Review

Not peer-reviewed version

Artificial Intelligence in Diagnostic Imaging: Enhancing Patient Care Through Advanced Algorithms and Data Integration

Shazia Hassan *

Posted Date: 5 March 2025

doi: 10.20944/preprints202503.0344.v1

Keywords: Artificial Intelligence; Diagnostics Imaging; Radiography; Cardiovascular Imaging; Cardiovascular Events; Clinical Workflows; Deep Learning; MRI; Imaging Biomarkers; Computed Tomography; Workflow Optimization

Review

Artificial Intelligence in Diagnostic Imaging: Enhancing Patient Care Through Advanced Algorithms and Data Integration

Shazia Hassan

Product Engineering & Development Department, Deloitte Consulting LLP, Loganville, GA, USA; hassanshazia1111182@gmail.com

Abstract: This paper presents a comprehensive overview of how artificial intelligence (AI) is revolutionizing diagnostic imaging through advanced machine learning and deep learning techniques. It explores the fundamental principles behind AI innovations—including traditional methods like Support Vector Machines and Random Forests, as well as deep learning models such as convolutional neural networks and transformer-based architectures—and their applications in detecting, classifying, and segmenting medical images. The discussion extends to the critical role of data curation, performance evaluation, and emerging strategies like transfer learning and multi-task learning in enhancing model robustness and generalizability. In addition, the paper reviews AI applications across various imaging modalities, including radiography, CT, MRI, ultrasound, and nuclear medicine, while highlighting key clinical tasks and use cases such as automated detection, segmentation, diagnosis, and workflow optimization. Finally, it examines the technical, operational, and regulatory challenges associated with integrating AI into clinical workflows, emphasizing the need for rigorous validation, compliance with international and national standards, and transparent risk management. Together, these insights underscore AI's transformative potential to improve diagnostic accuracy, streamline clinical decision-making, and ultimately enhance patient outcomes.

Keywords: Artificial Intelligence; Diagnostics Imaging; Radiography; Cardiovascular Imaging; Cardiovascular Events; Clinical Workflows; Deep Learning; MRI; Imaging Biomarkers; Computed Tomography; Workflow Optimization

---

I. INTRODUCTION

Artificial Intelligence (AI) is rapidly transforming diagnostic imaging by leveraging advanced machine learning and deep learning techniques to extract meaningful information from vast arrays of medical images. By deploying powerful algorithms such as convolutional neural networks and emerging transformer-based models, AI is enhancing tasks like detection, classification, and segmentation across modalities—including radiography, CT, MRI, ultrasound, and nuclear medicine. These innovations not only improve diagnostic accuracy and streamline clinical workflows but also enable personalized treatment planning through the integration of imaging biomarkers with clinical data. Moreover, as AI systems become increasingly embedded in imaging practices, their adoption introduces new technical, operational, and regulatory challenges that must be addressed to ensure safety, data integrity, and clinical utility. This paper provides a comprehensive overview of the fundamental principles, practical applications, clinical use cases, and regulatory considerations driving the future of AI in diagnostic imaging.

II. FUNDAMENTALS OF AI IN DIAGNOSTIC IMAGING

Machine learning (ML) and deep learning (DL) form the backbone of current AI innovations in diagnostic imaging, allowing computers to recognize patterns and make predictions from large sets

 doi:10.20944/preprints202503.0344.v1

of medical images. Traditional ML methods, such as Support Vector Machines (SVM) and Random Forests, have been widely adopted for tasks like classification and feature selection due to their ability to handle structured data and a moderate number of variables [3]. However, deep learning, particularly convolutional neural networks (CNNs), has demonstrated superior performance in imaging tasks that require complex feature extraction, such as lesion detection and segmentation [1]. Beyond CNNs, emerging transformer-based architectures—originally introduced in natural language processing—are being adapted for medical image analysis, leveraging self-attention mechanisms to capture long-range spatial dependencies within images [5]. From a learning perspective, AI models can be classified as supervised, relying on labeled data; unsupervised, identifying hidden patterns without labels; or reinforcement learning, which adjusts model parameters based on reward-driven feedback, each approach offering unique advantages for specific imaging scenarios [6].

