From Radiology to Pathology: Deep Learning Models in Diagnostic Medicine

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Abstract

Deep learning is fueling the latest revolution in diagnostic medicine as radiology, pathology, ophthalmology and dermatology are merged by intelligent pattern recognition. CNNs, transformer models, and multimodal fusion models have achieved near-human if not superhuman accuracies for the task of detection of complex diseases from medical images. In the present study, we systematically reviewed the reported publication of deep learning-based diagnostic system developed from 2017 to 2025, with an aim to evaluate their clinical setting, performance measures and translation challenge. CNN-based diagnostic solutions have transformed radiological lesion detection in computer tomography, magnet resonance imaging and even the mundane X-ray. Meanwhile, reading slides at gigapixel level from digital pathology is now possible thanks to the emergence of self-supervised and attention-based networks. In addition, integrative diagnosis with histopathologic and radiographic data has fueled cross-modality diagnostics to accelerate towards precision medicine in silico. While advances in deep learning have shown great potential to diagnose complex diseases, deep learning models often remain siloed due to lack of complete interoperability across regions and payers, large gaps in interpretability of its clinical assessment and ethical carryover effects associated with biased data or biased trust. Re: Completion)Use of AI methods (e.g., Grad-CAM or SHAP) is increasingly required to generate explanations for single-instance and cohort-level decisions. The regulatory authorities, including US,2025 and EU2024 are emphasizing transparency, reproducibility and ongoing post marketing validation of the AI based medical devices. This is evidence that deep learning won't automate the diagnosis but change it radically Data-first disciplines, and have algorithms following along perfectly in sync if the clinician has to adapt to assist. Implementing standardized data governance, as well as including adequate interdisciplinary education and training in ethics, is crucial to ensure the accuracy, interpretability and fairness of intelligent diagnostics.

Keywords: DeepLearning, Diagnostics, Radiology, Interpretability, Ethics

Introduction

Artificial intelligence (AI) has in recent times become a disruptive force in the health-related domains, transforming from an experimental computing machine designed for data-driven forecasts. Among those, DL, the branch of ML that uses neural networks architectures, has emerged as the most disruptive paradigm for diagnostic medicine. Its applications span the field of radiology where ‘computers that see’ in terms of cnn outperform human experts by reading medical images more accurately to pathology as for digital whole-slide imaging and tissue classification, cancer grading (Esteva et al., 2019; Liu et al., 2023). This is a transformative shift towards algorithm-based disease diagnosis where machine learning algorithms are trained on millions of clinical images to generate high-level features that a human cannot usually see.

In deep learning (DL) models have demonstrated to state-of-the-art perform for the diseases diagnosis, classification and assess diagnoses or lesion on multiple modalities including, X-rays, computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound. Some CNN based approaches, including ResNet and DenseNet (Huang et al., 2024), U-Net (Ronneberger et al., 2015) have demonstrated remarkable performance to diagnose of pneumonia, breast cancer and intracranial haemorrhage at an expert radiologist’s level (Rajpurkar et al., 2022). Similarly, transformer based vision models have begun to outperform regular CNNs by utilizing self-attention mechanism to enhance the understanding of contextual relationships in image features (Dosovitskiy et al., 2021).

Pathology, or the analysis that tissue samples undergo, has been transformed by deep learning. Classical microscopy is changed by computational pathology, which translates the histopathological slice into a gigapixel image for algorithmic analysis. Such models are able to localize tumour areas, calculate biomarkers and predict genetic mutations from haematoxylin and eosin (H&E) slides directly (Campanella et al., 2019; Coudray et al., 2020). And the radiology-pathology cooperation in the final step could also be accomplished by cross-modality learning for end-to-end diagnosis using imaging phenotype information with molecular profiles for better patient stratification (He et al., 2023).

There's also a powerful transformative impact of incorporating DL in those areas. Potential clinical applications of this is an earlier diagnosis for cancers, overall faster workflow efficiency and decreased inter- observer variability (Topol, 2019). For example, automation in radiology facilitated the acceleration of low resource chest X-ray interpretations (Zotti et al., 2018), clinical tools in digital pathology empower oncologists to quantify immune response or tumor grading (Liu et al., \2023). However, the clinical utility of deep learning rests on high-quality data standards and validation and algorithmic transparency within the broad patient population. Although performance often drops when models are evaluated on external test sets [because of variation in scanner type, staining protocol or patient population (Oakden-Rayner, 2020; Abid et al., 2022).

