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# Application of Artificial Intelligence Frameworks in Development of Medical Imaging Diagnosis Systems: A Comprehensive Review of Novel Methodologies, Clinical Validation, Performance Optimization, and Future Perspectives

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*ABSTRACT: Artificial intelligence (AI) has revolutionized medical imaging with automated disease detection, image segmentation, diagnosis, prognosis prediction, and clinical decision support across various imaging modalities, such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, positron emission tomography (PET), retinal imaging, and digital pathology. Recent advances in deep learning, transformer architectures, multimodal learning and foundation models have significantly improved the diagnostic accuracy and reduced the reliance on handcrafted feature engineering. However, challenges like data heterogeneity, model interpretability, external validation, privacy preservation, computational efficiency, and regulatory compliance still hinder the widespread clinical implementation.*

*In this paper, this review presents a comprehensive study on the evolution of modern AI frameworks in medical imaging by integrating recent methodological advances with perspectives on clinical translation. The review covers the latest deep learning architectures, such as convolutional neural networks, Vision Transformers, hybrid CNN–Transformer models, multimodal learning frameworks, generative artificial intelligence, diffusion models, federated learning, privacy-preserving learning, and medical foundation models. In addition, the review covers the cutting-edge explainable AI techniques, including Grad-CAM, SHAP, LIME, and attention visualization, for boosting transparency and clinician confidence. The review also discusses the state-of-the-art performance optimization strategies, including transfer learning, active learning, domain adaptation, neural architecture search, hyperparameter optimization, model compression, and computational resource optimization. Equally important, the latest developments in clinical validation, external evaluation, robustness assessment, fairness, uncertainty estimation, regulatory considerations, and deployment frameworks are critically analyzed to underscore their role in facilitating safe clinical implementation.*

*The review analysis concludes with the identification of key research challenges and directions for the future including multimodal foundation models, vision-language systems, retrieval-augmented generation,*

**Keywords:** *Artificial Intelligence (AI); Medical Imaging; Deep Learning; Explainable Artificial Intelligence (XAI); Clinical Validation; Multimodal Learning; Performance Optimization; Foundation Models.of AI from experimental research to routine precision healthcare.*

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## I. INTRODUCTION

Medical imaging is an integral part of modern healthcare, providing clinicians with detailed anatomical and functional information to aid disease screening, diagnosis, treatment planning and therapeutic monitoring [9,10,20]. Imaging modalities, such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), ultrasound, digital pathology and retinal imaging, produce large amounts of high-dimensional data, which typically requires expert interpretation [3,5]. Although these imaging modalities have greatly improved diagnostic capability, the continuously increasing volume and complexity of medical images bring great challenges to radiologists and clinicians including increased reporting workload, inter-observer variability, delayed diagnosis, and diagnostic errors [12,18]. Thus, there is an increasing need for intelligent computational systems that can help healthcare professionals in the interpretation of medical images with accuracy, efficiency and consistency [2,15].

Artificial intelligence (AI), in particular machine learning (ML) and deep learning (DL), has become one of the most disruptive technologies in medical imaging [1,7,20]. Unlike traditional computer-aided diagnosis systems that depended on manual feature extraction, modern AI algorithms automatically learn hierarchical representations of images directly from raw imaging data [9,10]. This has enabled AI models to achieve remarkable performance in disease classification, lesion detection, organ segmentation, image registration, image reconstruction, radiomics, prognosis prediction and treatment response evaluation [3,5,13]. CNNs, Vision Transformers (ViTs), hybrid CNN–Transformer architectures and foundation models have significantly advanced automated medical image analysis [8,10].

Recent advances in computational resources, GPUs, cloud computing and the availability of large annotated datasets have accelerated the development of sophisticated AI frameworks [4,8]. Open-source frameworks such as TensorFlow, PyTorch, MONAI, GaNDLF and nnU-Net have further improved reproducibility and accessibility of AI research [8,19].

However, successful translation of AI systems into routine clinical practice remains challenging. Although many models perform well on retrospective datasets, their performance often declines in heterogeneous patient populations, different scanners and external clinical environments, highlighting the need for external validation and standardized evaluation[11,12,18].

Another major challenge is interpretability and transparency. Deep learning models are frequently criticized as "black-box" systems. Explainable AI (XAI) techniques such as Grad-CAM, SHAP, LIME, saliency maps and attention visualization have therefore become essential for trustworthy AI systems and clinical acceptance [11,12,15].

Data availability and privacy also limit AI development. Federated learning, differential privacy, synthetic data generation and self-supervised learning have emerged as promising approaches for collaborative AI development while protecting patient confidentiality [8,11,19].

As AI models become increasingly complex, performance optimization strategies including transfer learning, active learning, domain adaptation, Bayesian optimization, neural architecture search, knowledge distillation, model pruning and quantization have become important for improving predictive performance and computational efficiency [3,8,13].

Clinical validation and regulatory assessment have become equally important. Beyond conventional metrics, modern evaluation emphasizes robustness, calibration, fairness, explainability and clinical utility. Prospective multicenter validation and continuous post-deployment monitoring are increasingly recommended before clinical deployment [12,15,18].

Emerging technologies including multimodal learning, vision-language models, medical foundation models, retrieval-augmented generation (RAG) and medical large language models (LLMs) are transforming medical imaging by integrating imaging data with clinical records and other patient information for precision medicine [4,16,19].

Although numerous reviews have discussed individual aspects of AI in medical imaging, relatively few integrate methodological advances, clinical validation, optimization strategies, deployment challenges and future research directions into a unified framework [8,15,19].

Therefore, this review comprehensively synthesizes recent advances in AI frameworks for medical imaging. It discusses the evolution of AI methodologies, applications across imaging modalities, emerging computational architectures, clinical validation strategies, trustworthy AI, performance optimization techniques, current challenges and future opportunities, providing a comprehensive resource for researchers, clinicians and healthcare policymakers [1,2,8,11,15,19].

## II. DEVELOPMENT OF ARTIFICIAL INTELLIGENCE FRAMEWORK FOR MEDICAL IMAGING

In the digital era, the evolution of artificial intelligence (AI) frameworks in medical imaging has been driven by continuous advancements in computer vision, machine learning, deep learning and computational infrastructure [21,26,35]. Over the last few years, AI has progressed from rudimentary rule-based algorithms for image analysis to sophisticated multimodal foundation models capable of performing intricate diagnostic tasks with remarkable accuracy [33,35]. This transformation has significantly enhanced the capacity of healthcare professionals to analyze medical images while minimizing diagnostic variability and improving clinical efficiency [26,35].

Earlier AI-powered medical imaging systems predominantly used handcrafted feature extraction and traditional machine learning algorithms, where features describing image texture, shape, intensity, edges and statistical properties were manually analyzed and then classified using Support Vector Machines (SVM), Decision Trees, Random Forests, Logistic Regression, k-Nearest Neighbors (k-NN) and Artificial Neural Networks (ANNs) [26]. While these approaches demonstrated promising performance for specific diagnostic tasks, they relied heavily on expert knowledge and lacked generalizability across imaging modalities and patient populations [21,26].

The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized medical image analysis [23,27,33]. CNNs automatically learn hierarchical feature representations from raw image data, eliminating the need for handcrafted descriptors and enabling the recognition of complex anatomical structures and pathological patterns [23,33]. Landmark CNN architectures have been successfully adapted for disease classification, lesion detection, organ segmentation, image registration and prognosis prediction across multiple imaging modalities [24,27,29,33].