A critical prerequisite for robust AI models is the availability of large, diverse, and accurately annotated datasets to prevent bias and ensure generalizability across various populations [3]. Data curation—encompassing preprocessing steps like normalization, noise reduction, and augmentation—further refines image inputs, boosting model performance and resilience to overfitting [1]. Once trained, the effectiveness of AI algorithms in diagnostic imaging is commonly measured using metrics such as accuracy, sensitivity, specificity, area under the receiver operating characteristic curve (AUC), and F1 score, each providing distinct insights into diagnostic performance [4]. To reinforce reproducibility and reliability, k-fold cross-validation or external validation with unseen datasets is recommended, as these methods rigorously test model stability and performance beyond the training data [2]. Ensuring rigorous evaluation is essential for translating AI-based diagnostic tools from experimental settings into routine clinical practice.

In addition to the foundational aspects discussed, emerging techniques such as transfer learning and multi-task learning are increasingly pivotal in medical imaging applications. Transfer learning enables models pretrained on large, generic image datasets to be adapted to specific diagnostic tasks with relatively limited labelled medical images [1]. This approach not only reduces the need for extensive annotated datasets but also shortens training times while maintaining high accuracy. Multi-task learning frameworks further enhance performance by enabling a single model to perform several related tasks—such as classification, segmentation, and localization—simultaneously. This integrated approach can improve consistency across diagnostic tasks and streamline clinical workflows.

A critical component in harnessing the full potential of these algorithms is meticulous data curation. Large, diverse, and well-annotated datasets are indispensable for building robust models that generalize well to various clinical scenarios. Public repositories like The Cancer Imaging Archive (TCIA) offer a wealth of imaging data, yet challenges remain in harmonizing datasets from different institutions, each with its own imaging protocols and quality standards. Advanced preprocessing steps, including image normalization, artifact correction, and noise reduction, help standardize the input data. Furthermore, data augmentation techniques—such as geometric transformations (rotation, scaling, flipping) and synthetic data generation using methods like generative adversarial networks (GANs)—play a crucial role in expanding the effective dataset size and diversity, thereby mitigating overfitting and enhancing model robustness [3].

Rigorous performance evaluation is essential to ensure that AI models meet the stringent demands of clinical diagnostic tasks. Standard metrics such as accuracy, sensitivity, specificity, area under the receiver operating characteristic curve (AUC), and F1 score offer quantitative insights into different facets of model performance. For instance, in screening applications, high sensitivity is critical to minimize false negatives, while high specificity helps reduce unnecessary follow-up procedures for benign cases. In addition to these metrics, calibration curves and decision curve analysis provide valuable information about the alignment of predicted probabilities with actual clinical outcomes. To ensure that models are robust and generalizable, validation techniques such as k-fold cross-validation and testing on independent external datasets are widely employed. These

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 March 2025 doi:10.20944/preprints202503.0344.v1

methods are fundamental not only for assessing performance but also for ensuring reproducibility—an essential criterion for transitioning AI applications from the laboratory to the clinic [2].

Furthermore, as AI systems in diagnostic imaging evolve to handle more complex tasks—including predictive analytics and personalized treatment planning—the integration of clinical data with imaging biomarkers is becoming increasingly important. This multidimensional approach necessitates even more sophisticated evaluation frameworks and standardized metrics to comprehensively assess model performance across varied patient populations and imaging modalities.

Together, these developments underscore a dynamic landscape where advanced algorithmic strategies, comprehensive data management, and rigorous performance evaluation converge to enhance diagnostic accuracy and clinical decision-making. As research in this field continues to progress, ongoing refinement in both methodology and evaluation standards will be essential to fully realize the transformative potential of AI in diagnostic imaging.

III. AI APPLICATIONS ACROSS IMAGING MODALITIES

A. Radiography (X-ray)

In radiography, AI has been harnessed to significantly improve diagnostic accuracy and workflow efficiency. Deep learning algorithms—particularly convolutional neural networks (CNNs)—have been employed for a range of tasks including lung nodule detection, tuberculosis (TB) screening, fracture identification, and the development of triage systems. For example, CNN-based models like CheXNet have demonstrated radiologist-level performance in detecting pneumonia and lung nodules on chest X-rays, thereby aiding in early diagnosis and management of pulmonary conditions [12]. In TB screening, algorithms analyze subtle radiographic patterns such as cavitations, consolidations, and nodular opacities, facilitating rapid and accurate identification of TB cases even in high-volume settings [9]. Additionally, fracture detection models help flag potential skeletal injuries in emergency departments, ensuring timely follow-up by specialists. The integration of these AI-driven systems into routine radiographic workflows can reduce diagnostic delays and help prioritize urgent cases, ultimately enhancing patient care. The changes in the role of radiologists will be observed due to AI intervention. The radiologists would be involved in the decision for making the diagnosis using AI saving some time for improving the patient interaction [14].