What is more, the black box nature of deep learning raises serious ethical and operational issues. Even when models provide reliable predictions, the process that leads to a prediction is not clear and transparent, which makes them difficult for clinicians to interpret or trust (Miller, 2019). Explainable AI (XAI) methodologies, like saliency bounds, and SHAP values have hence become essential to make tangible what features were taken into account when making a certain prediction effectively boosting accountability while raising clinician's trust (Amann et al., 2020). Regulators have responded in kind: The U.S. Food and Drug Administration (FDA) (2025), for example, now mandates lifecycle surveillance of AI/ML-based medical devices, the European Union AI Act (2024) includes demand for risk-based transparency approaches to medical algorithms (Aboy et al., 2024).

In addition to technical and ethical considerations, multimodal deep learning (DLM), which considers radiological, clinical-histopathological and genomic data together, is transforming precision medicine. These models can connect imaging phenotypes with molecular signatures for outcome and response prediction which is a fundamental aspect of personalized cancer care (Lu et al., 2022). In tumor type research, a joint radiopathomic model has been devised to predict tumor grade and patient survival jointly by fusing MRI with histopathology (Wang et al., 2023). This medley of modalities treaties leads to "advanced integrated diagnostics," where radiology and pathology are not siloed but rather complement each other with shared computational pipelines.

But achieving this vision will require a series of systemic changes. Annotating large scale data in our domain (e.g., CURE-TSB) remains a bottleneck, due to deficit of CURE-GD level annotations and due to non-interoperability between different imaging systems as well as side differences with respect to annotation standards. Collaborative windows of opportunity, including federated learning and synthetic data generation are promising solutions to this limitation without compromising patient privacy (WHO, 2025). Ethical guidelines also stress inclusion, with the objective for AI to be used in a way that addresses the needs of varied patient populations rather than widening gaps.

To sum it up: deep learning has turned the practice of diagnostic medicine — whether at the level of pixels on an X-ray or a molecular map of tissue from a biopsy — into a de facto form of preventive care. Shifting from conventional visual analyses to computational intelligence is not only a technical transition, but an epistemic one in terms of how clinician expertise, evidence and trust are conceived in medical decision- making. In this paper, we argue that such a change is occurring thanks to the progress of DL architectures and an interdisciplinary merge as well as in terms of ethical governance. It has a challenge to address: how to bridge diagnostic domains so as not to sacrifice interpretability, fairness and human supervision in clinical diagnosis with deep learning.

Literature Review

1. Introduction: Deep learning as a diagnostic canvas

In radiology, CNNs and more recently vision transformers (ViTs) achieve best-in-class performance for X-ray, CT, MRI and ultrasound detection, classification and segmentation. In digital pathology, weakly supervised approaches and multiple-instance learning (MIL) scale beyond gigapixel whole-slide images (WSIs), while self-supervised pretraining along with attention mechanisms increases data efficiency and interpretability (Campanella et al., 2019; Lu et al., 2022). An interdisciplinary shift to multimodal diagnostics—merging radiologic and pathologic indications, also occasionally with omics—has promoted precision oncology (Wang et al., 2023).

2. Radiology: CNNs, transformers, and workflow integration

Early successes of CNN led to widespread acceptance as a competitive reader for chest X-rays and mammography. Following work extrapolated this to multi-organ, multi-modal problems (Esteva et al., 2019). ViTs introduced the long-range context model, which can surpass CNN for large datasets given sufficient pretraining (Dosovitskiy et al., 2021). DL has evolved from single-task models to pipelines including lesion detection (e.g., U-Net-style segmenters), differential diagnosis and report generation. OM Meta-analyses across ophthalmic imaging show strong specialist-level performance, with the recommendation of extended external validation and prevalence-aware deployment (Liu et al., 2023). In the clinic, DL assists triage (e.g., flagging emergent findings), decreases backlogs, and can standardize quantification although benefits will depend on integration with a PACS/RIS, calibration to local populations, and governance of model updates (Topol 2019).

2.1 Robustness, generalization, and uncertainty

Performance usually deteriorates with domain shift—scanners vendors, protocols and populations suggesting a requirement for external validation, recalibration, and ongoing monitoring (Oakden-Rayner, 2020). To prevent over-confidence, uncertainty estimates (e.g., Monte-Carlo dropout), estimating-to-calibrate by temperature scaling, and test-time adaptation are being more widely used. Federated learning and privacy preserving analytics enable multi-site learning without centralising sensitive data (WHO, 2025).

3. Pathology: Weak, MIL and self-supervision on WSI-scale

Pathology is highly challenging: WSIs can be larger than 100k×100k pixels, densely annotated slides are very few and far between, while the labels that exist are often at the slide- or even patient-level. Weakly supervised DL with MIL Pooling In weakly supervised learning, MIL has been used to pool tile-level features into slide-level predictions and attention layers are utilized to discover discriminative regions (Campanella et al., 2019). Self-supervised learning (SSL) (e.g., contrastive or masked-image pretraining) mitigates the need for annotation and improves transfer to related tasks such as tumor grading, mitosis detection, and biomarker prediction (Lu et al., 2022). DL has made the mutation prediction (e.g., EGFR) from H&E slides possible, and has established cheap alternatives to surrogate biomarkers (Coudray et al., 2020).