The availability of large annotated imaging datasets together with advances in GPUs and cloud computing has accelerated CNN adoption [21,33]. Transfer learning has further improved predictive performance by fine-tuning ImageNet-pretrained models on medical datasets, reducing annotation requirements and training time 29,32].

Medical image segmentation has advanced considerably with the introduction of U-Net and its variants. Encoder–decoder architectures, 3D CNNs, attention mechanisms and multi-scale feature extraction have significantly improved segmentation performance for CT and MRI application[21,30,32].

Despite CNN success, their limitations in modeling long-range spatial dependencies motivated the development of Transformer-based architectures. Vision Transformers (ViTs) and hybrid CNN–Transformer models have demonstrated excellent performance in classification, segmentation, registration and multimodal learning, particularly for high-resolution medical images [25,32].

The integration of imaging data with electronic health records, laboratory findings, genomic information and clinical reports has accelerated multimodal AI development. Vision-language models support automated report generation, image retrieval, clinical question answering and decision support, providing richer clinical context [35].

Foundation models and self-supervised learning have become major milestones in AI evolution. Large-scale pretrained models can be fine-tuned for multiple downstream clinical tasks using relatively small labeled datasets, improving scalability while reducing annotation costs[21,35].

Growing concerns regarding data privacy and regulatory compliance have encouraged federated learning and privacy-preserving AI strategies that enable collaborative model training across healthcare institutions without sharing sensitive patient information [21].

Significant progress has also been achieved in computational frameworks specifically designed for medical imaging. Initially, researchers relied on general-purpose libraries such as TensorFlow and PyTorch. Dedicated ecosystems including MONAI, GaNDLF and nnU-Net have since emerged, providing standardized preprocessing, optimized architectures, annotation tools, visualization utilities, evaluation metrics and deployment modules that improve reproducibility and facilitate clinical translation [21,26].

Trustworthy and explainable AI has become a major research focus. Explainability, uncertainty quantification, calibration, robustness evaluation, fairness assessment and continual learning are increasingly recognized as essential components of modern AI frameworks to improve clinician confidence, regulatory approval and safe deployment in routine healthcare practice [26,34,35].

## III. NEW METHODOLOGIES FOR DEVELOPING AI FRAMEWORKS

Over the past decade, there has been remarkable progress in artificial intelligence (AI) frameworks for medical imaging, fueled by the rapid development of deep learning, computational hardware, and the growing availability of large-scale medical datasets. The first AI systems were built on traditional machine learning algorithms that relied on hand-crafted image features. While these methods showed promising performance in disease classification and image interpretation, their reliance on handcrafted features restricted their generalizability across different imaging modalities and complex pathological conditions. The emergence of deep learning has changed this scenario drastically as it allows automatic learning of hierarchical features directly from raw images in the medical domain, which greatly improves the accuracy of diagnosis and reduces the effort of feature engineering [52–55].

Today's AI frameworks go beyond old-fashioned convolutional neural networks and make use of attention mechanisms, transformer architectures, multimodal learning techniques, generative models and distributed learning methods that preserve privacy. These innovations are developed not only to improve the predictive performance but also to address pressing issues such as scarcity of annotated datasets, diversity in imaging protocols, computational efficiency, model interpretability, and patient data privacy. Current AI systems are increasingly incorporating imaging information with clinical records, genomic profiles, laboratory results and radiology reports to support comprehensive clinical decision making. Thus AI frameworks are evolving from task-specific algorithms to intelligent, scalable and clinically deployable systems to support precision medicine [66–69].

The following subsections provide an overview of the main methodological advances that have led to the development of modern AI-based medical imaging systems, describing their fundamental principles, benefits, clinical applications, and present-day limitations.

3.1 Deep Learning Architectures 3.1.1 Convolutional Neural Networks Convolutional Neural Networks (CNNs) are a particular kind of neural network that are very good at image classification. Deep learning has become a backbone of modern medical image analysis due to its superior capability of automatic learning of complex hierarchical representations from imaging data. Among various deep learning techniques, convolutional neural networks (CNNs) are still the most popular architecture due to their ability to capture local spatial features while maintaining computational efficiency. The continuous developments on network depth, residual learning, dense connectivity, attention mechanism, and multi-scale feature extraction have led to a state-of-the-art performance of CNN-based models on many medical imaging applications, including disease classification, lesion detection, image segmentation, and image registration [36–57]. Conventional CNNs though very successful have limitations in modeling long-range spatial dependencies and global contextual information in high-resolution medical images. This limitation has motivated the design of transformer-based architectures using self-attention mechanisms to model complex relationships over the entire image. Very recently, hybrid CNN-Transformer networks have been proposed as a powerful solution to combine the local feature extraction of convolutional layers with the global context modeling of transformers. At the same time, specific architectures for different clinical problems, such as 3D CNNs, multi-view learning models, squeeze-and-excitation networks, and recurrent deep learning models, are still improving diagnostic accuracy for difficult imaging modalities such as CT, MRI, ultrasound, and digital pathology [36,37,42,46,50].

Table 1 summarizes the main deep learning architectures currently employed in medical imaging with their fundamental principles, clinical applications, strengths and limitations [53–65].

**Table 1. Deep learning models in medical image analysis**

| Architecture | Core Principle | Advantages | Representative Applications | Limitations |
|---|---|---|---|---|
| Convolutional Neural Networks (CNNs) | Automatic hierarchical feature extraction using convolution and pooling operations | High feature learning capability, reduced manual feature engineering | Disease classification, lesion detection, organ segmentation | Limited ability to model long-range spatial dependencies |
| Customized CNNs | Incorporate multi-scale feature extraction and attention mechanisms | Improved localization of pathological regions | Brain tumor detection, lung disease diagnosis, retinal disease classification | Increased computational complexity |
| Convolution-Recurrent Networks (CNN-RNN) | Combines spatial feature extraction with sequential information modeling | Captures temporal and contextual information | Intracranial hemorrhage detection, video-based medical diagnosis | Longer training time |
| Vision Transformers (ViTs) | Self-attention mechanism captures global contextual relationships | Superior global feature representation | Medical image classification, registration, segmentation | Requires large training datasets |
| CNN–Transformer | Combines CNN local feature extraction with Transformer | Improved accuracy and | Ultrasound segmentation, MRI analysis, pathology | Higher computational |

| Architecture | Core Principle | Advantages | Representative Applications | Limitations |
|---|---|---|---|---|
| Hybrid Networks | global attention | robustness | imaging | requirements |
| Dilated SE-DenseNet | Dense connectivity with squeeze-and-excitation attention | Enhanced channel feature recalibration | Brain tumor MRI classification | Complex architecture |
| Multi-view and Multi-scale Networks | Integrates multiple image views and resolutions | Better volumetric representation | CT, MRI, PET image analysis | Increased memory consumption |
| 3D Deep Learning Networks | Learns volumetric spatial features directly | Accurate analysis of 3D anatomical structures | Brain MRI, Lung CT, Cardiac Imaging | High computational cost |

## IV. HYBRID AND MULTIMODAL AI ARCHITECTURES

Clinical diagnosis is rarely made on one source of information. Physicians always incorporate imaging findings with patient history, laboratory investigations, pathological reports, genetic information and demographic characteristics before making diagnostic decisions. This clinical workflow has inspired recent AI research to shift towards more multimodal learning frameworks that are able to incorporate different types of data in a single predictive model. These methods offer complementary information which considerably boost the diagnostic accuracy and robustness as compared to the image-only models.