B. Computed Tomography (CT):

CT imaging has witnessed robust AI integration for both diagnostic and quantitative assessment tasks. Deep learning models are being applied for tumor detection across several organ systems, including the lungs, liver, and brain. In lung cancer screening, for instance, AI assists in the detection and characterization of pulmonary nodules, thereby reducing the radiologist's burden and improving early detection rates. Similarly, in liver and brain imaging, AI facilitates the segmentation and volumetric measurement of lesions, which is crucial for surgical planning and radiotherapy [7]. Beyond tumor detection, AI algorithms have been pivotal in cardiovascular imaging; they can evaluate CT angiography images for coronary artery disease by identifying plaque buildup and vessel stenosis. The COVID-19 pandemic further accelerated the application of AI in CT, with models developed to differentiate COVID-19 pneumonia from other types of pneumonia based on imaging features [10]. Quantifying coronary artery calcium (CAC) from gated CT scans and evaluating heart chamber dimensions can predict cardiac risk by revealing calcification and structural changes linked to cardiovascular disease. AI can analyze routine chest CTs to uncover hidden prognostic features, enabling opportunistic screening and early intervention to potentially save lives [20]. AI integrated within CT scan by These tools not only enhance diagnostic precision but also support longitudinal monitoring and treatment response assessments by providing reliable, automated measurements.

 doi:10.20944/preprints202503.0344.v1

C. Magnetic Resonance Imaging (MRI)

In the realm of MRI, AI is revolutionizing both diagnostic accuracy and operational efficiency. Advanced deep learning techniques are used extensively in neuroimaging to segment and classify brain tumors, delineate lesions in multiple sclerosis, and assess other neurological abnormalities. This automated segmentation aids neurosurgeons and radiologists in accurately planning interventions and monitoring disease progression. Beyond neuroimaging, AI applications in musculoskeletal MRI help in identifying soft tissue injuries and joint abnormalities, contributing to improved diagnostic consistency. In cardiac MRI, AI algorithms analyze complex dynamic sequences to quantify ventricular function, measure myocardial strain, and assess tissue viability. One of the most impactful innovations has been the use of AI to accelerate image acquisition. Techniques like compressed sensing combined with deep learning reconstructions have significantly reduced scan times without compromising image quality [13]. MRI produces high-resolution images, but long scan times can affect patient comfort and diagnostic efficiency. AI deep learning techniques now enable faster, high-quality imaging, improving patient outcomes and accessibility across various clinical fields. This not only increases patient comfort but also enhances throughput in busy clinical settings, enabling more rapid diagnosis and treatment planning.

D. Ultrasound:

Ultrasound imaging, widely valued for its portability and real-time imaging capabilities, has seen significant improvements through AI integration. In obstetric ultrasound, AI systems are developed to automate the measurement of fetal anatomical structures—reducing inter-operator variability and ensuring consistent assessment of fetal growth. Similarly, in echocardiography, AI models are employed to identify standard cardiac views, quantify functional parameters such as ejection fraction, and detect subtle abnormalities in wall motion. These advancements are particularly important in emergency settings where rapid decision-making is critical. Portable ultrasound devices equipped with AI are increasingly used in resource-limited environments, where they help deliver point-of-care diagnostics by providing immediate, automated interpretations that assist less experienced operators [8]. By standardizing image acquisition and interpretation, AI not only enhances diagnostic accuracy but also expands access to advanced imaging modalities in rural or under-resourced healthcare settings.

E. Nuclear Medicine (PET, SPECT):

In nuclear medicine, AI is emerging as a powerful tool to enhance the interpretation and quantification of molecular imaging studies. Deep learning algorithms are used to improve lesion detection in positron emission tomography (PET) and single-photon emission computed tomography (SPECT) scans, particularly in oncologic applications where early identification of metastases is critical. These AI models can also optimize image reconstruction, thereby enhancing image quality and reducing noise—an essential factor when operating at low radiation doses. Furthermore, the integration of hybrid imaging modalities, such as PET-CT and PET-MRI, is enhanced by AI, which fuses anatomical and functional data to provide a more comprehensive assessment of disease. This hybrid approach allows for more precise quantification of tracer uptake and improved lesion characterization, facilitating personalized treatment planning in both oncology and neurology [11]. As a result, AI-driven nuclear medicine applications are poised to refine diagnostic workflows and contribute to more tailored therapeutic strategies.

