

AI in Medical Imaging & Diagnostics: Review

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ABSTRACT: Artificial Intelligence (AI) is rapidly transforming medical diagnostics by enhancing accuracy, efficiency, and decision-making across radiology, pathology, laboratory medicine, and robotic-assisted procedures. AI-driven models, including deep learning, convolutional neural networks, vision transformers, and multiple instance learning, have demonstrated expert-level performance in disease detection, tumor classification, hematology analysis, and microbiological diagnostics. Intelligent robotics and autonomous systems further optimize workflow efficiency, enable real-time interventions, and facilitate remote diagnostics. Expert systems and clinical decision support tools integrate AI with medical knowledge to support differential diagnoses, treatment planning, and personalized medicine. Despite these advancements, challenges remain in data heterogeneity, algorithmic bias, interpretability, regulatory compliance, and integration into clinical workflows. Emerging solutions, such as explainable AI (XAI), federated learning, self-supervised learning (SSL), and multimodal AI integration, aim to address these challenges, promoting transparency, security, and equitable outcomes. The convergence of AI with clinical workflows, data governance frameworks, and human-AI collaboration has the potential to transform diagnostics into a precise, efficient, and ethically guided component of modern healthcare.

Keywords: Artificial Intelligence (AI), Medical Diagnostics, Deep Learning, Computer-Aided Diagnosis (CAD), Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), Explainable AI (XAI), Generative Adversarial Networks (GANs), Robotic-Assisted Biopsy, Precision Oncology, Automated Blood Analyzers, Digital Pathology.



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1. INTRODUCTION

The adoption of Artificial Intelligence (AI) in healthcare has significantly enhanced disease detection and prognosis by providing high levels of accuracy, efficiency, and scalability [1]. The exponential growth of healthcare data has driven the development of AI models, particularly for medical imaging, laboratory tests, and genomic data analyses, to support clinical decision-making. Deep learning (DL) and machine learning (ML) algorithms have been central to these advancements.

Applications of convolutional neural networks (CNNs) in deep learning have transformed radiology by enabling automated detection of abnormalities in X-ray, computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) scans, often achieving accuracy comparable to or exceeding that of human

radiologists [2]. Similarly, AI-assisted histopathology and digital pathology systems employ whole slide imaging (WSI) and multiple instance learning (MIL) algorithms to classify tumor types, grade cancer severity, and improve diagnostic consistency [3].

AI has also advanced laboratory diagnostics by automating blood tests, facilitating the discovery of novel biomarkers, and supporting predictive genomics [4][5]. Natural Language Processing (NLP) AI models further enable automated extraction of clinically relevant information from unstructured electronic health records (EHRs) [6]. Additionally, AI performance is increasingly enhanced through image quality improvement techniques based on generative adversarial networks (GANs) and self-supervised learning (SSL), which allow models to generate, complete, or refine diagnostic outputs without relying on fully labeled datasets [7].

Despite these advancements, integrating AI into diagnostic workflows presents challenges, including data heterogeneity, interpretability of AI decisions, regulatory limitations, and ethical concerns such as algorithmic bias [8]. Future developments in explainable AI (XAI), federated learning for data protection, and multimodal AI that integrates imaging, transcriptomics, and clinical patient data are expected to further transform diagnostic processes.

Medicine in terms of accuracy, ease, and efficiency while improving patient care outcomes, the summary of AI applications in medicine is illustrated in Fig.1.

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2. AI IN RADIOLOGY: ENHANCING IMAGING ANALYSIS

Radiology has been significantly transformed by innovations in AI, which enhance the accuracy, speed, and reliability of diagnostic imaging, thereby reducing the workload for radiologists and improving patient care. Convolutional Neural Networks (CNNs), including architectures such as ResNet, DenseNet, and EfficientNet, have demonstrated performance that surpasses expert radiologists in detecting anomalies in X-ray, CT, MRI, and PET images, achieving higher diagnostic accuracy [9]. In pulmonary imaging, deep learning models such as CheXNet have shown remarkable capability in identifying and classifying chest abnormalities with expert-level precision.