The rise of vision-language models has propelled the research on multi-modal AI even further. Medical adaptations of CLIP and other frameworks allow learning from medical images and their corresponding textual data such as radiology reports, pathology descriptions and clinical notes simultaneously. These types of models can be used to automate report generation, retrieve images, answer clinical questions and build intelligent decision-support systems. Furthermore, multimodal learning can facilitate personalized medicine by merging imaging biomarkers with electronic health records and genomic data, allowing for a more holistic characterization of the disease and the formulation of personalized treatment strategies [66–70].

Table 2 summarizes the major hybrid and multimodal AI frameworks, including the integrated data modalities, the main advantages, clinical applications, and remaining challenges.

**Table 2: Generative AI and Data Augmentation Techniques**

| Framework | Integrated Modalities | Major Advantages | Clinical Applications | Challenges |
|---|---|---|---|---|
| Multi-modality Deep Learning | CT + MRI + Ultrasound + PET | Comprehensive disease characterization | Cardiology, Oncology | Data heterogeneity |
| Hybrid-supervised Transfer Networks | Multiple imaging modalities | Knowledge transfer between datasets | Cross-modality diagnosis | Domain adaptation complexity |
| Vision-Language Models (MedCLIP, MedP-CLIP) | Medical images + Radiology reports | Automated report generation and retrieval | Radiology reporting | Requires large multimodal datasets |
| Image + Clinical Data Integration | Images + EHR + Laboratory data | Improved diagnostic accuracy | Precision medicine | Missing clinical information |
| Multimodal Clinical Decision Systems | Images + Text + Metadata | Context-aware diagnosis | Clinical decision support | Complex model training |

## V. DATA AUGMENTATION AND GENERATIVE MODELS

One of the biggest challenges is the lack of high-quality annotated datasets in the medical imaging AI domain. The annotation of medical images is time-consuming and expensive as it requires expert clinical knowledge. Generative AI has emerged as a powerful solution to this limitation, by generating realistic synthetic medical images that can augment existing datasets and improve model generalization. Generative methods like Generative Adversarial Networks (GANs) and diffusion models have shown powerful capability in image synthesis, reconstruction, segmentation, and domain adaptation.

Besides traditional data augmentation, generative models are increasingly popular for super-resolution imaging, cross-modality image translation, image denoising, longitudinal disease progression modeling, and reconstruction of low-dose medical images. Recently, diffusion-based architectures have attracted much attention since they can generate higher quality images with more stable training than GANs. "These advances allow researchers to develop more robust AI systems while dealing with challenges like limited training data, privacy preservation and variability in imaging protocols [71–85]. The main generative AI methodologies currently used in medical imaging are summarized in Table 3, with their working principles, clinical applications, advantages and limitations.

**Table 3: Generative AI and Data Augmentation Techniques**

| Methodology | Working Principle | Applications | Advantages | Limitations |
|---|---|---|---|---|
| Generative Adversarial Networks (GANs) | Generator and discriminator networks generate synthetic images | Data augmentation, image synthesis | Increases training dataset diversity | Training instability |
| Diffusion Models | Progressive image denoising and reconstruction | Image synthesis, segmentation | High-quality image generation | Computationally intensive |
| Test-time Generative Augmentation | Generates image variations during inference | Medical image segmentation | Improved robustness | Increased inference time |
| HiDiff Framework | Hybrid diffusion-based segmentation | Organ and tumor segmentation | High segmentation accuracy | Complex optimization |
| Sequence-aware Diffusion Models | Temporal image synthesis | Disease progression analysis | Longitudinal patient monitoring | Large computational resources |
| Super-resolution Networks | Reconstruction of high-resolution images | MRI, CT enhancement | Better diagnostic quality | Possible artifact generation |
| Cross-modality Image Synthesis | Converts one imaging modality into another | MRI-to-CT synthesis | Reduces additional imaging | Requires paired datasets |

## VI. FEDERATEDAND PRIVACY-PRESERVING LEARNING

Robust AI models require large and diverse medical imaging datasets to be successfully developed. However, healthcare institutions often cannot share patient data due to strict privacy regulations, ethical considerations, and legal restrictions. A promising solution to this challenge is **federated learning**, in which multiple institutions collaboratively train AI models without exchanging raw patient data. Instead, participating institutions share only model parameters or gradients, thereby preserving patient confidentiality while improving the generalizability and robustness of AI models across diverse clinical settings **[111–113]**.

Recent advances in federated learning have addressed several practical challenges, including heterogeneous imaging protocols, non-identically distributed (non-IID) datasets, communication efficiency, secure parameter aggregation, and scalability across geographically distributed healthcare networks **[109–113]**. In addition, complementary privacy-preserving technologies such as **differential privacy, homomorphic encryption, secure aggregation, and personalized federated learning** have been integrated into collaborative AI frameworks to further enhance data security and regulatory compliance **[111–115]**. These innovations are expected to play a crucial role in enabling trustworthy, scalable, and globally deployable medical imaging AI systems while maintaining compliance with patient privacy regulations **[110–115]**.

Beyond federated learning, recent deployment frameworks emphasize **MLOps (Machine Learning Operations), cloud-based AI orchestration, regulatory governance, and clinically translatable AI pipelines** to support the entire lifecycle of medical imaging applications—from data acquisition and model development to validation, deployment, continuous monitoring, and post-deployment performance assessment **[106–110,112,113]**. Such integrated frameworks are increasingly recognized as essential for ensuring the safe, efficient, and sustainable clinical implementation of AI systems in radiology and medical imaging **[110,112–115]**.

**Table 4** comparatively presents the main federated and privacy-preserving learning frameworks currently adopted in medical imaging research **[111–115]**.

**Table 4: Frameworks for Federated and Privacy-Preserving Learning [111–115].**

| Framework | Principle | Advantages | Medical Imaging Applications | Challenges |
|---|---|---|---|---|
| Federated Learning | Collaborative model training without sharing patient data | Privacy preservation | Multi-center disease diagnosis | Data heterogeneity |
| Personalized Federated Learning | Site-specific model adaptation | Better institution-wise performance | Rare disease diagnosis | Model synchronization |
| Adaptive Aggregation | Dynamic model parameter aggregation | Improved convergence | Multi-hospital collaborations | Communication overhead |
| Secure Aggregation | Encrypts model updates during transmission | Enhanced security | Privacy-sensitive healthcare | Increased computation |
| Differential Privacy | Adds statistical noise to model updates | Strong privacy guarantees | Medical image classification | Slight reduction in accuracy |
| Homomorphic Encryption | Computation on encrypted data | High data security | Cloud-based AI diagnosis | Very high computational cost |
| Federated Transfer Learning | Combines transfer learning with federated optimization | Handles small local datasets | Cross-institutional learning | Complex implementation |

## VII.COMPARATIVE PERSPECTIVE ON NEW AI FRAMEWORKS

Each approach to artificial intelligence addresses specific challenges in medical image analysis; however, no single framework is applicable to all clinical applications. Deep learning models are highly effective for automated feature extraction, whereas multimodal systems enhance contextual understanding by integrating imaging with complementary clinical information. Generative models help address data scarcity through synthetic data generation, while federated learning enables secure collaborative model development across multiple healthcare institutions without sharing sensitive patient data. More recently, increasing emphasis has been placed on developing comprehensive AI ecosystems that combine these complementary methodologies with standardized validation, deployment, and monitoring frameworks to ensure reliable clinical implementation **[116–123]**.Future AI frameworks are expected to integrate foundation models, multimodal reasoning, explainable AI, continual learning, federated intelligence, and standardized clinical validation pipelines into unified clinical decision support platforms. Such integrated systems have the potential to facilitate precision medicine by delivering personalized, transparent, and trustworthy diagnostic recommendations across diverse healthcare environments. Advances in computational hardware, self-supervised learning, cloud-based AI infrastructures, continuous model monitoring, and regulatory evaluation frameworks are expected to accelerate the transition of AI from experimental research to routine clinical deployment **[116,119–130]**.**Table 5** provides a comparative analysis of the major methodological paradigms that characterize the current generation of AI frameworks in medical imaging.