IV. KEY CLINICAL TASKS AND USE CASES

A. Detention and Classification:

One of the most transformative applications of AI in diagnostic imaging is the automated detection and classification of pathological findings. Deep learning algorithms—especially

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 March 2025 doi:10.20944/preprints202503.0344.v1

convolutional neural networks (CNNs)—have been developed to automatically identify nodules, calcifications, lesions, and other subtle abnormalities across various imaging modalities. These systems analyze complex image features such as shape, texture, and intensity, enabling the differentiation between benign and malignant lesions with a performance that in many cases approaches that of expert radiologists [3][1]. For instance, in chest radiography, AI algorithms are adept at detecting lung nodules and classifying them based on malignancy risk, thereby facilitating early intervention. This automated detection not only accelerates the diagnostic process but also reduces interobserver variability, ensuring a more consistent assessment across different clinical settings

B. Segmentation:

Accurate segmentation—the delineation of organs, tumors, or other regions of interest—is crucial in modern diagnostic imaging, and AI has markedly advanced this area. Automated segmentation tools powered by deep learning enable precise boundary detection of anatomical structures, which is indispensable for treatment planning in oncology, surgical navigation, and radiation therapy. In practice, these algorithms can generate volumetric measurements of tumors, monitor changes over time, and aid in the quantification of disease burden [13]. For example, in the management of brain tumors or liver lesions, AI-driven segmentation provides reliable metrics that inform both surgical and radiotherapeutic decisions. This level of precision is essential not only for accurate diagnosis but also for tracking disease progression and evaluating treatment efficacy

C. Diagnosis and Prognosis:

Beyond detecting and segmenting lesions, AI is increasingly integral to enhancing diagnostic accuracy and informing prognosis. By integrating imaging findings with complementary clinical data—such as laboratory results, patient demographics, and medical history—AI systems can perform comprehensive risk stratification and predict patient outcomes. Predictive models developed using multi-modal data have been shown to guide personalized treatment planning, such as determining the aggressiveness of therapy in oncology or anticipating adverse cardiovascular events [7]. This fusion of imaging biomarkers with clinical variables not only refines the diagnostic process but also supports the development of tailored treatment paths that improve overall patient management and outcomes.

D. Triage and Workflow/ Process Optimization:

AI is also revolutionizing operational workflows in diagnostic imaging departments. Automated triage systems employ AI to sort imaging studies by urgency, ensuring that high-priority cases are flagged for immediate review. This prioritization is particularly beneficial in high-volume clinical settings, where timely intervention can significantly affect patient outcomes. Moreover, AI algorithms contribute to quality assurance by detecting artifacts such as motion blur, verifying that imaging protocols are correctly followed, and flagging suboptimal image quality that could compromise diagnostic accuracy [4]. By streamlining these processes, AI not only alleviates the workload of radiologists but also enhances overall efficiency, reduces backlogs, and improves the reliability of imaging studies, thereby contributing to a more effective and patient-centric workflow.

V. ADDITIONAL USE CASES IN AI-DRIVEN DIAGNOSTIC IMAGING

Beyond the core tasks of detection, classification, segmentation, and workflow optimization, several emerging use cases underscore AI's transformative potential in diagnostic imaging:

A. Radiomics and Imaging Biomarker Extraction:

Radiomics involves the extraction of high-dimensional quantitative features from medical images that capture subtle textural, shape, and intensity characteristics of tissues. AI algorithms have

 doi:10.20944/preprints202503.0344.v1

been instrumental in analyzing these features to reveal correlations with underlying genetic profiles and clinical outcomes. In oncology, radiomics has demonstrated promise in predicting treatment response and patient prognosis, thereby supporting precision medicine initiatives [15]. By converting imaging data into actionable biomarkers, AI-driven radiomics facilitates a more personalized approach to patient care.

B. Image Reconstruction and Enhancement:

AI is revolutionizing the image reconstruction process in modalities such as CT and MRI. Traditional reconstruction techniques are being enhanced by deep learning methods that significantly reduce noise and artifacts, enabling faster scan times and improved image quality. For example, deep learning-based reconstruction algorithms have shown the potential to lower radiation doses in CT imaging while preserving diagnostic detail [16]. Enhanced image quality not only boosts diagnostic confidence but also positively impacts subsequent tasks such as segmentation and quantitative analysis.