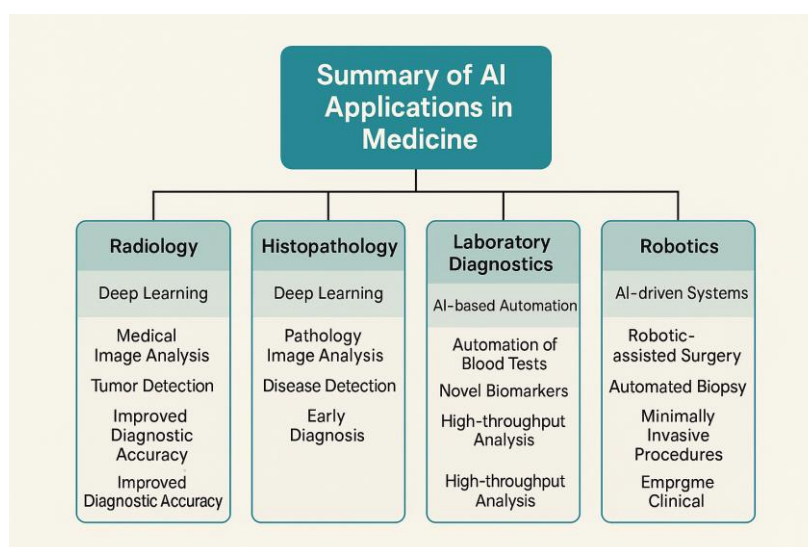


Figure 1. summary of AI applications in medicine

Trained on the ChestX-ray14 dataset, models such as CheXNet have achieved an AUC of 0.97, outperforming humans in pneumonia detection [10]. Significant progress has also been made in AI-enabled lung nodule detection, exemplified by Google's deep learning system for lung cancer screening, which achieved a sensitivity of 94.4% while reducing the false-positive rate in CT scans [9]. In neuroimaging, deep learning has facilitated real-time triage for ischemic stroke, reducing door-to-treatment time by one hour and improving patient survival rates [11]. Similarly, CNN models employing U-Net and DeepMedic architectures have been applied to early detection of Alzheimer's disease using MRI scans, achieving 93% accuracy in classifying hippocampal atrophy [12]. In breast cancer screening, the Google Health AI model has improved diagnostic performance by reducing false positives by 5.7% and false negatives by 9.4% in mammography evaluations [13].

A comprehensive assessment of medical imaging data demonstrated that radiologists' performance often exceeded expectations when analyzing subjects with tumor nodules [13]. Beyond CNNs, vision transformers have further advanced medical image interpretation by capturing long-range dependencies within imaging data, with models such as the Swin Transformer outperforming traditional CNNs in tumor segmentation tasks [14]. Generative Adversarial Networks (GANs) are also being employed to enhance low-resolution MRI scans and to generate synthetic medical images, facilitating model training in data-scarce scenarios [7]. Despite these advancements, persistent challenges remain, including data heterogeneity, limited generalizability across diverse populations, regulatory approval processes, and the need for explainable AI (XAI) to foster clinician trust in AI-generated diagnoses [15]. Ongoing developments in self-supervised learning (SSL), feature-preserving AI, and multimodal integration that combine radiology, genomics, and clinical history are expected to further transform radiology, making diagnostics more accurate, efficient, and accessible.

3. AI IN HISTOPATHOLOGY & DISEASE DETECTION

The development of artificial intelligence (AI) has significantly advanced the automation of whole slide image (WSI) analysis in histopathology, enhancing disease detection while improving diagnostic accuracy, consistency, and efficiency. Traditional histopathology relies on manual microscopic analysis, which is labor-intensive and prone to observer variability. In contrast, AI-based deep learning models, including Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and Multiple Instance Learning (MIL) frameworks, have demonstrated superior performance in analyzing histopathological slides, detecting cancerous lesions, and grading disease severity [16].

In breast carcinoma and prostate cancer diagnosis, AI-based Gleason grading models applied to WSI datasets have achieved performance comparable to expert pathologists, with some studies reporting area under the curve (AUC) values exceeding 0.98 [3]. Self-supervised learning (SSL) techniques have further enhanced AI systems by extracting relevant histopathological features from unlabeled data, reducing the need for extensive manual annotation and improving model generalizability [17]. AI has also been successfully integrated into lymph node metastasis detection, with systems such as Paige.AI and PathAI outperforming pathologists in identifying micrometastases, thereby increasing diagnostic sensitivity and reducing false negatives [18]. Class imbalance in training datasets has been addressed through the generation of synthetic pathological images using AI-based HistoGAN models [19].