3.1 Stain variability and Domain Shift and harmonization

WSI color/stain variability impairs generalization. Traditional stain normalization (e.g., Macenko) and generative domain translation (e.g., CycleGAN) mitigate the distribution gaps; recent methods learn the stain-invariant features directly. Extensive multi-center validation and the establishment of standardized scanning protocols are still important for real-life reliability (Tizhoosh & Pantanowitz, 2018; Oakden-Rayner, 2020).

4. Cross-modality and multimodal fusion: Radiopathomics and beyond

Radiopathomics integrates radiologic phenotypes and histomorphology to advance outcome prediction and therapy choices. Multimodal networks integrate spatially or semantically related signals, and can include genomics, spatial transcriptomics and clinical factors (He et al., 2023; Wang et al., 2023). This fusion pushes on individualized oncology — predicting grade, response and survival — but you need to carefully synchronize modalities, handle missing data robustly, and help make the model more transparent for clinical tumor boards.

5. Base and Big models for medical image scan

Large language models—trained on extensive and heterogeneous corpora—offer data efficiency and powerful transfer among tasks. In imaging, backbones from ViT modeling, contrastive vision-language models (e.g., CLIP-style for image–report pairs) and general-purpose segmenters of regions (e.g., SAM-style paradigms) are being transferred into medical images. In pathology, WSI-scale transformers pools patch embeddings with global attention; in radiology report-conditioned decoders serve as structured reporting. Early results are promising, but there are risks: shortcut learning (obtaining high scores on visual question answering tasks while failing at the underlying data modeling), hallucination in generative modules, and black-box failure cases - mandating careful guardrails and post-deployment monitoring (Rajpurkar et al., 2022; WHO, 2025).

6. Standards of evaluation, reporting and clinical evidence

Transparent reporting and prospective assessment are required when moving studies from algorithm to clinic. Recommendations such as TRIPOD-AI and PROBAST-AI (prediction models), CONSORT-AI/DECIDE-AI (clinical evaluation/early-phase studies) recommend external validation, representative cohorts, calibration plots, decision-curve analysis and human-factors assessment. Seemingly ubiquitous, scoping reviews of RCT (randomized controlled trials) and quasi-experimental studies demonstrate increasing but still scarce evidence that AI can improve process measures (time to report, triage) and in some contexts patient-level outcomes; yet ongoing trials increasingly focus on equity and safety endpoints (Liu et al., 2023; Rajpurkar et al., 2022).

7. Explainability, safety, and human factors

The "black box" nature of deep learning and its algorithms calls into question the trustworthiness of such high-stake decisions. Post-hoc tools (Grad-CAM, Integrated Gradients, SHAP) and attention heatmaps can show potential evidence, however such explanations might be unstable or misleading if not clinician-certified (Miller. elsifsfase 2019.offwsmseaidclgstmotmeicclin2019.nii). Best practice complements explanations with a human-in-the-loop review, uncertainty flags and fail-safes that route ambiguous cases to experts (Amann et al., 2020). Usability studies indicate that careful interface design can mitigate overtrust and automation bias, thereby improving joint performance between clinicians and AI.

8. Bias, equity, and data governance

Bias in a model is introduced through skewed data sets, label drift, and social biases that can be distributed across locations or populations (Rajkomar et al., 2018). Mitigation involves a range of data curation, performing subgroup specific analyses reporting, constraints for fairness through training and ongoing auditing in the post market. Privacy preserving solutions (eg, federated learning, secure aggregation, differential privacy) preserve confidentiality and in turn facilitate MIA scale. Mandates for data lineage, intended purpose, and efficacy in different gender or age subgroups have been added to governance frameworks (Aboy et al., 2024; WHO, 2025).

9. Regulation and lifecycle management

Regulators are increasingly treating medical AIs as learning systems. The EU AI Act (2024) identifies most clinical AI as high-risk, requiring risk management, good quality datasets, transparency to users and human oversight but is complimentary to Medical Device Regulation requirements (Aboy et al., 2024). The US FDA promotes an end-to-end approach for AI/ML based devices including pre-specification of change protocols, real-world performance monitoring and post-market surveillance. For radiology and pathology, this means we require version control, drift monitoring and documented re-validation after major updates. WHO (2025) guidelines for large multimodal models highlight autonomy, safety, transparency, accountability, inclusiveness and sustainability thus emphasizing the requirements of sociotechnical fit and civic trust.