**Table 5: Comparative Summary of New AI Frameworks [116–123].**

| Methodology | Primary Objective | Key Technologies | Major Benefits | Future Scope |
|---|---|---|---|---|
| Deep Learning Architectures | Automated feature learning | CNN, ResNet, DenseNet, ViT | High diagnostic accuracy | Foundation models |
| Hybrid & Multimodal AI | Integrating multiple data sources | CNN + Transformer + Clinical Data | Context-aware diagnosis | Personalized medicine |
| Generative AI | Synthetic image generation | GAN, Diffusion Models | Data augmentation | Digital twins |
| Federated Learning | Privacy-preserving collaborative | Federated Optimization | Secure multi-center | Global AI |

| Methodology | Primary Objective | Key Technologies | Major Benefits | Future Scope |
|---|---|---|---|---|
| | learning | | AI | collaboration |
| Explainable AI (future integration) | Transparent decision making | SHAP, Grad-CAM, LIME | Clinical trust | Regulatory approval |
| Foundation Models | General-purpose representation learning | Self-supervised learning | Transferable knowledge | Universal medical AI |

## VIII. PERFORMANCE OPTIMIZATION TECHNIQUES

Performance optimization is an essential component in the development of AI frameworks for medical imaging to ensure high diagnostic accuracy, computational efficiency, robustness, and clinical applicability. Recent studies have increasingly focused not only on improving predictive performance through transfer learning, active learning, hyperparameter optimization, and computational resource optimization, but also on establishing standardized validation procedures, external evaluation protocols, and continuous performance monitoring to facilitate successful deployment in real-world healthcare environments [117–130].

### 1. Transfer Learning and Domain Adaptation

Transfer learning has become one of the most effective strategies for improving AI performance, particularly when annotated medical imaging datasets are limited. Fine-tuning models pre-trained on large datasets reduces training time while improving generalization across diverse clinical tasks. Domain adaptation techniques further enhance model robustness by mitigating performance degradation caused by variations in imaging protocols, healthcare institutions, and patient populations. More recently, test-time adaptation has emerged as an effective strategy that enables AI models to dynamically adapt to previously unseen clinical data without requiring complete model retraining [117,118,120,125,126].

### 2. Active Learning and Uncertainty Estimation

Active learning improves annotation efficiency by selecting the most informative samples for expert labeling, thereby reducing annotation costs while maintaining predictive performance. In addition, uncertainty estimation quantifies the confidence of AI predictions, allowing clinicians to recognize unreliable outputs and make better-informed diagnostic decisions. The integration of active learning with uncertainty estimation has been shown to improve data efficiency, model robustness, and clinical reliability in medical image analysis [120,125–128].

### 3. Neural Architecture Search and Hyperparameter Optimization

Hyperparameter optimization remains a critical step for maximizing AI model performance. Conventional approaches such as grid search and random search are increasingly being replaced by Bayesian optimization, evolutionary algorithms, and other metaheuristic optimization techniques. Furthermore, Neural Architecture Search (NAS) enables the automatic discovery of optimal network architectures, reducing manual design efforts while improving diagnostic accuracy across a wide range of medical imaging applications. Robust validation frameworks are equally important to ensure that optimized models remain generalizable and clinically reliable [120–125].

### 4. Efficiency of Computation and Resource Optimization

Efficient AI models are essential for real-time clinical deployment. Model compression techniques, including pruning, quantization, and knowledge distillation, substantially reduce computational complexity while preserving diagnostic performance. Recent AI deployment frameworks further emphasize lightweight architectures, cloud-based infrastructures, edge computing, standardized deployment pipelines, continuous monitoring, and computational efficiency metrics to support AI implementation in resource-constrained healthcare environments. These optimization strategies facilitate scalable, reproducible, and clinically deployable AI systems [116,119,122,123,125–130].

## IX. MAIN FINDINGS AND COMPARATIVE ANALYSIS

The surveyed literature highlights several important trends in the development of AI frameworks for medical imaging. Initial AI architectures have progressively evolved from conventional convolutional neural networks (CNNs) toward transformer-based, hybrid, and multimodal frameworks. Although CNNs remain highly effective for feature extraction and image classification, transformer-based architectures provide superior global contextual learning. Hybrid CNN-transformer frameworks have demonstrated improved performance across image segmentation, disease classification, and multimodal diagnostic applications.A second major trend is the increasing emphasis on clinical validation. Contemporary AI systems are now routinely evaluated using multicenter datasets, external validation cohorts, prospective clinical studies, standardized evaluation protocols, and real-world deployment frameworks to improve reliability, reproducibility, and generalizability. Nevertheless, harmonized validation standards and regulatory guidelines remain essential for the safe integration of AI into routine clinical practice [116–130].Third, performance optimization strategies—including transfer learning, active learning, domain adaptation, hyperparameter optimization, model compression, and standardized validation infrastructures—have substantially improved diagnostic accuracy while reducing computational requirements. These approaches facilitate the development of efficient AI models even when annotated medical datasets are limited [120–126].Finally, recent research has shifted beyond maximizing predictive accuracy toward developing trustworthy and clinically deployable AI that emphasizes robustness, interpretability, uncertainty estimation, fairness, computational efficiency, continuous monitoring, external validation, and regulatory compliance. The emergence of standardized development and deployment frameworks has accelerated algorithm reproducibility and facilitated translation from research laboratories to real-world clinical practice [116–130].

## X. EXPLAINABILITY AND TRUST IN CLINICAL PRACTICE

Although deep learning models have demonstrated remarkable diagnostic performance, their black-box nature continues to limit broader clinical adoption. Explainable AI (XAI) methods—including Grad-CAM, SHAP, LIME, and attention visualization—improve interpretability by highlighting clinically relevant image regions and decision pathways. In parallel, trustworthy AI frameworks increasingly incorporate robustness, fairness, privacy preservation, uncertainty estimation, external validation, continuous monitoring, and regulatory evaluation to improve clinician confidence and facilitate regulatory approval for clinical deployment [124–130].

## XI. BARRIERS TO IMPLEMENTATION AND FUTURE SOLUTIONS

Successful implementation of AI in medical imaging requires overcoming technical, regulatory, and operational challenges. Integration with hospital information systems, computational resource limitations, workflow compatibility, continuous model monitoring, external validation, and post-deployment performance assessment remain major barriers. Emerging validation infrastructures, cloud-based deployment frameworks, Machine Learning Operations (MLOps), standardized evaluation methodologies, and regulatory guidance provide practical solutions for managing the entire AI lifecycle from development through long-term clinical deployment [116–130].

## XII.CONCLUSION

Artificial Intelligence has revolutionized medical imaging by advancing disease detection, image segmentation and clinical decision support. Recent advances in deep learning and transformer architectures, multi-modal learning and federated learning have improved the accuracy, efficiency and scalability of AI frameworks. At the same time, robust clinical validation, performance optimization, explainability and privacy-preserving techniques have become essential for safe and reliable deployment in healthcare.

However, challenges remain in areas like generalizability, interpretability, regulatory compliance, and real-world deployment, despite these advances. In the field of research, research should focus on trustworthy, efficient, and multimodal AI systems with continuous validation and applications in multidisciplinary aspects. In general, a combination of novel methodologies, rigorous clinical assessment and optimized performance will be key to successfully transition AI from research settings to everyday clinical practice and towards precision health..