Beyond oncology, AI has shown remarkable performance in hematology, with CNN-based classifiers achieving 99% accuracy in distinguishing acute lymphoblastic leukemia (ALL) from normal blood samples [20]. In infectious disease pathology, deep learning models have enabled automated tuberculosis detection from sputum smear microscopy images, achieving results comparable to expert microbiologists [21]. Recent advances in explainable AI (XAI), including Gradient-weighted Class Activation Mapping (Grad-CAM), have improved interpretability, providing visual explanations for diagnostic decisions and fostering greater clinical trust [22].

Despite these advancements, challenges remain, including heterogeneity in histopathological slides, variability in staining protocols, regulatory barriers, and the need for robust clinical validation [23]. Future developments in federated learning, multimodal AI integrating genomics and pathology, and real-time AI-assisted digital pathology are expected to further revolutionize diagnostics, enabling earlier disease detection, more accurate prognostication, and personalized treatment strategies.

4. AI IN CLINICAL LABORATORY DIAGNOSTICS

The advancement of artificial intelligence (AI) has transformed machine learning (ML) and deep learning (DL) algorithms, enabling the automation of healthcare laboratory diagnostics by enhancing the precision and efficiency of disease identification, tasks previously performed manually. AI has significantly improved unsupervised blood test analyses and biomarker interpretation, reducing human error while increasing diagnostic speed and accuracy. Traditionally, microscope inspection and biochemical analysis of blood samples, combined with manual detection of active genetic markers, were the standard approaches [24]. Automated blood smear analysis powered by AI has achieved over 99% accuracy in classifying leukemia types and distinguishing benign from malignant blood cell

irregularities [25]. Implementation of deep learning models, such as ResNet and XGBoost, has further accelerated flow-cytometry analyses, improving the speed of hematological malignancy detection [26].

AI has also advanced microbiological diagnostics, with deep neural networks (DNNs) and natural language processing (NLP) models automating the interpretation of mass spectrometry (MALDI-TOF) data. Integration of long short-term memory (LSTM) networks with MALDI-TOF data has achieved 92.24% accuracy in identifying *E. coli* strains, demonstrating the potential of deep learning to enhance bacterial identification beyond the species level [27]. In clinical chemistry and serology, AI-powered predictive models, such as Random Forests (RF) and XGBoost, have improved early detection of chronic kidney disease (CKD), with some studies reporting accuracy exceeding 97% through analysis of patient biomarker trends [28]. Similarly, AI/ML models, including XGBoost, have demonstrated high accuracy in early risk detection and personalized management of sepsis-associated acute kidney injury (SA-AKI), thereby improving patient outcomes [29].

AI has further revolutionized genomic and molecular diagnostics. Tools such as DeepVariant (Google Health) and SpliceAI (Illumina) have shown superior performance in DNA variant calling and RNA splicing mutation detection, reducing false positive rates by approximately 30% compared to conventional bioinformatics pipelines [30]. Graph neural networks (GNNs) and multi-omics frameworks integrating genomic, transcriptomic, and proteomic data have facilitated advancements in personalized medicine and biomarker discovery. Mathematical methodologies for multi-omics data integration highlight AI's potential to uncover complex biological relationships, enhancing biomarker identification and enabling tailored therapeutic strategies [31].

Federated learning has also contributed to laboratory diagnostics by enabling privacy-preserving AI models that allow collaborative training across institutions without direct data sharing, thereby improving model generalizability and ensuring compliance with HIPAA and GDPR regulations [32]. Nevertheless, challenges such as data heterogeneity, model reproducibility, regulatory approval, and integration into existing clinical workflows remain significant barriers to widespread AI adoption in laboratory medicine [33]. Future directions include self-supervised learning (SSL) for label-efficient AI, real-time AI-assisted diagnostic devices, and multi-modal AI approaches that combine laboratory results, imaging, and electronic health records (EHRs) to enable more accurate and comprehensive disease diagnostics.

5. INTELLIGENT ROBOTS IN MEDICAL DIAGNOSTICS

The use of intelligent robotics in clinical settings—such as AI-powered robotic imaging systems, laboratory sample analyses, and robotic biopsies—has significantly enhanced accuracy and efficiency in medical diagnostics. Real-time decision-making is facilitated by robots integrated with machine learning (ML), computer vision, and sensor fusion, improving diagnostic precision while reducing human error [34]. In robotic-assisted biopsy techniques, a systematic review and meta-analysis demonstrated that AI-guided robotic biopsy systems provide clinical advantages, including higher detection rates, fewer complications, and improved workflow efficiency in tissue sampling and imaging [35].

