Foundations of Artificial Intelligence in Healthcare Diagnostics: A Systematic Survey/ Review article

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Abstract

Artificial Intelligence (AI) is becoming the cornerstone of the future of healthcare diagnostics, that has to ability to change the healthcare diagnostic landscape in terms of diagnostic accuracy, speed, and availability. This systematic review investigates the basic methods, tools, applications, and challenges involved in the integration of AI in diagnostic medicine. It emphasizes the using of machine learning models, deep learning networks (e.g., CNNs), NLP for clinical documentation, and smart computing infrastructures, such as edge device and IoMT. They are making possible real-time, data-driven decision making that is already at human-expert-level performance or, in some cases, even better (in the analysis of medical images, pathology and biosignal, for example). Despite these breakthroughs, a number of significant challenges remain, such as data diversity and heterogeneity, lack of high-quality labeled data, model interpretability and ethical issues (e.g. algorithmic bias and patient privacy). In addition, there are strong compatibility, clinician reliance, regulation validation (these are the most commonly neglected part of technical development) factors, which will keep AI supported systems tightly engrafted to the existing health systems. This paper further attempts to compare AI based and conventional diagnostic methods, presents recent literature insights and scopes the research gaps in the ongoing research endeavors. The aim of the survey is, within the broader picture of the underpinning principles of the 'fitness for purpose' of predictive models, to capture these foundations fully in order to assist future developments that are driven by a desire for transparency, fairness, and clinical relevance. It emphasizes the necessity of interdisciplinary cooperation and of standard assessment methods to achieve a safe and effective application. As AI transforms diagnostics, the future of healthcare will rely on creating AI systems that are inclusive, interpretable and ethically grounded, and that can tackle global health problems and respond flexibly to the demands of clinical practice.

Keywords: Artificial Intelligence, Healthcare Diagnostics, Machine Learning, Deep Learning, Medical Imaging, Clinical Decision Support, Ethical Challenges.

1. Introduction

Artificial Intelligence (AI) is quickly transforming healthcare, especially the medical diagnostic field where quick and precise decision making is crucial. As the size and complexity of clinical data, from medical images to genomic profiles, show no signs of slowing down the traditional diagnostic methods, often involving manual interpretation and rule-based heuristics, are falling behind the trend of modern healthcare. AI, infused with advancements in deep learning, machine learning and intelligent computing architectures, is now being harnessed in ways that have opened up new possibilities and levels of diagnostic accuracy, error reduction, and real-time clinical decision making.

In recent years, performance of AI models has rivaled and sometimes surpassed that of experienced clinicians in a wide range of diagnostic tasks. For example, the use of convolutional neural networks (CNNs) has reached dermatologist-level accuracy in the classification of skin cancer [1], and has achieved high sensitivity and specificity in detection of diabetic retinopathy from retinal images using deep learning algorithms [2]. “AI is not limited to imaging for imaging, and it’s not just used for radiology; it is changing the way that we do biosignal analyses, pathology, and even natural language processing for clinical documentation, allowing for a more data-driven and comprehensive approach to the diagnosis,” he explained.

An enabling factor of this transformation is the advent of intelligent machines to efficiently execute AI workloads, in many cases in real time. Smart hardware platforms, like GPUs, FPGAs, or application-specific integrated circuits (ASICs), are currently including on medical devices and will make it possible for AI algorithm deployment at the patient's bed side. In addition, the emergence of edge computing, and Internet of Medical Things (IoMT) make it possible to integrate diagnostic capacity into a wearable device, a mobile platform, or a remote monitoring tool to provide the continuous patient evaluation with the least latency [3], [4].

Artificial Intelligence in Healthcare Infographic 1 shows the role of AI in data acquisition, automated detection, and real-time decision support in various aspects of medical diagnosis at different levels of sample collection and data analysis. It incorporates sources of data (imaging, biosignals), AI models (CNNs, NLP, etc.and, computing platforms (cloud, edge, IoMT), as well as the ultimate diagnostic results.