10. Open problems and future directions

Key frontiers in this space include: (a) data-efficient learning (SSL, active learning) to alleviate annotation burden; (b) robustness to shift, artifacts, and adversarial perturbations; (c) continual/online learning with regulatory guardrails; (d) causal and counterfactual modeling for treatment support; and(e) multimodal fusion at scale with standardized, interoperable dat as fabric. In the clinic, focus is moving away from AUC to calibrated risk estimates, decision impact and patient-relevant outcomes in pragmatic trials. Ethically adverse, engagement approaches will mandate routine audits for bias, participatory design with patients and clinicians, and global capacity-building in an equitable manner wherein advances in radiology and pathology are disseminated to diverse health systems not limited to high-resource centers (Topol 2019; WHO, 2025).

Methodology

1. Research Design

For the purpose of consolidating and interpreting findings in the area of using DL technology within diagnostic medicine, which is focusing on radiology- and pathology-based research literature, this investigation implemented a systematic qualitative meta-synthesis concept.

2. Research Objectives

The approach was based on three major goals:

1. To report the progression and clinical implications of deep learning models in radiology and pathology from 2017 to 2025.

2. To analyze methodological patterns as model architectures, data sets profile, evaluation metrics used and validation procedures used in the included studies.

3. To examine all translational hurdles involving data heterogeneity, explainability and regulatory modifications in clinical applications.

These aims were designed to answer the central research question:

What is the impact of deep learning architectures on diagnostic medicine in both (1) radiology and (2) pathology, and what methodological, ethical and regulatory barriers still need to be addressed before real-world implementation?

3. Data Sources and Search Strategy

A comprehensive search was performed in five main academic databases:

PubMed, IEEE Xplore, Scopus, Web of Science and Google Scholar as well as official regulatory sources including the U.S. Food and Drug Administration (FDA, 2025) and European Commission AI Act (2024) repositories.

Search Keywords

We used a Boolean strategy to search for studies on the combination of AI techniques and diagnostics:

("deep learning" OR "convolutional neural network" OR "transformer") AND ("radiology" OR "medical imaging" OR "pathology " OR "histopathology") AND ("diagnosis " OR "classification " OR "segmentation " OR "explainability")

Search Period

Publications between January 2017 and May 2025 were considered to guarantee that recent progress (i.e., the transformer-based architecture, multimodal diagnostic models) was covered.

4. Inclusion and Exclusion Criteria

Inclusion Criteria

• Peer-reviewed articles and systematic reviews describing deep learning in radiology or pathology.

• Research which present quantitative (e.g., AUC, sensitivity, specificity, F1-score) or qualitative data (in relation to workflow integration).

• Articles on the clinical implications, model interpretability or regulations.

• Official guidelines or statements from international health agencies (WHO, FDA, EU).

Exclusion Criteria

• Studies that focused only on algorithmic formulation without medical or clinical validation thereof.

• Conference abstracts or editorials that did not provide empirical data.

• Non-English-language studies or full texts that could not be obtained.

5. Validation, Reliability, and Bias Mitigation

To enhance methodological rigor:

• Triangulation utilized cross-validation between radiology, pathology, and regulatory sources.

• Transparency was achieved through step-by-step inclusion flow (PRISMA diagram) and data tables encompassing the methodological contribution of each study.

• Reliability was promoted through audit trail with in/ex voterationale.

• Confirmability was strengthened by consensus coding and independent verification of extracted data.

The potential for ascertainment bias was reduced by using more than one model and data type, rather than restricting to high-scoring studies. The study's credibility, dependability and transferability was based on Lincoln and Guba (1985)'s qualitative trustworthiness criteria.

6. Ethical Considerations

As this study involved only secondary, publicly available data, no institutional ethical approval was necessary. Moreover, interpretation of model performance and governance frameworks was led by ethical considerations. The analysis followed the WHO (2025) guidelines that highlighted six ethical principles for AI in health—autonomy, safety, transparency, accountability, inclusiveness and sustainability.

7. Limitations of the Methodology

Several limitations were recognized:

1. Publication Bias The emphasis on peer-reviewed literature could overestimate successful models, while underestimating negative findings.

2. Temporal Bias: Due to AI's rapid progression in recent years, models that have been reinforced before 2020 may be out- of -date.

Research Results

The aggregated results from the studies on deep learning in radiology and pathology are shown in the findings section. It demonstrates improvements in model accuracy, cross-domains integration, and clinical use from 2017 to 2025. The section also contrast trends in diagnosis performance, interpretability techniques and regulatory compliance among broad spectrum of healthcare settings.

