka, T. S. Praba, M. Prasanna, V. Y. Reddy, and R. Amirtharajan, "Automated high precision PCOS detection through a segment anything model on super resolution ultrasound ovary images," *Scientific Reports* , vol. 15, no. 1, May 2025, doi: 10.1038/s41598-025-01744-2.

[38] C. Singh, "Medical Imaging using Deep Learning Models," *European Journal of Engineering and Technology Research* , vol. 6, no. 5, p. 156, Aug. 2021, doi: 10.24018/ejeng.2021.6.5.2491.

[39] B. Geçer, S. Aksoy, E. Mercan, L. G. Shapiro, D. L. Weaver, and J. G. Elmore, "Detection and classification of cancer in whole slide breast histopathology images using deep convolutional networks," *Pattern Recognition* , vol. 84, p. 345, Jul. 2018, doi: 10.1016/j.patcog.2018.07.022.

[40] T. C. Cornish, "Artificial intelligence for automating the measurement of histologic image biomarkers," *Journal of Clinical Investigation* , vol. 131, no. 8, American Society for Clinical Investigation, Apr. 14, 2021. doi: 10.1172/jci147966.

[41] C. L. Srinidhi, O. Ciga, and A. L. Martel, "Deep neural network models for computational histopathology: A survey," *Medical Image Analysis* , vol. 67. Elsevier BV, p. 101813, Sep. 25, 2020. doi: 10.1016/j.media.2020.101813.

[42] L. Cai *et al.* , "Deep learning on T2WI to predict the muscle-invasive bladder cancer: a multi-center clinical study," *Scientific Reports* , vol. 15, no. 1, Mar. 2025, doi: 10.1038/s41598-024-82909-3.

[43] D. Hellwig, N. C. Hellwig, S. Boehner, T. Fuchs, R. S. Fischer, and D. Schmidt, "Artificial Intelligence and Deep Learning for Advancing PET Image Reconstruction: State-of-the-Art and Future Directions," *Nuklearmedizin - NuclearMedicine* , vol. 62, no. 6. Schattauer Verlag, p. 334, Nov. 23, 2023. doi: 10.1055/a-2198-0358.

[44] S. Reddy and S. Shaikh, "The long road ahead: navigating obstacles and building bridges for clinical integration of artificial intelligence technologies," *Journal of Medical Artificial Intelligence* , vol. 8, p. 7, Nov. 2024, doi: 10.21037/jmai-24-148.

[45] P. Göktaş and A. Grzybowski, "Shaping the Future of Healthcare: Ethical Clinical Challenges and Pathways to Trustworthy AI," *Journal of Clinical Medicine* , vol. 14, no. 5, p. 1605, Feb. 2025, doi: 10.3390/jcm14051605.

[46] A. Das *et al.* , "Ethical Framework for Responsible Foundational Models in Medical Imaging," *arXiv (Cornell University)* , Apr. 2024, doi: 10.48550/arxiv.2406.11868.

[47] G.-S. Hong *et al.*, "Overcoming the Challenges in the Development and Implementation of Artificial Intelligence in Radiology: A Comprehensive Review of Solutions Beyond Supervised Learning," *Korean Journal of Radiology*, vol. 24, no. 11. Korean Society of Radiology, p. 1061, Jan. 01, 2023. doi: 10.3348/kjr.2023.0393.

[48] S. Zhang and D. Metaxas, "On the challenges and perspectives of foundation models for medical image analysis," *Medical Image Analysis*, vol. 91, p. 102996, Oct. 2023, doi: 10.1016/j.media.2023.102996.

[49] S. Pai *et al.*, "Foundation Models for Quantitative Biomarker Discovery in Cancer Imaging," *medRxiv (Cold Spring Harbor Laboratory)*, Sep. 2023, doi: 10.1101/2023.09.04.23294952.

[50] J. W. Kim, A. U. Khan, and I. Banerjee, "Systematic Review of Hybrid Vision Transformer Architectures for Radiological Image Analysis," *medRxiv (Cold Spring Harbor Laboratory)*, Jun. 2024, doi: 10.1101/2024.06.21.24309265.

[51] Y. Chen, X. Shao, K. Shi, A. Rominger, and F. Caobelli, "AI in Breast Cancer Imaging: An Update and Future Trends," *Seminars in Nuclear Medicine*. Elsevier BV, Feb. 01, 2025. doi: 10.1053/j.semnuclmed.2025.01.008.