Similarly, AI-enabled blood analyzer robots have been developed using reagent-free imaging hematology systems capable of accurately classifying leukocyte subpopulations with minimal sample preparation. By integrating quantitative phase imaging with a deep learning-based residual neural network, these systems enable fast, cost-

effective, and automated hematology analysis, suitable for point-of-care diagnostics and resource-limited settings [36]. Another innovative device performs end-to-end blood testing by combining image-guided venipuncture with centrifuge-based blood analysis. By integrating robotic phlebotomy with microfluidic processing, the device reduces contamination risks and standardizes procedures, providing automated quantitative hematology measurements at the point-of-care [37].

In radiology, Autonomous Radiology Robots (ARRs) employ computer vision and reinforcement learning to optimize patient positioning, imaging angles, and diagnostic consistency across imaging modalities [38]. Remote diagnosis and pathology consultations are also supported by AI-powered telepresence robots, enabling specialists to virtually assist in automated examinations using real-time image segmentation, augmented reality (AR), and AI-based voice recognition, thereby enhancing medical collaboration [39].

Despite these advancements, challenges remain, including robotic system adaptability, high implementation costs, regulatory approval, and integration into existing healthcare infrastructures. Future developments in human-robot interaction (HRI), deep reinforcement learning (DRL), and multimodal AI for sensor fusion are expected to further enhance robotic diagnostic systems, increasing automation, precision, and accessibility in global healthcare.

6. EXPERT SYSTEMS IN MEDICAL DIAGNOSTICS

Expert systems in medical diagnostics are AI-driven decision-support tools designed to assist clinicians by reducing the cognitive burden of complex decision-making. These systems utilize knowledge-based inference engines, rule-based reasoning, and probabilistic models to integrate medical databases, clinical protocols, and patient data in real time, providing support for clinical diagnoses, differential diagnoses, and treatment recommendations grounded in evidence-based medicine [40]. Among the earliest and most notable examples is MYCIN, which employed rule-based reasoning and fuzzy logic to diagnose bacterial infections and recommend appropriate antibiotic therapy [41]. Modern expert systems have evolved to incorporate deep learning (DL), natural language processing (NLP), and Bayesian reasoning, offering instantaneous clinical decision support across multiple specialties, including radiology, cardiology, oncology, and pathology.

In oncology, machine learning is increasingly integrated with expert systems to enhance diagnostic precision and personalized treatment. For example, Watson Health Imaging technologies, including Watson and IBM AnalyzeIt, combine with expert systems to analyze MRI and CT scans, automatically detect abnormalities, and recommend follow-up actions [42]. AI-powered expert systems also facilitate automated tumor classification and bespoke treatment suggestions, exemplified by OncoKB for genetic mutation interpretation and DeepMind's AlphaFold for optimizing personalized cancer therapies [43].

In cardiology, AI-enabled expert systems, such as CardioExpert, integrate electrocardiogram (ECG) and hemodynamic data to predict arrhythmias, heart failure, and coronary artery disease, achieving over 85% accuracy in large clinical studies [44]. Clinical decision support systems (CDSS) based on Bayesian networks and deep reinforcement learning have improved intensive care unit (ICU) patient monitoring, enabled early sepsis detection, and automated triage in emergency medicine, resulting in significant reductions in mortality [45]. Additionally, natural language processing

(NLP)-based AI models have automated the reporting of pathology cases by extracting conclusions from electronic health records (EHRs) and clinical notes, thereby improving productivity and reducing clinician fatigue [46].

Despite these advancements, challenges persist, including the lack of real-time data integration, the need for continuous knowledge-base updates, model interpretability, and compliance with clinical AI regulations. The reliability and flexibility of AI-driven diagnostic systems can be further enhanced through hybrid expert systems that integrate symbolic reasoning with deep learning, opening new avenues for research and development in clinical AI applications.

7. DISCUSSION: CHALLENGES IN AI-BASED DIAGNOSTICS

Although artificial intelligence (AI) holds significant potential for innovation, its integration into medical diagnostics presents several challenges, including data variability, algorithmic bias, limited interpretability, regulatory compliance, and workflow integration. A primary concern is the heterogeneity of medical data, as AI algorithms trained on specific populations or imaging protocols often fail to generalize across different hospitals, regions, or demographic groups, leading to variable diagnostic performance and accuracy [47]. Algorithmic bias is another critical issue, particularly when datasets underrepresent certain ethnic, age, or socio-economic groups, resulting in erroneous predictions and exacerbating disparities in healthcare delivery [48]. Additionally, the lack of interpretability and explainability in AI models—especially deep learning approaches such as convolutional neural networks (CNNs) and transformer-based architectures—poses a significant barrier, as these models often operate as "black boxes," making their decision-making processes difficult to trace and validate.