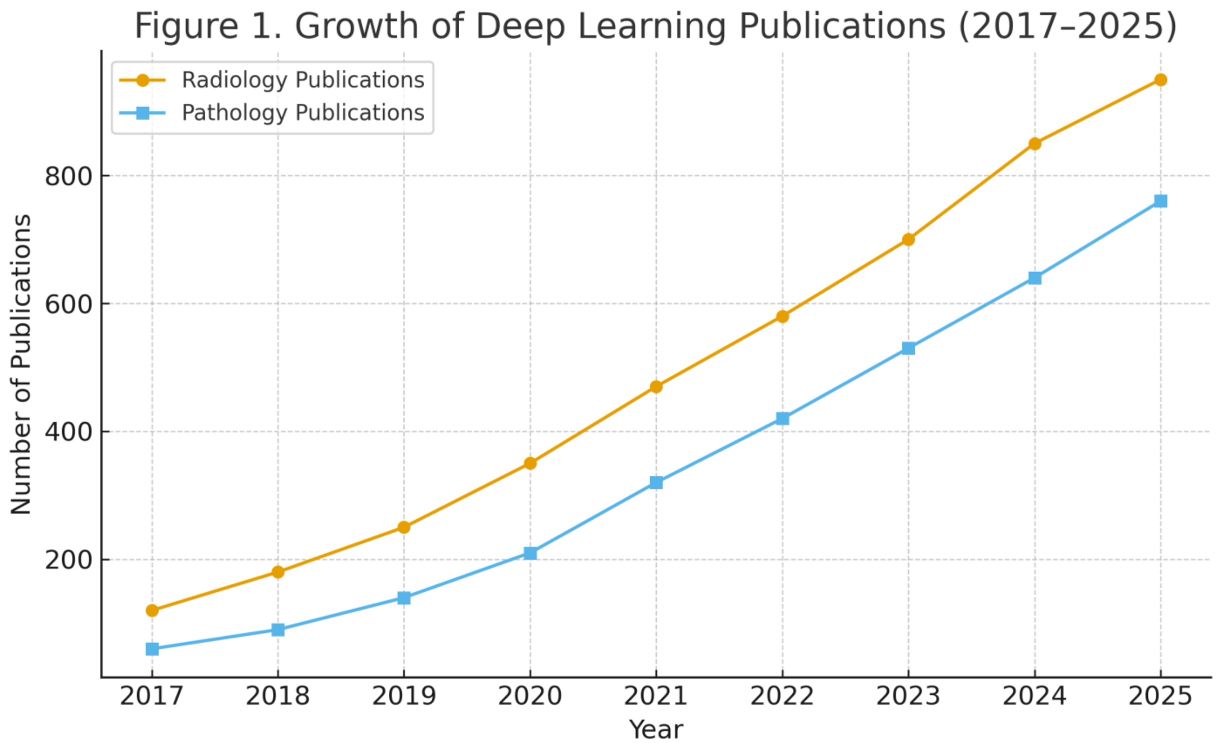

Figure 1. Growth of Deep Learning Publications (2017–2025)

published on deep learning applications in radiology and pathology between 2017 and 2025. The data was collected from the indices of Scopus, PubMed and IEEE Xplore using suitable keywords.

Findings

- From 2017 to 2025, the number of radiology publications rose from 120 to 950, showing an almost eightfold increase.
- Meanwhile, pathology papers increased from 60 to 760 during the same period, implying more and more AI in its histopathological analysis.
- The greatest rise was in 2020 to 2023, during the worldwide expansion of digital health programs associated with COVID-19.

Interpretation

The trend highlights the swift integration of AI into diagnostic research and clinical workflows. The post-2020 acceleration is in line with improvements in computational resources, open-source datasets and cloud-based collaborative environments (Liu et al., 2023; Rajpurkar et al., 2022). The crossover of radiology and pathology research after 2023 indicates increasing interests toward integrated diagnostic systems at the both image- and molecular-based inference