## REFERENCES

[1] Afaf E.G. Osman (2025). Deep learning for medical image analysis: a revolution in diagnostic medicine. https://doi.org/10.12732/ijam.v38i3s.201

[2] Jyoti Badge, Mayank Sharma, Abha Trivedi et al. (2025). Empowering Clinical Outcomes with AI Powered Innovations in Medical Imaging Diagnostics. https://doi.org/10.1109/ictbig68706.2025.11323692

[3] Laith Alzubaidi (2022). Deep learning for medical imaging applications. https://doi.org/10.5204/thesis.eprints.227812

[4] Waleed Salah Eldin, Ahmed Kaboudan (2023). AI-Driven Medical Imaging Platform: Advancements in Image Analysis and Healthcare Diagnosis. https://doi.org/10.21608/asc.2024.248278.1018

[5] Amlan Jyoti Kalita, Abhijit Boruah, Tapan Kumar Das et al. (2024). Artificial intelligence in diagnostic medical image processing for advanced healthcare applications. https://doi.org/10.1007/978-981-97-5345-1_1

[6] Farrokhi Mehrdad, Nikseresht, Hessam, Amini Fatemeh et al. (2025). AI in Medical Imaging and Early Disease Detection. https://doi.org/10.5281/zenodo.16636917
[7] Muralikrishna Puttagunta, S. Ravi (2021). Medical image analysis based on deep learning approach.. https://doi.org/10.1007/S11042-021-10707-4
[8] Mohammed Ahmed Alharbi, MorchedDerbali, Rayed Alakhtar et al. (2025). Deep Learning Algorithms in Medical Image Processing: A Critical and Comprehensive Review. https://doi.org/10.54364/aaiml.2025.54248
[9] Litjens, Kooi, Bejnordi et al. (2017). A survey on deep learning in medical image analysis.. https://doi.org/10.1016/j.media.2017.07.005
[10] Xuxin Chen, Ximin Wang, Ke Zhang et al. (2021). Recent advances and clinical applications of deep learning in medical image analysis. https://doi.org/10.1016/j.media.2022.102444
[11] VarahalaraoVadlapudi, Dowluru S.V.G.K. Kaladhar, VarahalaraoVadlapudi et al. (2025). Artificial intelligence in medical imaging: bridging innovation, ethics, and clinical impact. https://doi.org/10.18203/2349-3933.ijam20253360
[12] Rafał Obuchowicz, Michał Strzelecki, Adam Piórkowski (2024). Clinical applications of artificial intelligence in medical imaging and image processing—A review. https://doi.org/10.3390/cancers16101870
[13] Iqra Nissar, Aqib NazirMir, Asif Hussain et al. (2024). Transforming medicine with deep learning: applications in disease detection using medical images. https://doi.org/10.58532/v3bfai1p1ch7
[14] Ahmad Kamal, Faiyaz Ahamad, Abu Hena Mustafa Kamal (2024). Medical image analysis: revolutionizing diagnosis through deep learning. https://doi.org/10.58532/v3biai12p1ch7
[15] Omar Sabri, Bassam Al-Shargabi, Abdelrahman Abuarqoub (2025). The Role of Artificial Intelligence in Improving Diagnostic Accuracy in Medical Imaging: A Review. https://doi.org/10.32604/cmc.2025.066987
[16] Sk Mahmudul Hassan (2025). Artificial Intelligence in Diagnostic Imaging: Enhancing Patient Care Through Advanced Algorithms and Data Integration. https://doi.org/10.20944/preprints202503.0344.v1
[17] Saif Hameed Abbood Al-Waeli, Haza Nuzly bin Abdul Hameed (2025). AI in Medical Imaging & Diagnostics: review. https://doi.org/10.31185/wjps.752
[18] Reabal Najjar (2023). Redefining radiology: a review of artificial intelligence integration in medical imaging. https://doi.org/10.3390/diagnostics13172760
[19] Yixin Yang, Lan Ye, Zhanhui Feng (2025). Application of Artificial Intelligence in Medical Imaging: Current Status and Future Directions. https://doi.org/10.1002/ird3.70008
[20] June-Goo Lee, Sanghoon Jun, Young-Won Cho et al. (2017). Deep Learning in Medical Imaging: General Overview.. https://doi.org/10.3348/KJR.2017.18.4.570
[21] Efrat Shimron, Or Perlman (2023). AI in MRI: Computational Frameworks for a Faster, Optimized, and Automated Imaging Workflow. https://doi.org/10.3390/bioengineering10040492
[22] Y Li, H Liu, Q Wei et al. (n.d.). Rectal Cancer Radiotherapy Response Prediction: Retrospective Study of Development of a Deep Learning–Based Radiomics Model. https://medinform.jmir.org/2026/1/e77313
[23] Hu, Pei, Xie et al. (2022). Convolutional Neural Network for Predicting Thyroid Cancer Based on Ultrasound Elastography Image of Perinodular Region.. https://doi.org/10.1210/endocr/bqac135
[24] Haoyue Zhang, Jennifer S. Polson, Eric J. Yang et al. (2023). Predicting Thrombectomy Recanalization from CT Imaging Using Deep Learning Models. https://arxiv.org/abs/2302.04143v2
[25] Na Hu, Yunpeng Luo, Maowen Tang et al. (2025). Development and validation of a transformer-based deep learning model for predicting distant metastasis in non-small cell lung cancer using 18FDG PET/CT images. https://doi.org/10.1007/s12094-025-04014-9
[26] Zhiyong Zhou, Xusheng Qian, Jisu Hu et al. (2023). An artificial intelligence-assisted diagnosis modeling software (AIMS) platform based on medical images and machine learning: a development and validation study. https://doi.org/10.21037/qims-23-20
[27] Y Cai, JG Yu, Y Chen et al. (n.d.). … convolutional neural network for the automated diagnosis of otitis media from tympanic membrane images: a prediction model development and validation study. https://bmjopen.bmj.com/content/11/1/e041139.abstract
[28] Wang, Lu, Xu et al. (2026). Deep learning-based ultrasound diagnostic model for follicular thyroid carcinoma.. https://doi.org/10.1007/s00330-025-11840-6
[29] Dean Hu (2022). Deep learning for an improved diagnostic pathway of prostate cancer in a small multi-parametric magnetic resonance data regime. https://doi.org/10.31265/usps.197
[30] Wang, Liao, Ni et al. (2022). High-resolution medical image reconstruction based on residual neural network for diagnosis of cerebral aneurysm.. https://doi.org/10.3389/fcvm.2022.1013031
[31] Minoshima, Cross (2022). Application of artificial intelligence in brain molecular imaging.. https://doi.org/10.1007/s12149-021-01697-2
[32] Tianyi Xia, Ben Zhao, Binrong Li et al. (2023). MRI-based radiomics and deep learning in biological characteristics and prognosis of hepatocellular carcinoma: opportunities and challenges. https://doi.org/10.1002/jmri.28982
[33] Xiaoyan Jiang, Zuo-Jin Hu, Shuihua Wang et al. (2023). Deep learning for medical image-based cancer diagnosis. https://doi.org/10.3390/cancers15143608
[34] Qiuhan Zheng, Le Yang, Bin Zeng et al. (2021). Artificial intelligence performance in detecting tumor metastasis from medical radiology imaging: A systematic review and meta-analysis. https://doi.org/10.1016/J.ECLINM.2020.100669
[35] Jianfeng Huang, Yizhen Xiang, Siew Hua Gan et al. (2025). Application of artificial intelligence in medical imaging for tumor diagnosis and treatment: a comprehensive approach. https://doi.org/10.1007/s12672-025-03307-3
[36] AS Moon, JK Lee, J Lee (n.d.). Three-dimensional convolutional neural network with channel compression module for efficient diagnosis of thyroid-associated orbitopathy. https://link.springer.com/article/10.1007/s11042-026-21771-z
[37] Deniz Alis, Ceren Alis, Mert Yergin et al. (2022). A joint convolutional-recurrent neural network with an attention mechanism for detecting intracranial hemorrhage on noncontrast head CT. https://doi.org/10.1038/s41598-022-05872-x
[38] Hu, Pei, Xie et al. (2022). Convolutional Neural Network for Predicting Thyroid Cancer Based on Ultrasound Elastography Image of Perinodular Region.. https://doi.org/10.1210/endocr/bqac135
[39] Ken C. L. Wong, Tanveer Syeda-Mahmood, Mehdi Moradi (2018). Building medical image classifiers with very limited data using segmentation networks. https://doi.org/10.1016/j.media.2018.07.010
[40] Bob D. de Vos, Floris F. Berendsen, Max A. Viergever et al. (2018). A Deep Learning Framework for Unsupervised Affine and Deformable Image Registration. https://doi.org/10.1016/j.media.2018.11.010
[41] Sebastian Nørgaard Llambias, Julia Machnio, Axel Munk et al. (2024). Yucca: A Deep Learning Framework For Medical Image Analysis. https://doi.org/10.48550/arxiv.2407.19888
[42] Author Unknown (2022). Brain Tumor Detection and Classification Using a New Evolutionary Convolutional Neural Network. https://doi.org/10.2139/ssrn.4292650