C. Real-Time Guidance in Interventional Procedures:

In interventional radiology and intraoperative imaging, real-time AI applications are emerging as valuable tools for procedure guidance. AI systems can automatically register preoperative images with live intraoperative data, thereby providing clinicians with enhanced navigation during procedures such as biopsies, catheter placements, and ablations. This real-time integration improves the accuracy of device placement and minimizes the risk of complications, ultimately contributing to better procedural outcomes.

D. Automated Reporting and Decision Support:

The generation of structured radiology reports is another area where AI is making significant strides. Leveraging natural language processing (NLP) and deep learning, automated reporting systems analyze imaging findings and suggest differential diagnoses, thereby assisting radiologists in producing preliminary reports. These systems help reduce reporting times, standardize diagnostic language, and serve as a decision support tool—ensuring that critical findings are not overlooked during high-volume workflows.

E. Multi-Modal Data Integration:

The convergence of imaging data with other clinical information, such as electronic health records, genomic data, and laboratory results, is paving the way for a more comprehensive view of patient health. AI algorithms are increasingly adept at integrating these diverse data sources, leading to more robust risk stratification models and personalized treatment plans. This holistic approach enhances diagnostic accuracy and improves prognostic assessments, facilitating tailored therapeutic strategies and better overall patient management.

VI. INTEGRATING AI INTO CLINICAL WORKFLOWS

A. Technical Integration:

A critical step in successfully incorporating AI into clinical workflows is its seamless integration with existing health information systems. AI tools must interface efficiently with Picture Archiving and Communication Systems (PACS) and Radiology Information Systems (RIS) to ensure that image data and associated patient records are readily accessible for analysis. This integration enables AI algorithms to automatically retrieve imaging studies, process them in real time, and then return annotated results that radiologists can review directly within their existing workstations [4].

 doi:10.20944/preprints202503.0344.v1

B. Operational Considerations:

The introduction of AI into diagnostic imaging workflows is not merely a technical upgrade—it also has profound operational implications. One of the most significant impacts is on radiologist productivity and job roles. AI systems, when used as a first or second reader, can automatically pre-screen studies to flag urgent cases or identify potential abnormalities. This triage function can reduce the time radiologists spend on routine tasks and allow them to focus on more complex cases. However, the integration of AI also necessitates a shift in roles; radiologists may need to evolve into "information specialists" who validate AI outputs and incorporate them into clinical decision-making [4].

This shift often requires targeted re-training and upskilling. Institutions are increasingly developing training programs that focus on AI literacy, helping clinicians understand the capabilities, limitations, and optimal use cases for these technologies. Moreover, workflow redesign is essential to fully leverage AI insights. For instance, some centers have adopted hybrid reading models where AI functions as a second reader, prompting radiologists to re-examine cases flagged by the system. Others have experimented with fully automated preliminary reads for specific high-volume screening tasks. In both scenarios, careful workflow redesign ensures that AI tools complement rather than disrupt established clinical processes, thereby maintaining diagnostic accuracy while enhancing efficiency.

C. Case Studies/ Real-World Implementations:

Several pilot projects and fully deployed AI systems have demonstrated tangible benefits in real-world clinical settings, supporting the argument for broader integration. For example, [7]. showcased an AI model for the detection of intracranial hemorrhage on CT scans. Their study demonstrated that the integration of the AI system within the clinical workflow not only improved detection rates but also significantly reduced time-to-diagnosis, leading to better patient outcomes in emergency settings.

Similarly, the implementation of systems like CheXNet for pneumonia detection on chest radiographs has shown promising results. These systems have achieved radiologist-level performance, improved turnaround times, and increased throughput in high-volume departments [12]. Pilot studies in various institutions have also reported positive return on investment (ROI) by reducing unnecessary follow-up procedures and optimizing resource allocation. User acceptance studies further indicate that when AI systems are integrated thoughtfully—accompanied by proper training and workflow adjustments—clinicians are more likely to trust and effectively use these tools, ultimately contributing to enhanced patient care [4].