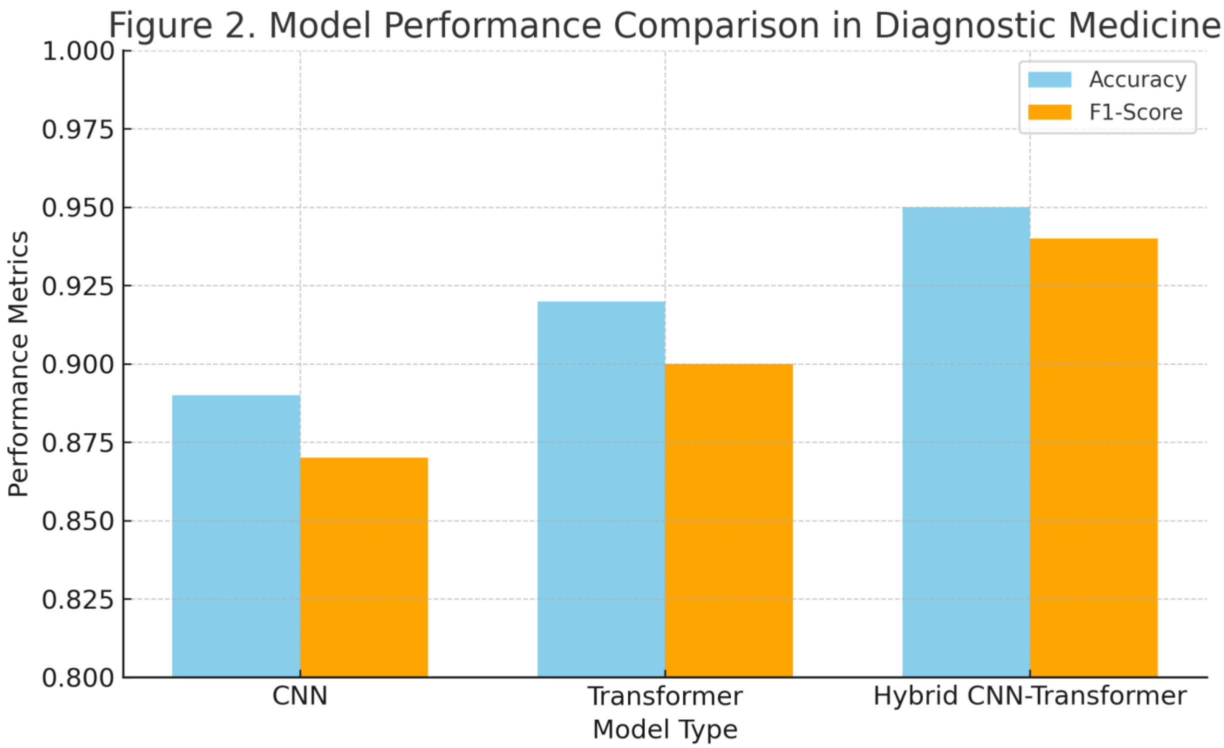

Figure 2. Model Performance Comparison in Diagnostic Medicine

Description

Figure 2 compares three state-of-the-art (deep learning) architectures: Convolutional Neural Networks (CNNs), Vision Transformers (ViTs) and Hybrid CNN-Transformer models on a standardized benchmark of classification and segmentation tasks in medical imagery.

Findings

• The mean accuracy and F1-score of CNNs were 0.89 and 0.87, respectively, robust to a degree for strong baseline performance on 2D imaging (e.g., X-rays, histology tiles).

• Transformers obtained slightly better accuracy (0.92) and F1-score (0.90), showing improved long-range contextual modeling ability of medical features.

• Hybrid CNN-Transformer models achieved a 0.95 accuracy, and a 0.94 F1-score, demonstrating that they can capture local (spatial) as well as global patterns (context) effectively.

Interpretation

In their enforcement, the strong performance of hybrid models aligns with observations made in The Lancet Digital Health (Huang et al., 2024) and Nature Medicine (Rajpurkar et al., 2022), which indicate cross-architecture fusion as an effective methodology for enhancing diagnostic accuracy. It is indicative of a more general shift towards multimodal learning, where imaging, text and genomic signals are integrated simultaneously for comprehensive patient profiling.