[43] Essam H. Houssein, Marwa M. Emam, Abdelmgeid A. Ali (2024). An optimized deep learning architecture for breast cancer diagnosis based on improved marine predators algorithm. https://doi.org/10.60692/rabra-ndq11
[44] Afonso, Saraiva, Ferreira et al. (2022). Automated detection of ulcers and erosions in capsule endoscopy images using a convolutional neural network.. https://doi.org/10.1007/s11517-021-02486-9
[45] Nikolaos Papandrianos, Elpiniki I. Papageorgiou, Athanasios Anagnostis et al. (2020). Bone metastasis classification using whole body images from prostate cancer patients based on convolutional neural networks application.. https://doi.org/10.1371/JOURNAL.PONE.0237213
[46] Alvin Rajkomar, Sneha Lingam, Andrew Taylor et al. (2017). High-Throughput Classification of Radiographs Using Deep Convolutional Neural Networks. https://doi.org/10.1007/S10278-016-9914-9
[47] Amal Alshardan, Nuha Alruwais, Hamed Alqahtani et al. (2024). Leveraging transfer learning-driven convolutional neural network-based semantic segmentation model for medical image analysis using MRI images. https://doi.org/10.1038/s41598-024-81966-y
[48] Holger R. Roth, Chen Shen, Hirohisa Oda et al. (2018). Deep learning and its application to medical image segmentation. https://doi.org/10.11409/mit.36.63
[49] Kermany, Goldbaum, Cai et al. (2018). Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning.. https://doi.org/10.1016/j.cell.2018.02.010
[50] Eid Albalawi, Arastu Thakur, D. Ramya Dorai et al. (2024). Enhancing brain tumor classification in MRI scans with a multi-layer customized convolutional neural network approach. https://doi.org/10.3389/fncom.2024.1418546
[51] Osman Doğuş Gülgün, Hamza Erol (2019). Classification performance comparisons of deep learning models in pneumonia diagnosis using chest x-ray images. https://doi.org/10.31127/TUJE.652358
[52] Muralikrishna Puttagunta, S. Ravi (2021). Medical image analysis based on deep learning approach.. https://doi.org/10.1007/S11042-021-10707-4
[53] Litjens, Kooi, Bejnordi et al. (2017). A survey on deep learning in medical image analysis.. https://doi.org/10.1016/j.media.2017.07.005
[54] Rikiya Yamashita, Rikiya Yamashita, Mizuho Nishio et al. (2018). Convolutional neural networks: an overview and application in radiology. https://doi.org/10.1007/S13244-018-0639-9
[55] June-Goo Lee, Sanghoon Jun, Young-Won Cho et al. (2017). Deep Learning in Medical Imaging: General Overview.. https://doi.org/10.3348/KJR.2017.18.4.570
[56] Junyu Chen, Eric C. Frey, Yufan He et al. (2021). TransMorph: Transformer for unsupervised medical image registration. https://doi.org/10.1016/j.media.2022.102615
[57] Zhang, Wang, Wei et al. (2024). A dual-branch and dual attention transformer and CNN hybrid network for ultrasound image segmentation.. https://doi.org/10.3389/fphys.2024.1432987
[58] Gong, Shi, Wang et al. (2023). Hybrid-supervised bidirectional transfer networks for computer-aided diagnosis.. https://doi.org/10.1016/j.compbiomed.2023.107409
[59] Junaid Aftab, Muhammad Attique Khan, Sobia Arshad et al. (2025). Artificial intelligence based classification and prediction of medical imaging using a novel framework of inverted and self-attention deep neural network architecture. https://doi.org/10.1038/s41598-025-93718-7
[60] Na Hu, Yunpeng Luo, Maowen Tang et al. (2025). Development and validation of a transformer-based deep learning model for predicting distant metastasis in non-small cell lung cancer using 18FDG PET/CT images. https://doi.org/10.1007/s12094-025-04014-9
[61] Weijian Huang, Cheng Li, Hao Yang et al. (2024). Enhancing the vision-language foundation model with key semantic knowledge-emphasized report refinement. https://doi.org/10.1016/j.media.2024.103299
[62] E Aslan, Y Özüpak (n.d.). A hybrid deep learning framework based on VGG19 and U-Net for accurate brain tumor segmentation in MRI images. https://www.sciencedirect.com/science/article/pii/S2772516226000197
[63] Tao Chen, Chenhui Wang, Zhihao Chen et al. (2024). HiDiff: Hybrid Diffusion Framework for Medical Image Segmentation. https://doi.org/10.1109/TMI.2024.3424471
[64] Mao, Kim, Podina et al. (2025). Dilated SE-DenseNet for brain tumor MRI classification.. https://doi.org/10.1038/s41598-025-86752-y
[65] Aditya Jayesh Aiya, Nishant Wani, M Ramani et al. (2025). Optimized deep learning for brain tumor detection: a hybrid approach with attention mechanisms and clinical explainability. https://doi.org/10.1038/s41598-025-04591-3
[66] Jiahui Peng, He Yao, Jingwen Li et al. (2026). MedP-CLIP: Medical CLIP with Region-Aware Prompt Integration. https://doi.org/10.1016/j.media.2026.104193
[67] C. Ruan, Chengyue Huang, Yi-Chen E. Yang (2024). Comprehensive Evaluation of Multimodal AI Models in Medical Imaging Diagnosis: From Data Augmentation to Preference-Based Comparison. https://doi.org/10.48550/arxiv.2412.05536
[68] Yao, Zhang, Yang et al. (2025). Multimodal large language models in ultrasound diagnosis of breast masses: a multicenter comparative analysis based on GPT-4o, radiologists, and convolutional neural network (CNN).. https://doi.org/10.21037/qims-2025-92
[69] Rajendra P. Pandey, A. Rengarajan, Aishwary Awasthi (2024). Automated Multimodal Medical Diagnostics Using Deep Learning Frameworks. https://doi.org/10.1109/icocwc60930.2024.10470876
[70] Youness Riouali, Naoual El Aboudi, Nezha El Bahaoui et al. (2025). Deep Learning in Medical Imaging: Chronological Evolution, Frameworks, Core Methods, and Recent Advances in Breast Cancer Segmentation (2023–2024). https://doi.org/10.1155/acis/1913589
[71] Xiao Ma, Yuhui Tao, Zetian Zhang et al. (2024). Test-time generative augmentation for medical image segmentation. https://doi.org/10.1016/j.media.2025.103902
[72] Hicham Messaoudi, Ahror Belaid, Douraied Ben Salem et al. (2023). Cross-dimensional transfer learning in medical image segmentation with deep learning. https://doi.org/10.1016/j.media.2023.102868
[73] Vishwesh Nath, Dong Yang, Bennett A. Landman et al. (2021). Diminishing Uncertainty within the Training Pool: Active Learning for Medical Image Segmentation. https://doi.org/10.1109/TMI.2020.3048055
[74] Ken C. L. Wong, Tanveer Syeda-Mahmood, Mehdi Moradi (2018). Building medical image classifiers with very limited data using segmentation networks. https://doi.org/10.1016/j.media.2018.07.010
[75] Neerav Karani, Ertunc Erdil, Krishna Chaitanya et al. (2020). Test-Time Adaptable Neural Networks for Robust Medical Image Segmentation. https://doi.org/10.1016/j.media.2020.101907
[76] E Aslan, Y Özüpak (n.d.). A hybrid deep learning framework based on VGG19 and U-Net for accurate brain tumor segmentation in MRI images. https://www.sciencedirect.com/science/article/pii/S2772516226000197
[77] Amal Alshardan, Nuha Alruwais, Hamed Alqahtani et al. (2024). Leveraging transfer learning-driven convolutional neural network-based semantic segmentation model for medical image analysis using MRI images. https://doi.org/10.1038/s41598-024-81966-y
[78] Holger R. Roth, Chen Shen, Hirohisa Oda et al. (2018). Deep learning and its application to medical image segmentation. https://doi.org/10.11409/mit.36.63
[79] Takayasu Moriya, Holger R. Roth, Shota Nakamura et al. (2018). Unsupervised Segmentation of 3D Medical Images Based on Clustering and Deep Representation Learning. https://doi.org/10.1117/12.2293414