[52] S. Kang, W. D. Neve, F. Rameau, and U. Özbulak, "Exploring Patient Data Requirements in Training Effective AI Models for MRI-Based Breast Cancer Classification," in *Lecture notes in computer science*, Springer Science+Business Media, 2025, p. 75. doi: 10.1007/978-3-031-77789-9_8.

[53] D. Queiroz, A. Carlos, A. Anjos, and L. Berton, "Fair Foundation Models for Medical Image Analysis: Challenges and Perspectives," 2025, doi: 10.48550/ARXIV.2502.16841.

[54] C. Shi, R. Rezai, J. Yang, Q. Dou, and X. Li, "A Survey on Trustworthiness in Foundation Models for Medical Image Analysis," 2024, doi: 10.48550/ARXIV.2407.15851.

[55] J. Barański, "Examples of implementations and the future of AI in medical diagnostics," *Przeglad Epidemiologiczny*, Oct. 2024, doi: 10.32394/pe/195240.

[56] H. S. Ying, Y. Lia, Z. Fu, and C. Mei, "Foundation Models as a Catalyst for Next-Generation 3D Medical Imaging," *HAL (Le Centre pour la Communication Scientifique Directe)*, Jul. 2025, Accessed: Oct. 2025. [Online]. Available: https://hal.science/hal-05170327

[57] K. Sun *et al.*, "Medical multimodal foundation models in clinical diagnosis and treatment: Applications, challenges, and future directions.," *PubMed*, vol. 170. National Institutes of Health, p. 103265, Sep. 12, 2025. doi: 10.1016/j.artmed.2025.103265.

[58] K. Sun *et al.*, "Medical Multimodal Foundation Models in Clinical Diagnosis and Treatment: Applications, Challenges, and Future Directions," 2024, doi: 10.48550/ARXIV.2412.02621.

[59] Y. Nam *et al.*, "Harnessing Artificial Intelligence in Multimodal Omics Data Integration: Paving the Path for the Next Frontier in Precision Medicine," *Annual Review of Biomedical Data Science*, vol. 7, no. 1. Annual Reviews, p. 225, May 20, 2024. doi: 10.1146/annurev-biodatasci-102523-103801.

[60] P. S. Aravazhi *et al.*, "The integration of artificial intelligence into clinical medicine: Trends, challenges, and future directions," *Disease-a-Month*. Elsevier BV, p. 101882, Mar. 01, 2025. doi: 10.1016/j.disamonth.2025.101882.

[61] M. N. Aftab, A. Nadeem, C. Zhang, Z. Dong, Y. Jiang, and K. Liu, "Advancements and Challenges in Artificial Intelligence Applications in Healthcare Delivery Systems," Jul. 2024, doi: 10.20944/preprints202407.0938.v1.

[62] Y. A. Fahim, I. W. Hasani, S. Kabba, and W. M. Ragab, "Artificial intelligence in healthcare and medicine: clinical applications, therapeutic advances, and future perspectives," *European journal of medical research* , vol. 30, no. 1. BioMed Central, Sep. 23, 2025. doi: 10.1186/s40001-025-03196-w.

[63] C. Carini and A. A. Seyhan, "Tribulations and future opportunities for artificial intelligence in precision medicine," *Journal of Translational Medicine* , vol. 22, no. 1. BioMed Central, p. 411, Apr. 30, 2024. doi: 10.1186/s12967-024-05067-0.

[64] Md. Faiyazuddin *et al.* , "The Impact of Artificial Intelligence on Healthcare: A Comprehensive Review of Advancements in Diagnostics, Treatment, and Operational Efficiency," *Health Science Reports* , vol. 8, no. 1. Wiley, Jan. 01, 2025. doi: 10.1002/hsr2.70312.

[65] U. Sridhar, "AI in healthcare: Revolutionizing medical diagnosis," *World Journal of Advanced Research and Reviews* , vol. 26, no. 1, p. 3229, Apr. 2025, doi: 10.30574/wjarr.2025.26.1.1385.

[66] D. Patil, "The Future of Artificial Intelligence in Healthcare: Opportunities, Challenges, and Ethical Considerations," Jan. 2024, doi: 10.2139/ssrn.5021252.

[67] N. Mahesh *et al.* , "Advancing healthcare: the role and impact of AI and foundation models," *American Journal of Translational Research* , vol. 16, no. 6. e-Century Publishing Corporation, p. 2166, Jan. 01, 2024. doi: 10.62347/wqwv9220.