VII. CONCLUSIONS

In summary, the integration of AI in diagnostic imaging marks a significant milestone in the evolution of medical technology. By harnessing advanced machine learning and deep learning techniques, AI systems are now capable of detecting, classifying, and segmenting complex imaging data with unprecedented accuracy, thereby enhancing diagnostic precision and patient care. The paper has highlighted how critical components—such as data curation, robust evaluation methodologies, and emerging strategies like transfer learning—contribute to building reliable AI models. Furthermore, the exploration of AI applications across various modalities demonstrates its broad clinical utility, from routine screenings to complex interventional procedures. However, the deployment of these technologies introduces technical, operational, and regulatory challenges that must be carefully managed to ensure safety and efficacy. As research progresses, continued collaboration among clinicians, researchers, and regulatory bodies will be essential for refining these innovations and integrating them effectively into clinical practice, ultimately paving the way for a more efficient and patient-centric healthcare system.

 doi:10.20944/preprints202503.0344.v1

References

1. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. Nature Medicine. 2019;25(1):24-29.
2. Larson DB, Chen MC, Lungren MP, et al. Performance of a deep-learning neural network model in assessment of chest radiographs for pneumonia. Radiology. 2018;287(2):544-552.
3. Litjens G, Kooi T, Bejnordi BE, et al. A survey on deep learning in medical image analysis Medical Image Analysis. 2017;42:60-88.
4. Tang A, Tam R, Cadrin-Chênevert A, et al. Canadian Association of Radiologists White Paper on Artificial Intelligence in Radiology. Canadian Association of Radiologists Journal. 2018;69(2):120-135.
5. Vaswani A, Shazeer N, Parmar N, et al. Attention is all you need. In: Advances in Neural Information Processing Systems. 2017;29:5998-6008.
6. Zhou SK, Greenspan H, Shen D (Eds). Deep Learning for Medical Image Analysis. Academic Press, 2017.
7. Arbabshirani, M. R., Fornwalt, B. K., Mongelluzzo, G. J., et al. (2018). Advanced machine learning in action: Identification of intracranial hemorrhage on computed tomography scans of the head with clinical workflow integration. NPJ Digital Medicine, 1, 9.
8. Baumgartner, C. F., Kamnitsas, K., Matthew, J., et al. (2017). SonoNet: Real-time detection and localization of fetal standard scan planes in freehand ultrasound. IEEE Transactions on Medical Imaging, 36(11), 2318-2330.
9. Lakhani, P., & Sundaram, B. (2017). Deep learning at chest radiography: Automated classification of pulmonary tuberculosis by using convolutional neural networks. Radiology, 284(2), 574-582.
10. Li, L., Qin, L., Xu, Z., et al. (2020). Artificial Intelligence Distinguishes COVID-19 from Community Acquired Pneumonia on Chest CT. Radiology, 296(2), E65–E71.
11. Ouyang, G., Wang, X., Dong, Q., et al. (2019). Deep learning for automated diagnosis in nuclear medicine. EJNMMI Physics, 6, 33.
12. Rajpurkar, P., Irvin, J., Zhu, K., et al. (2017). CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. arXiv preprint arXiv:1711.05225.
13. Zhu, B., Liu, J. Z., Cauley, S. F., Rosen, M. S., & Rosen, M. A. (2018). Image reconstruction by domain-transform manifold learning. Nature, 555(7697), 487-492.
14. Zanardo, M., Visser, J.J., Colarieti, A. et al. Impact of AI on radiology: a EuroAIM/EuSoMII 2024 survey among members of the European Society of Radiology. Insights Imaging 15, 240 (2024).
15. Lambin, P., Rios-Velazquez, E., Leijenaar, R., et al. (2017). Radiomics: Extracting more information from medical images using advanced feature analysis. European Journal of Cancer, 48(4), 441-446.
16. Wang, G., Ye, J. C., Mueller, K., & Fessler, J. A. (2018). Image reconstruction is a new frontier of machine learning. IEEE Transactions on Medical Imaging, 37(6), 1289-1296.
17. European Commission. (2017). Regulation (EU) 2017/745 of the European Parliament and of the Council on Medical Devices. Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32017R0745
18. World Health Organization. (2011). WHO Global Model Regulatory Framework for Medical Devices. Retrieved from https://www.who.int/medical_devices/assessment/en/
19. International Medical Device Regulators Forum. (2013). Software as a Medical Device (SaMD): Clinical Evaluation – Guidance for Industry and Regulators. Retrieved from https://www.imdrf.org/documents/documents.asp

 doi:10.20944/preprints202503.0344.v1

20. Rosen, S., Cohen, E., Hren, K., Harris, C., & Lazo Green, K. (2024). Unique strategies at cedars-sinai to screen for and address social determinants of health in older adults. Innovation in Aging, 8(Supplement_1), 892. https://doi.org/10.1093/geroni/igae098.2881