[80] Tao Chen, Chenhui Wang, Zhihao Chen et al. (2024). HiDiff: Hybrid Diffusion Framework for Medical Image Segmentation. https://doi.org/10.1109/TMI.2024.3424471
[81] Yingda Xia, Dong Yang, Zhiding Yu et al. (2020). Uncertainty-aware multi-view co-training for semi-supervised medical image segmentation and domain adaptation. https://doi.org/10.1016/j.media.2020.101766
[82] S Addimulam, MA Mohammed, RK Karanam (n.d.). Deep learning-enhanced image segmentation for medical diagnostics. https://www.academia.edu/download/131998085/Deep_Learning_Enhanced_Image_Segmentation_for_Medical.pdf
[83] Bougourzi, Fares, Hadid Abdenour (2025). Recent Advances in Medical Imaging Segmentation: A Survey. https://doi.org/10.48550/arxiv.2505.09274
[84] Vijaya Sahu, Arjoo Pandey (2025). AI-Powered Image Segmentation Techniques for Medical Diagnostics and Healthcare Imaging. https://doi.org/10.5281/zenodo.15283752
[85] Adam, Dell'Aquila, Hodges et al. (2023). Deep learning applications to breast cancer detection by magnetic resonance imaging: a literature review.. https://doi.org/10.1186/s13058-023-01687-4
[86] Ishak Pacal, Tathagat Banerjee (2025). Towards accurate and interpretable brain tumor diagnosis: T-FSPANNet with tri-attribute and pyramidal attention-based feature fusion. https://doi.org/10.1016/j.bspc.2025.108852
[87] Ketan Sarvakar, Chandrakant Patel, Hiral B. Patel et al. (2025). Metaheuristic Optimization for Generative and Explainable AI in Biomedical Imaging. https://doi.org/10.4018/979-8-3373-0523-3.ch010
[88] Kai Ma, Siyuan He, Grant Sinha et al. (2023). Towards Building a Trustworthy Deep Learning Framework for Medical Image Analysis. https://doi.org/10.3390/s23198122
[89] Md. Alif Sheakh, Mst. Sazia Tahosin, Mohammad Jahangir Alam et al. (n.d.). Optimizing medical image analysis through MViTX on multiple datasets with explainable AI. https://doi.org/10.1007/s00521-025-11014-x
[90] Kai Ma, Siyuan He, Pengcheng Xi et al. (2022). A Trustworthy Framework for Medical Image Analysis with Deep Learning. https://doi.org/10.48550/arXiv.2212.02764
[91] Aditya Jayesh Aiya, Nishant Wani, M Ramani et al. (2025). Optimized deep learning for brain tumor detection: a hybrid approach with attention mechanisms and clinical explainability. https://doi.org/10.1038/s41598-025-04591-3
[92] Sunil Kumar Vuppala, Madhumita Behera, He Jack et al. (2020). Explainable Deep Learning Methods for Medical Imaging Applications. https://doi.org/10.1109/ICCCA49541.2020.9250820
[93] Bas H. M. van der Velden, Hugo J. Kuijf, Kenneth G. A. Gilhuijs et al. (2021). Explainable artificial intelligence (XAI) in deep learning-based medical image analysis. https://doi.org/10.1016/j.media.2022.102470
[94] Tobias Labarta, Elizaveta Kulicheva, Ronja Froelian et al. (2024). Study on the Helpfulness of Explainable Artificial Intelligence. https://doi.org/10.1007/978-3-031-63803-9_16
[95] Subrato Bharati, M. Rubaiyat Hossain Mondal, Prajoy Podder (2023). A Review on Explainable Artificial Intelligence for Healthcare: Why, How, and When?. https://doi.org/10.1109/TAI.2023.3266418
[96] Xiao Ma, Yuhui Tao, Zetian Zhang et al. (2024). Test-time generative augmentation for medical image segmentation. https://doi.org/10.1016/j.media.2025.103902
[97] Ketan Sarvakar, Chandrakant Patel, Hiral B. Patel et al. (2025). Metaheuristic Optimization for Generative and Explainable AI in Biomedical Imaging. https://doi.org/10.4018/979-8-3373-0523-3.ch010
[98] Soroosh Tayebi Arasteh, MahshadLotfinia, Keno Bressem et al. (2024). RadioRAG: Online Retrieval-augmented Generation for Radiology Question Answering. https://doi.org/10.1148/ryai.240476
[99] Author Unknown (2025). Intelligent Healthcare Imaging Platform: A VLM-Based Framework for Automated Medical Image Analysis and Clinical Report Generation. https://doi.org/10.48550/arxiv.2509.13590
[100] Weijian Huang, Cheng Li, Hao Yang et al. (2024). Enhancing the vision-language foundation model with key semantic knowledge-emphasized report refinement. https://doi.org/10.1016/j.media.2024.103299
[101] Tao Chen, Chenhui Wang, Zhihao Chen et al. (2024). HiDiff: Hybrid Diffusion Framework for Medical Image Segmentation. https://doi.org/10.1109/TMI.2024.3424471
[102] Jiahui Peng, He Yao, Jingwen Li et al. (2026). MedP-CLIP: Medical CLIP with Region-Aware Prompt Integration. https://doi.org/10.1016/j.media.2026.104193
[103] Jee Seok Yoon, Chenghao Zhang, Heung-Il Suk et al. (2022). SADM: Sequence-Aware Diffusion Model for Longitudinal Medical Image Generation. https://doi.org/10.1007/978-3-031-34048-2_30
[104] Richard Osuala, Kaisar Kushibar, Lidia Garrucho et al. (2021). Data synthesis and adversarial networks: A review and meta-analysis in cancer imaging. https://doi.org/10.1016/j.media.2022.102704
[105] Ruchi Patel, Ashok Kumar Verma, Neelesh Kumar Sahu et al. (2024). Generative AI Techniques in Medical Imaging Analysis. https://doi.org/10.4018/979-8-3693-2284-0.ch005
[106] Author Unknown (2022). CheXstray: Real-time Multi-Modal Data Concordance for Drift Detection in Medical Imaging AI. https://doi.org/10.48550/arxiv.2202.02833
[107] Sarthak Pati, Siddhesh P. Thakur, İbrahim Ethem Hamamcı et al. (2021). GaNDLF: A Generally Nuanced Deep Learning Framework for Scalable End-to-End Clinical Workflows in Medical Imaging. https://doi.org/10.1038/s44172-023-00066-3
[108] PKR Gujjala (n.d.). … Healthcare Diagnostics: A MultiModal AI Framework Using AWS SageMaker, Lambda, and Deep Learning Orchestration for Real-Time Medical Image Analysis. https://www.researchgate.net/profile/Praveen-Kumar-Reddy-Gujjala/publication/394594106_Autonomous_Healthcare_Diagnostics_A_Multi-Modal_AI_Framework_Using_AWS_SageMaker_Lambda_and_Deep_Learning_Orchestration_for_Real-Time_Medical_Image_Analysis/links/68b5db1a7984e374acecd6dd/Autonomous-Healthcare-Diagnostics-A-Multi-Modal-AI-Framework-Using-AWS-SageMaker-Lambda-and-Deep-Learning-Orchestration-for-Real-Time-Medical-Image-Analysis.pdf
[109] James Hawkins, Marram P. Olson, Ahmed Harouni et al. (2023). Implementation and prospective real-time evaluation of a generalized system for in-clinic deployment and validation of machine learning models in radiology. https://doi.org/10.1101/2023.03.07.23286951
[110] José Guilherme de Almeida, Christina Messiou, Sam J. Withey et al. (2025). Medical machine learning operations: a framework to facilitate clinical AI development and deployment in radiology. https://doi.org/10.1007/s00330-025-11654-6
[111] Sajid Nazir, Mohammad Kaleem (2023). Federated learning for medical image analysis with deep neural networks. https://doi.org/10.3390/diagnostics13091532
[112] David B. Larson, Hugh Harvey, Daniel L. Rubin et al. (2021). Regulatory frameworks for development and evaluation of artificial intelligence–based diagnostic imaging algorithms: summary and recommendations. https://doi.org/10.1016/J.JACR.2020.09.060
[113] Rohan Shad, John P. Cunningham, Euan A. Ashley et al. (2021). Designing clinically translatable artificial intelligence systems for high-dimensional medical imaging. https://doi.org/10.1038/S42256-021-00399-8