As previously noted, the "black box" nature of many AI models reduces clinician trust and limits flexibility, highlighting the need for explainable AI (XAI) methods—such as SHAP, Grad-CAM, and attention-based algorithms—to enhance model transparency and foster confidence in AI-assisted decisions [49]. Additionally, the regulatory landscape for AI-enabled diagnostics remains fragmented. Agencies such as the FDA, EMA, and HIPAA impose extensive requirements for clinical validation, face validation, and long-term post-market surveillance before AI-based diagnostic systems can be widely adopted [50]. Ensuring data security and patient privacy also presents a major challenge, as AI models must comply with regulations like GDPR and HIPAA. This necessitates the use of techniques such as federated learning and homomorphic encryption to train AI systems on sensitive, decentralized datasets while maintaining confidentiality [32]. Furthermore, operationalizing AI within healthcare systems is complicated by the reliance of many institutions on legacy infrastructures that are not compatible with AI-based decision-support tools.

To maximize usability in clinical practice, AI models must be seamlessly integrated into electronic health records (EHRs), radiology information systems (RIS), and pathology workflows without disrupting existing process [51]. Addressing these challenges will require multiple strategies, including the development of self-supervised learning (SSL) approaches to reduce dependence on annotated data, federated AI systems to enable secure collaborative model training, and AI fairness benchmarking initiatives to ensure clinical validity and equity. As human-AI collaboration advances—through multi-modal AI integration and real-time human-machine interaction—the field of AI is poised to transform medical diagnostics into a precise, data-driven science while maintaining adherence to ethical and legal standards.

8. CONCLUSION

Artificial Intelligence (AI) is transforming the healthcare industry, evolving from a complementary tool into an integral component that is redefining the future of diagnostics. AI enhances accuracy across clinical domains including radiology, pathology, and laboratory medicine, and extends its capabilities to robotic systems. Beyond improving diagnostic precision, AI supports workflow optimization and advances precision medicine. The integration of autonomous systems with diagnostic intelligence enables faster decision-making and facilitates real-time, personalized interventions in complex, high-risk clinical settings.

However, the most significant contributions of AI are rooted in its ethical deployment, explainability, and meaningful clinical integration. As AI becomes increasingly embedded within healthcare systems, challenges such as algorithmic bias, data heterogeneity, and model opacity threaten trust and equitable outcomes. The development of explainable AI (XAI), federated learning for secure data collaboration, and multimodal integration strategies seeks to address these challenges, fostering transparency and fairness. Establishing reliable frameworks for interdisciplinary collaboration, robust data governance, and responsible innovation will be essential to maximize AI's clinical impact. Moreover, self-supervised learning (SSL) and real-time human-AI interaction have the potential to reduce reliance on annotated datasets and extend diagnostic capabilities to underserved areas.

In conclusion, AI's transformative impact on diagnostics stems not only from algorithmic advances but also from strategic management, equitable implementation, and adherence to clinical principles of precision, safety, and accessibility.