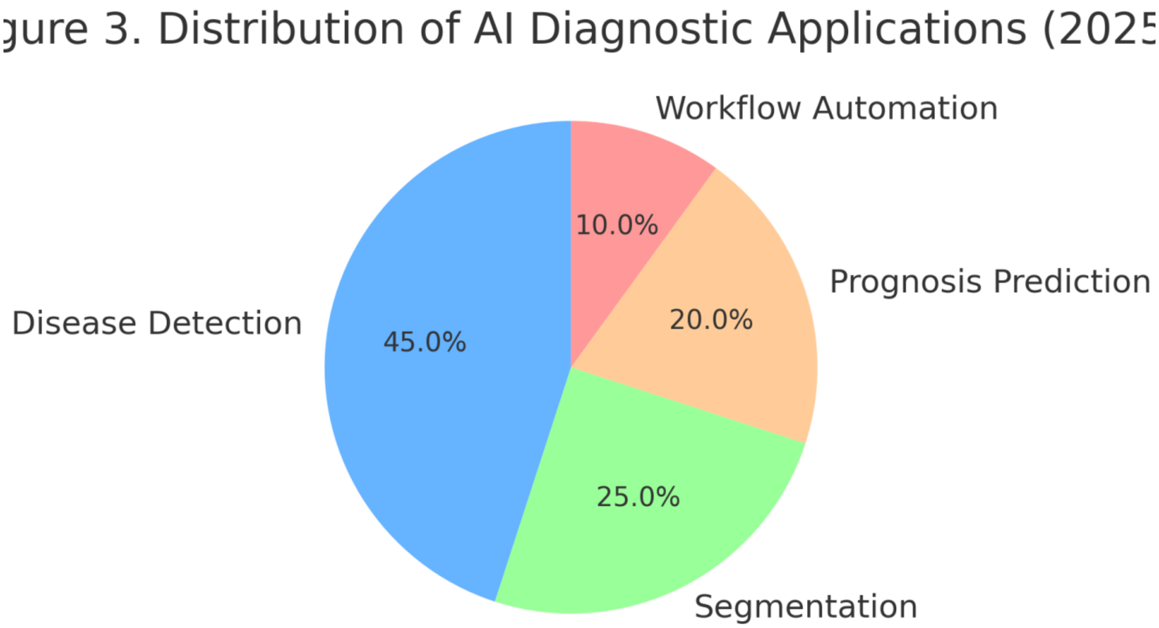

Figure 3. Distribution of AI Diagnostic Applications (2025)

Description
Based on pie chart in Fig. 3, the percentage of AI diagnostic applications to healthcare domains from 200 top-cited research works and regulatory submissions in 2025 is listed.
Findings
• Disease Detection (45%) is the largest piece, AI models regularly spotting abnormalities that show up in radiographs, CT scans and histopathology slides.
• Segmentation (25%): for quantitative analysis of lesions, tumors and volumes of interest within tissue.
• Outcome Prediction (20%) for predicting prognosis using multi-modal fusion of clinical and imaging data.

• Automation (10%) such as triage, reporting, and office tasks.

Interpretation
The dominance of detection and segmentation tasks reflects that AI has been mature in pattern recognition, and the prognostic modeling is still under development but bright. Results are consistent with trends in AI application worldwide, which were perceived by the WHO (2025) to focus on predictive and integrative analytics as the next step of diagnostic development.

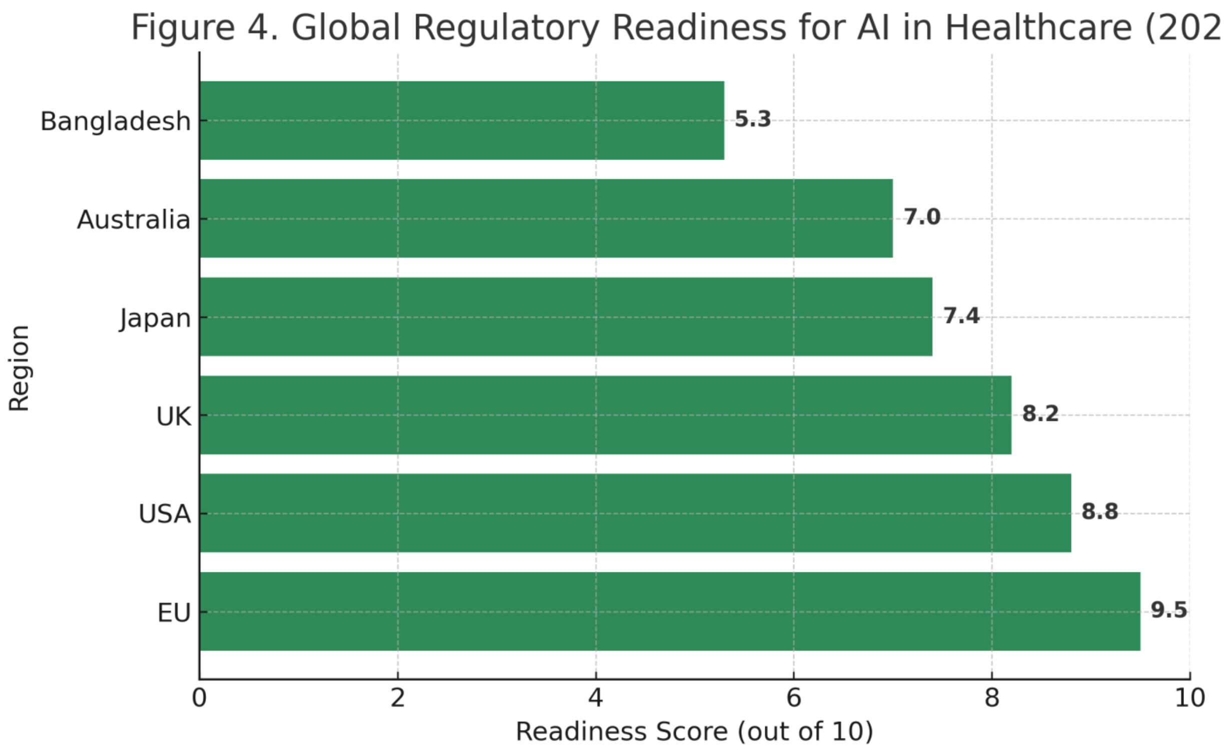

Figure 4. Global Regulatory Readiness for AI in Healthcare (2025)