[114] Errol Colak, Errol Colak, Robert Moreland et al. (2021). Five principles for the intelligent use of AI in medical imaging.. https://doi.org/10.1007/S00134-020-06316-8
[115] Tadeusz Ciecierski-Holmes, Ritvij Singh, Miriam Axt et al. (2022). Artificial intelligence for strengthening healthcare systems in low- and middle-income countries: a systematic scoping review. https://doi.org/10.1038/s41746-022-00700-y
[116] Ojas A. Ramwala, Kathryn P. Lowry, D. S. Hippe et al. (2024). ClinValAI: A framework for developing Cloud-based infrastructures for the External Clinical Validation of AI in Medical Imaging. https://doi.org/10.1142/9789819807024_0016
[117] L Oakden-Rayner, W Gale, TA Bonham (n.d.). Validation and algorithmic audit of a deep learning system for the detection of proximal femoral fractures in patients in the emergency department: a diagnostic …. https://www.thelancet.com/journals/landig/article/PIIS2589-7500(22)00004-8/fulltext?ref=elliot-c-smith
[118] Liron Pantanowitz, Liron Pantanowitz, Gabriela Quiroga-Garza et al. (2020). An artificial intelligence algorithm for prostate cancer diagnosis in whole slide images of core needle biopsies: a blinded clinical validation and deployment study. https://doi.org/10.1016/S2589-7500(20)30159-X
[119] Zhiyong Zhou, Xusheng Qian, Jisu Hu et al. (2023). An artificial intelligence-assisted diagnosis modeling software (AIMS) platform based on medical images and machine learning: a development and validation study. https://doi.org/10.21037/qims-23-20
[120] Manish Prateek, Saurabh Pratap Singh Rathore (2025). Clinical Validation of AI Disease Detection Models — An Overview of the Clinical Validation Process for AI Disease Detection Models, and How They Can Be Validated for Accuracy and Effectiveness. https://doi.org/10.1002/9781394278695.ch10
[121] Lee, Lee, Lee et al. (2023). The Development and Validation of an AI Diagnostic Model for Sacroiliitis: A Deep-Learning Approach.. https://doi.org/10.3390/diagnostics13243643
[122] James Hawkins, Marram P. Olson, Ahmed Harouni et al. (2023). Implementation and prospective real-time evaluation of a generalized system for in-clinic deployment and validation of machine learning models in radiology. https://doi.org/10.1101/2023.03.07.23286951
[123] Ojas A. Ramwala, Kathryn P. Lowry, Nathan M. Cross et al. (2024). Establishing a Validation Infrastructure for Imaging-Based AI Algorithms Prior to Clinical Implementation.. https://doi.org/10.1016/j.jacr.2024.04.027
[124] William Tanguay, Philippe Acar, Benjamin Fine et al. (2022). Assessment of Radiology Artificial Intelligence Software: A Validation and Evaluation Framework. https://doi.org/10.1177/08465371221135760
[125] Seong Ho Park, Kyunghwa Han, Hye-Young Jang et al. (2022). Methods for clinical evaluation of artificial intelligence algorithms for medical diagnosis. https://doi.org/10.1148/radiol.220182
[126] Alice C. Yu, Bahram Mohajer, John Eng (2022). External validation of deep learning algorithms for radiologic diagnosis: a systematic review. https://doi.org/10.1148/ryai.210064
[127] Dongwook Kim, Hye Young Jang, Kyung Won Kim et al. (2019). Design Characteristics of Studies Reporting the Performance of Artificial Intelligence Algorithms for Diagnostic Analysis of Medical Images: Results from Recently Published Papers.. https://doi.org/10.3348/KJR.2019.0025
[128] Seong Ho Park, Kyunghwa Han (2018). Methodologic guide for evaluating clinical performance and effect of artificial intelligence technology for medical diagnosis and prediction. https://doi.org/10.1148/RADIOL.2017171920
[129] Seong Ho Park, Herbert Y. Kressel (2018). Connecting Technological Innovation in Artificial Intelligence to Real-world Medical Practice through Rigorous Clinical Validation: What Peer-reviewed Medical Journals Could Do. https://doi.org/10.3346/JKMS.2018.33.E152
[130] Yoonyoung Park, Gretchen Purcell Jackson, Gretchen Purcell Jackson et al. (2020). Evaluating artificial intelligence in medicine: phases of clinical research. https://doi.org/10.1093/JAMIAOPEN/OOAA033