REFERENCES

- [1] R. R. Kothinti, "Artificial Intelligence in Disease Prediction: Transforming Early Diagnosis and Preventive Healthcare," *Int. J. Acad. Res. Dev.*, vol. 9, pp. 1330–1340, May 2024.
- [2] G. Litjens *et al.*, "A survey on deep learning in medical image analysis," *Med. Image Anal.*, vol. 42, pp. 60–88, 2017.
- [3] W. Bulten *et al.*, "Automated deep-learning system for Gleason grading of prostate cancer using biopsies: a diagnostic study," *Lancet Oncol.*, vol. 21, no. 2, pp. 233–241, Feb. 2020, doi: 10.1016/S1470-2045(19)30739-9.
- [4] U. A. Shams *et al.*, "Bio-net dataset: AI-based diagnostic solutions using peripheral blood smear images," *Blood Cells, Mol. Dis.*, vol. 105, p. 102823, 2024, doi: <https://doi.org/10.1016/j.bcmd.2024.102823>.
- [5] W. DeGroat *et al.*, "Multimodal AI/ML for discovering novel biomarkers and predicting disease using multi-omics profiles of patients with cardiovascular diseases," *Sci. Rep.*, vol. 14, no. 1, p. 26503, 2024, doi: 10.1038/s41598-024-78553-6.
- [6] P. Rani, N. Priyadarshini, E. R. Rajkumar, and K. Rajamani, "Retinal vessel segmentation under pathological conditions using supervised machine learning," in *2016 International Conference on Systems in Medicine and Biology (ICSMB)*, 2016, pp. 62–66. doi: 10.1109/ICSMB.2016.7915088.
- [7] S. Kazemina *et al.*, "GANs for medical image analysis," *Artif. Intell. Med.*, p. 101938, 2020.
- [8] N. Mehrabi, F. Morstatter, N. Saxena, K. Lerman, and A. Galstyan, "A Survey on Bias and Fairness in Machine Learning," *CoRR*, vol. abs/1908.0, 2019, [Online]. Available: <http://arxiv.org/abs/1908.09635>

- [9] D. Ardila *et al.*, “End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography,” *Nat. Med.*, vol. 25, no. 6, pp. 954–961, 2019, doi: 10.1038/s41591-019-0447-x.
- [10] P. Rajpurkar *et al.*, “CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning,” *CoRR*, vol. abs/1711.0, 2017, [Online]. Available: <http://arxiv.org/abs/1711.05225>
- [11] N. M. Murray, M. Unberath, G. D. Hager, and F. K. Hui, “Artificial intelligence to diagnose ischemic stroke and identify large vessel occlusions: a systematic review,” *J. Neurointerv. Surg.*, vol. 12, no. 2, pp. 156 LP – 164, Feb. 2020, doi: 10.1136/neurintsurg-2019-015135.
- [12] J. Wen *et al.*, “Convolutional neural networks for classification of Alzheimer’s disease: Overview and reproducible evaluation,” *Med. Image Anal.*, vol. 63, p. 101694, 2020, doi: <https://doi.org/10.1016/j.media.2020.101694>.
- [13] S. M. McKinney *et al.*, “International evaluation of an AI system for breast cancer screening,” *Nature*, vol. 577, no. 7788, pp. 89–94, 2020, doi: 10.1038/s41586-019-1799-6.
- [14] A. Dosovitskiy *et al.*, *An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale*. 2020. doi: 10.48550/arXiv.2010.11929.
- [15] S. Patel and H. Amin, “Explainable AI in Healthcare: Methods, Concepts, and Challenges BT - Proceedings of International Conference on Recent Innovations in Computing,” 2024, pp. 305–318.
- [16] G. Campanella *et al.*, “Clinical-grade computational pathology using weakly supervised deep learning on whole slide images,” *Nat. Med.*, vol. 25, p. 1, Aug. 2019, doi: 10.1038/s41591-019-0508-1.
- [17] O. Ciga, T. Xu, and A. L. Martel, “Self supervised contrastive learning for digital histopathology,” *Mach. Learn. with Appl.*, vol. 7, p. 100198, 2022, doi: <https://doi.org/10.1016/j.mlwa.2021.100198>.
- [18] B. Ehteshami Bejnordi *et al.*, “Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer,” *JAMA*, vol. 318, pp. 2199–2210, Dec. 2017, doi: 10.1001/jama.2017.14585.
- [19] M. Afifi, M. A. Brubaker, and M. S. Brown, “HistoGAN: Controlling Colors of GAN-Generated and Real Images via Color Histograms,” *CoRR*, vol. abs/2011.1, 2020, [Online]. Available: <https://arxiv.org/abs/2011.11731>
- [20] L. Zare, M. Rahmani, N. Khaleghi, S. Sheykhivand, and S. Danishvar, “Automatic Detection of Acute Leukemia (ALL and AML) Utilizing Customized Deep Graph Convolutional Neural Networks,” *Bioengineering*, vol. 11, no. 7. 2024. doi: 10.3390/bioengineering11070644.
- [21] P. Lakhani and B. Sundaram, “Deep Learning at Chest Radiography: Automated Classification of Pulmonary Tuberculosis by Using Convolutional Neural Networks,” *Radiology*, vol. 284, no. 2, pp. 574–582, Apr. 2017, doi: 10.1148/radiol.2017162326.
- [22] T. Yiugit, N. cSengoz, O. Ozmen, J. Hemanth, and A. H. Icsik, “Diagnosis of Paratuberculosis in Histopathological Images Based on Explainable Artificial Intelligence and Deep Learning,” *ArXiv*, vol. abs/2208.0, 2022, [Online]. Available: <https://api.semanticscholar.org/CorpusID:251174406>
- [23] J. S. Reis-Filho and J. N. Kather, “Overcoming the challenges to implementation of artificial intelligence in pathology,” *JNCI J. Natl. Cancer Inst.*, vol. 115, no. 6, pp. 608–612, Jun. 2023, doi: 10.1093/jnci/djad048.
- [24] E. J. Topol, “High-performance medicine: the convergence of human and artificial intelligence,” *Nat. Med.*, vol. 25, no. 1, pp. 44–56, 2019, doi: 10.1038/s41591-018-0300-7.
- [25] M. Jawahar, L. J. Anbarasi, S. Narayanan, and A. H. Gandomi, “An attention-based deep learning for acute

