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AI in Healthcare For Medical Image Analysis: A Review Of Classification, Segmentation, Foundation Models And Responsible Use

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Abstract—Medical imaging allows clinicians to examine internal structures and identify disease, and Artificial Intelligence, particularly machine learning and deep learning, is increasingly used to analyse X-rays, CT, MRI, ultrasound and retinal photographs. This review summarizes common AI techniques, major applications, benefits, limitations and responsible-use considerations in medical image analysis. Convolutional neural networks for image classification and transfer learning, encoder–decoder networks such as U-Net and its self-configuring and three-dimensional variants for organ and lesion segmentation, and detection of abnormalities for case prioritization are examined. Newer approaches including vision transformers, hybrid transformer–CNN segmenters and foundation models trained on large image collections, which can be adapted to many tasks or prompted to segment arbitrary structures, are discussed. Evidence from systematic comparisons with clinicians and from studies of generalization across hospitals is reviewed. A five-layer architecture for an AI-assisted imaging workflow is proposed, with research gaps, objectives, a comparison of model families and an analysis of challenges including dataset shift, annotation cost, bias, explainability, privacy and regulation. The review concludes that AI should support clinicians within validated workflows rather than replace their judgement.

Index Terms—Medical image analysis, deep learning, CNN, U-Net, segmentation, vision transformers, foundation models, radiology, responsible AI

I. INTRODUCTION

1.1 Motivation

Radiology departments face rising imaging volumes while specialist numbers grow slowly, leading to reporting backlogs and fatigue. Many imaging tasks, such as measuring a tumour, outlining an organ or checking a chest X-ray for pneumonia, involve repetitive visual pattern recognition well suited to AI.

Deep learning has transformed medical image analysis. Shen *et al.* [1] and Litjens *et al.* [2] reviewed early successes across modalities and organs. Since then, models have matched specialists on specific tasks [3], [4], and foundation models now promise broad capabilities from a single pre-trained network.

This paper reviews AI techniques and applications in medical image analysis, proposes an AI-assisted workflow architecture and discusses responsible use.

1.2 Objectives Of The Review

- To review AI techniques for classification, segmentation and detection in medical images.
- To examine foundation models and their potential.
- To propose an AI-assisted medical imaging workflow architecture.
- To compare model families in accuracy, data needs and interpretability.
- To analyse limitations and responsible-use requirements.

II. OVERVIEW OF KEY CONCEPTS

2.1 Imaging Modalities And Tasks

Fig. 1 maps imaging modalities (X-ray, CT, MRI, ultrasound, fundus photography) to the main AI tasks of classification, segmentation, detection and triage.

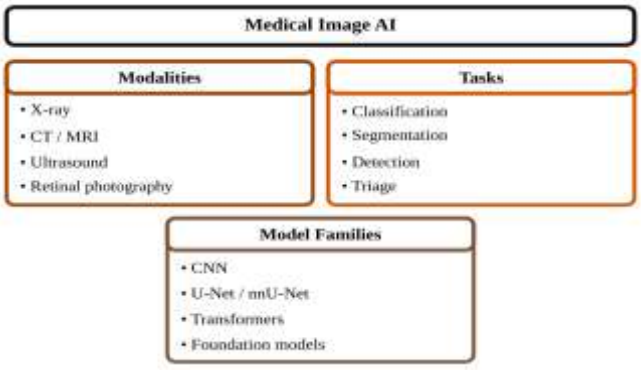


Fig. 1. Imaging modalities and AI tasks in medical image analysis.

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2.2 Transfer Learning

Medical datasets are often small. Tajbakhsh *et al.* [5] showed that fine-tuning networks pre-trained on natural images generally performs as well as or better than training from scratch, especially with limited data.

III. REVIEW OF EXISTING WORK

Segmentation. Ronneberger *et al.* [6] introduced U-Net, whose skip connections preserve spatial detail, and Çiçek *et al.* [7] extended it to 3D U-Net for volumetric scans. Isensee *et al.* [8] developed nnU-Net, which automatically configures preprocessing, architecture and training for each new dataset and achieved state-of-the-art results across many segmentation challenges. Chen *et al.* [9] combined a transformer encoder with a U-Net decoder in TransUNet to capture global context.

Foundation models. Zhou *et al.* [10] trained RETFound on large numbers of unlabelled retinal images with self-supervised learning and showed it adapts efficiently to detect eye and systemic diseases. Ma *et al.* [11] adapted the Segment Anything approach [12] to medical images in MedSAM, enabling segmentation of diverse structures from simple box prompts.

Evidence and generalization. Liu *et al.* [13] systematically compared deep learning with health-care professionals and found comparable diagnostic performance in studies that reported both, but noted that few studies were externally validated. Zech *et al.* [14] showed that a pneumonia model trained at one hospital performed worse at others and could exploit hospital-specific cues, a warning about dataset shift. Table @lit summarizes these works.