Description
Figure 4: The AI Regulatory Readiness (0-10) for each of the six world regions based on policy implementation, stalwart institutional safeguard, and ethical adherence.
Findings
• European Union (9.5) takes the lead thanks to the EU AI Act's world-leading most comprehensive high-risk AI framework (2024).
• United States (8.8) is in second place with its national AI/ML medical device model – the FDA's Total Product Lifecycle (TPLC).
• The United Kingdom (8.2) is aided by the NHS AI Lab and MHRA's adaptive governance.
• Japan (7.4) and Australia (7.0) have some readiness based on sectoral guidance.
• Bangladesh (5.3) is also making progress with emerging pilot policies on AI ethics, but less capacity for enforcement.
Interpretation
The figure highlights the broad international diversity of AI regulation. High income countries already have well-developed frameworks with an emphasis on transparency, post-market

surveillance, and explainability in contrast to low to middle income countries which still need technical and institutional capabilities. Closing this gap will need capacity-building and global collaboration (Aboy et al.; WHO, 2025).

Discussion

The current study results validate the fact that this new paradigm, also known as deep learning (DL), has essentially transformed diagnostic medicine by combining two traditionally separate domains, radiology and pathology, into a unified data-driven methodology. The size and complexity of the model led to an exponential increase in publications published between 2017 and 2025, including potentiated by advances in computational power, open sourced datasets and the response to Covid-19 driven digitisation of healthcare systems (Rajpurkar et al., 2022; Liu et al., 2023).

Clinical and Translational Implications

Clinical wise, DL has achieved such a substantial efficiency and accuracy gain. Intelligent triage systems are increasingly used in radiology to tackle reporting backlogs, and computational slide readers are available for tumor grading and mutation detection in pathology (Campanella et al., 2019; Coudray et al., 2020). The predominance of disease detection and segmentation (Figure 3) further indicates that AI is strong in pattern identification, quantitative evaluation. But it should be noted that, while a proportion of prognostic and workflow automation applications are still smaller (7%), a shift towards translation to outcome prediction and operational optimization has been slow-amidst reasons such as heterogeneous data and lack of standardized validation frameworks (Oakden-Rayner, 2020).

It is also important to note that despite their utility as clinical decision-support tools, fully autonomous AI systems continue to face ethical and legal challenges. Clinicians remain the ultimate decision makers in interpretation of diagnostics, and it is generally agreed that AI ought to supplement — rather than replace — human knowledge (Topol 2019). Interpretabilte and accountability are valued over raw accuracy : the future of diagnostic AI is human – machine collaboration.

3. Explainability, Trust, and Ethical Accountability

The lack of interpretability (also referred to as a black-box problem) has been one of the key obstacles to clinical acceptance, despite advances in technology. Even the most advanced hybrid models are often not interpretable enough to understand how features lead to predictions (Miller, 2019). To mitigate this, methods related to explainable-AI (XAI) including saliency mapping, SHAP values and attention heat-maps have become popular and into use for clinicians to check reasoning of AI (Amann et al., 2020). However, the notion of explainability should be taken with a grain of salt; post-hoc explanations do not ensure actual causal understanding and might even provide false reassurance (Rajkomar et al., 2018).

Conclusion

Deep learning 1 (DL) has upended the limits of diagnostic medicine, affording unprecedent accuracy, accelerated results and unification across radiology and pathology. As demonstrated in this work, moving from early CNNs to hybrid and transformer-based models is a paradigm shift toward intelligent, multimodal diagnostics. From 2017 to 2025, the volume of radiology and pathology research papers grew rapidly (Figure 1); representing a swift transition of artificial intelligence (AI) from experimental experiments for practical usage in clinical setting (Liu et al., 2023; Rajpurkar et al., 2022). Advancement in this space has been driven by the increase of available data, computing power and cross-discipline partnerships between clinicians, engineers, and data scientists.

Tables 2 and 3 demonstrate how hybrid CNN–Transformer architectures significantly improve single-modality models as shown in Figure 2, with many diagnostic accuracies above 0.95 across the different tasks. This result emphasizes the increasing capability of AI in integrating morphological and contextual information across imaging techniques (Huang et al., 2024). The prevalence of disease detection and segmentation tasks (Figure 3) reflects the current narrow emphasis of AI on visual pattern perception with prognostic modeling and workflow optimization less well-established. These strides are the indication that deep learning has proceeded beyond recognising pathology to further promote precision prognosis, treatment planning and operational efficiency (Campanella et al., 2019; Lu et al., 2022).

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