- lymphoblastic leukemia classification,” *Sci. Rep.*, vol. 14, no. 1, p. 17447, 2024, doi: 10.1038/s41598-024-67826-9.
- [26] N. C. Spies, A. Rangel, P. English, M. Morrison, B. O’Fallon, and D. P. Ng, “Machine Learning Methods in Clinical Flow Cytometry,” *Cancers*, vol. 17, no. 3. 2025. doi: 10.3390/cancers17030483.
- [27] Q. Mao, X. Zhang, Z. Xu, Y. Xiao, Y. Song, and F. Xu, “Identification of Escherichia coli strains using MALDI-TOF MS combined with long short-term memory neural networks,” *Aging (Albany. NY)*, vol. 16, Jun. 2024, doi: 10.18632/aging.205995.
- [28] M. J. Raihan, M. A.-M. Khan, S.-H. Kee, and A.-A. Nahid, “Detection of the chronic kidney disease using XGBoost classifier and explaining the influence of the attributes on the model using SHAP,” *Sci. Rep.*, vol. 13, no. 1, p. 6263, 2023, doi: 10.1038/s41598-023-33525-0.
- [29] M. A. Islam, M. Z. H. Majumder, and M. A. Hussein, “Chronic kidney disease prediction based on machine learning algorithms,” *J. Pathol. Inform.*, vol. 14, p. 100189, 2023, doi: <https://doi.org/10.1016/j.jpi.2023.100189>.
- [30] R. Poplin *et al.*, “A universal SNP and small-indel variant caller using deep neural networks,” *Nat. Biotechnol.*, vol. 36, no. 10, pp. 983–987, 2018, doi: 10.1038/nbt.4235.
- [31] E. Baldwin *et al.*, “On fusion methods for knowledge discovery from multi-omics datasets,” *Comput. Struct. Biotechnol. J.*, vol. 18, pp. 509–517, 2020, doi: <https://doi.org/10.1016/j.csbj.2020.02.011>.
- [32] G. A. Kaissis, M. R. Makowski, D. Rückert, and R. F. Braren, “Secure, privacy-preserving and federated machine learning in medical imaging,” *Nat. Mach. Intell.*, vol. 2, no. 6, pp. 305–311, 2020, doi: 10.1038/s42256-020-0186-1.
- [33] N. Tomašev *et al.*, “Use of deep learning to develop continuous-risk models for adverse event prediction from electronic health records,” *Nat. Protoc.*, vol. 16, no. 6, pp. 2765–2787, 2021, doi: 10.1038/s41596-021-00513-5.
- [34] G.-Z. Yang *et al.*, “Medical robotics—Regulatory, ethical, and legal considerations for increasing levels of autonomy,” *Sci. Robot.*, vol. 2, no. 4, p. eaam8638, Mar. 2017, doi: 10.1126/scirobotics.aam8638.
- [35] V. Petov *et al.*, “Robot-Assisted Magnetic Resonance Imaging-Targeted versus Systematic Prostate Biopsy; Systematic Review and Meta-Analysis,” *Cancers*, vol. 15, no. 4. 2023. doi: 10.3390/cancers15041181.
- [36] X. Shu *et al.*, *Artificial Intelligence Enabled Reagent-free Imaging Hematology Analyzer*. 2021. doi: 10.22541/au.163578446.63711797/v1.
- [37] M. Balter, J. Leipheimer, A. Chen, A. Shrirao, T. Maguire, and M. L. Yarmush, “Automated end-to-end blood testing at the point-of-care: Integration of robotic phlebotomy with downstream sample processing,” *TECHNOLOGY*, vol. 6, pp. 1–8, Jun. 2018, doi: 10.1142/S2339547818500048.
- [38] T. Habuza *et al.*, “AI applications in robotics, diagnostic image analysis and precision medicine: Current limitations, future trends, guidelines on CAD systems for medicine,” *Informatics Med. Unlocked*, vol. 24, p. 100596, 2021, doi: <https://doi.org/10.1016/j.imu.2021.100596>.
- [39] M. Bhandari, T. Zeffiro, and M. Reddiboina, “Artificial intelligence and robotic surgery: Current perspective and future directions,” *Curr. Opin. Urol.*, vol. 30, p. 1, Nov. 2019, doi: 10.1097/MOU.0000000000000692.
- [40] E. H. Shortliffe and M. J. Sepúlveda, “Clinical Decision Support in the Era of Artificial Intelligence,” *JAMA*, vol. 320, no. 21, pp. 2199–2200, Dec. 2018, doi: 10.1001/jama.2018.17163.
- [41] W. R. Swartout, “Rule-based expert systems: The mycin experiments of the stanford heuristic programming