TABLE I Summary of Literature Survey

Ref.	Authors	Year	Technique Used	Merits	Demerits
[5]	Tajbakhsh et al.	2016	Fine-tuning vs. training from scratch	Fine-tuning works well with small data	Few modalities tested
[7]	Çiçek et al.	2016	3D U-Net	Volumetric segmentation from sparse labels	Memory intensive
[14]	Zech et al.	2018	Cross-hospital generalization study	Exposed dataset shift	Pneumonia task only
[13]	Liu et al.	2019	Meta-analysis vs. clinicians	Comparable performance reported	Few external validations
[8]	Isensee et al.	2021	nnU-Net self-configuration	State-of-the-art across challenges	Long training time
[9]	Chen et al.	2021	TransUNet hybrid	Global context for segmentation	Data hungry
[10]	Zhou et al.	2023	RETFound foundation model	Efficient adaptation to many diseases	Retinal images only
[11]	Ma et al.	2024	MedSAM promptable segmentation	Segments diverse structures	Needs box prompts

IV. IDENTIFIED RESEARCH GAPS

- Most models are validated retrospectively and on data from few institutions.
- Pixel-level annotation is expensive and requires expert time.
- Under-represented populations, devices and protocols lead to biased performance.
- Foundation models need careful evaluation for safety and failure modes.
- Integration with PACS and reporting workflows is rarely described.

V. SYSTEM ARCHITECTURE

The workflow architecture is shown in Fig. 2.



Fig. 2. Proposed AI-assisted medical imaging workflow architecture.

5.1 Acquisition Layer

Scanners produce images that are stored in the PACS with acquisition details.

5.2 Preprocessing Layer

Images are de-identified, intensity-normalized and resampled to a standard resolution.

5.3 Model Layer

Validated models classify studies, segment organs and lesions and detect urgent findings. Each model has documentation describing its intended use.

5.4 Explanation And Quality Layer

Saliency maps [15], segmentation overlays and uncertainty estimates are generated; out-of-distribution checks flag unusual images.

5.5 Clinical Review Layer

Radiologists see AI results as prioritized worklists and overlays, accept or modify them and issue the final report. Feedback is recorded for monitoring.

VI. IMPLEMENTATION METHODOLOGY

Fig. 3 shows the workflow. Segmentation overlap is measured with the Dice similarity coefficient

$$DSC = 2|P \cap G| / (|P| + |G|) \qquad (1)$$

where P is the predicted region and G the ground truth. Classification performance is reported with sensitivity, specificity and AUC, and external validation at a different hospital is required before deployment.

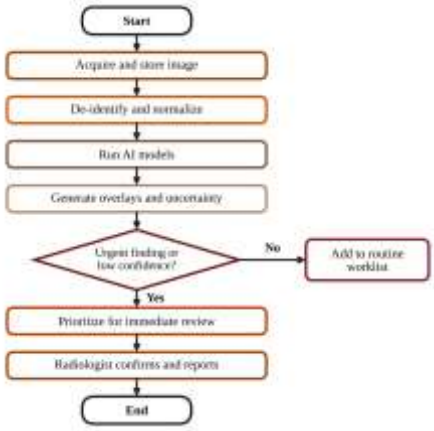


Fig. 3. AI-assisted imaging workflow.

VII. PERFORMANCE COMPARISON

Table II compares model families. CNN classifiers are mature and efficient; U-Net variants dominate segmentation; transformers capture global context; foundation models reduce labelling needs but require careful validation.

TABLE II Comparison of Model Families

Model Family	Main Task	Data Need	Interpretability
CNN classifier	Classification	Medium	Saliency maps
U-Net / nnU-Net	Segmentation	Medium	Visual masks
Transformer hybrids	Segmentation	High	Attention maps
Foundation models	Many tasks	Low labelled	Limited

VIII. OPEN ISSUES AND FUTURE DIRECTIONS

Table III summarizes key challenges. Future directions include multimodal models combining images with reports and clinical data, federated learning across hospitals, continuous post-deployment monitoring and regulatory frameworks adapted to adaptive AI.

TABLE III Challenges and Mitigation

Challenge	Mitigation
Dataset shift	External validation; site adaptation
Annotation cost	Self-supervised and foundation models
Bias	Diverse data; subgroup analysis
Explainability	Overlays, uncertainty, documentation
Privacy	De-identification; federated learning

IX. CONCLUSION

AI has become a powerful tool for medical image analysis, delivering expert-level performance on specific tasks and promising broader capability through foundation models. The reviewed literature also shows that generalization across hospitals, annotation cost, bias and explainability remain serious concerns. AI should therefore be integrated into validated clinical workflows in which clinicians remain responsible for decisions.

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