- project: B.G. Buchanan and E.H. Shortliffe, (Addison-Wesley, Reading, MA, 1984); 702 pages, \$40.50,” *Artif. Intell.*, vol. 26, no. 3, pp. 364–366, 1985, doi: [https://doi.org/10.1016/0004-3702\(85\)90067-0](https://doi.org/10.1016/0004-3702(85)90067-0).
- [42] A. Esteva *et al.*, “A guide to deep learning in healthcare,” *Nat. Med.*, vol. 25, no. 1, pp. 24–29, 2019, doi: 10.1038/s41591-018-0316-z.
- [43] P. Courtiol *et al.*, “Deep learning-based classification of mesothelioma improves prediction of patient outcome,” *Nat. Med.*, vol. 25, no. 10, pp. 1519–1525, 2019, doi: 10.1038/s41591-019-0583-3.
- [44] P. Rajpurkar, A. Y. Hannun, M. Haghighpanahi, C. Bourn, and A. Y. Ng, “Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks,” *CoRR*, vol. abs/1707.0, 2017, [Online]. Available: <http://arxiv.org/abs/1707.01836>
- [45] N. Tomašev *et al.*, “A clinically applicable approach to continuous prediction of future acute kidney injury,” *Nature*, vol. 572, no. 7767, pp. 116–119, 2019, doi: 10.1038/s41586-019-1390-1.
- [46] X. Liu *et al.*, “A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis,” *Lancet Digit. Heal.*, vol. 1, no. 6, pp. e271–e297, Oct. 2019, doi: 10.1016/S2589-7500(19)30123-2.
- [47] M. Ghassemi, L. Oakden-Rayner, and A. L. Beam, “The false hope of current approaches to explainable artificial intelligence in health care,” *Lancet Digit. Heal.*, vol. 3, no. 11, pp. e745–e750, Nov. 2021, doi: 10.1016/S2589-7500(21)00208-9.
- [48] Z. Obermeyer, B. Powers, C. Vogeli, and S. Mullainathan, “Dissecting racial bias in an algorithm used to manage the health of populations,” *Science (80-.)*, vol. 366, no. 6464, pp. 447–453, Oct. 2019, doi: 10.1126/science.aax2342.
- [49] W. Samek, G. Montavon, S. Lapuschkin, C. Anders, and K.-R. Müller, *Toward Interpretable Machine Learning: Transparent Deep Neural Networks and Beyond*. 2020. doi: 10.48550/arXiv.2003.07631.
- [50] S. Benjamens, P. Dhunoo, and B. Meskó, “The state of artificial intelligence-based FDA-approved medical devices and algorithms: an online database,” *npj Digit. Med.*, vol. 3, no. 1, p. 118, 2020, doi: 10.1038/s41746-020-00324-0.
- [51] J. He, S. L. Baxter, J. Xu, J. Xu, X. Zhou, and K. Zhang, “The practical implementation of artificial intelligence technologies in medicine,” *Nat. Med.*, vol. 25, no. 1, pp. 30–36, 2019, doi: 10.1038/s41591-018-0307-0.