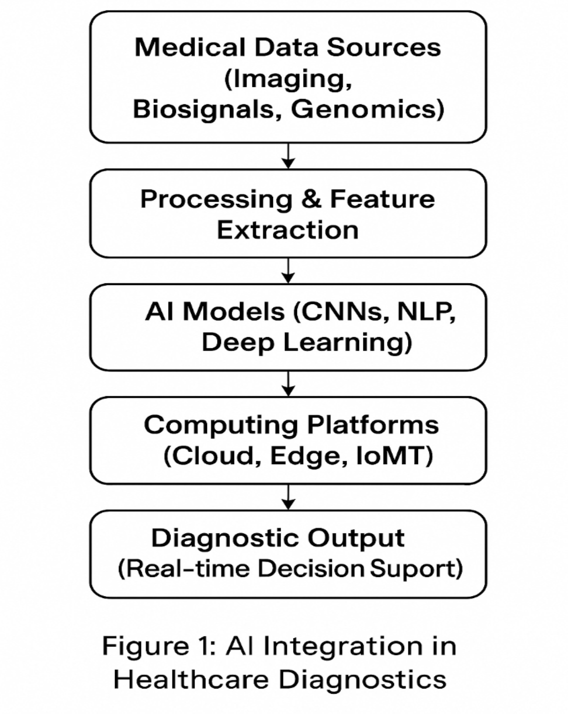

Figure 1: AI Integration in Healthcare Diagnostics

Although there has been great progress, there are still obstacles to overcome. The heterogeneous nature of data, lack of high-quality labeled datasets, model interpretability and ethical considerations regarding algorithmic bias and patient privacy are some of the most critical barriers that are preventing large-scale clinical deployment of AI-based clinical solutions [5]. And what's more, the embedding of AI into existing healthcare infrastructure requires strong interoperability standards, regulatory approvals and clinician trust factors which are commonly overlooked in strictly technical research.

As a rough comparison between artificial intelligence systems and conventional diagnostic systems, Table 1 shows the improvement in accuracy, speed, scalability, and flexibility, in addition to real-life examples Table 1 Differences between traditional diagnostic systems and artificial intelligence systems.

Table 1: Comparison of AI and Traditional Diagnostic Systems

Aspect	Traditional Systems	AI-based Systems	Example
Diagnostic Accuracy	Heuristic/Experience-Based	Data-Driven, High Precision	AI in skin cancer classification
Speed	Manual Analysis	Real-time Processing	Retinal screening in seconds
Scalability	Limited to Specialist Availability	Deployable on Cloud/Edge	Telemedicine platforms
Interpretability	Transparent Rules	Often Black-Box Models	Explainable AI efforts

In summary, this survey aims to provide a structured and comprehensive overview of the current prospects of AI in healthcare diagnostic, especially in the real-time intelligent systems. Specifically, this paper analyzed the recent contributions in algorithmic innovation and hardware design, identified medical domains where AI has shown the most promising outcomes, and surveyed the architectural models in which AI deployments are conducted in the cloud, edge, and hybrid settings. Through a thematic organization of the literature and highlighting the directions of the emerging trends and existing gaps and challenges, this paper should serve as a helpful read for researchers, developers, and policymakers aiming to advance the incorporation of AI technologies into diagnostic. Lastly, this work hopes to contribute to the connection of AI breakthroughs to the actual medical practice, creating a pathway for next-generation diagnostic system creation that is smart and quick, but also ethical, interpretable, and aligned with the clinical settings.

2. Literature Review

Intelligence artificial (AI) has made an incredible headway in the diagnoses in health from the power to find complex patterns in medical data. The early AI systems were largely rule-based expert systems where professional expertise was encapsulated in deterministic decision trees. Although being transparent and interpretable, these systems lacked generalizability in different diagnostic settings and performed suboptimally on noisy or unstructured data [6]. The rise of machine learning (ML), in particular supervised learning algorithms, including support vector machines, and decision trees facilitated data-based modeling. These approaches enabled greater accuracy and efficiency, however required significant hand-crafted features and domain specific pre-processing [7].

The emergence of deep learning technology, and in particular CNNs, revolutionized AI diagnostics -- and especially medical imaging. CNNs have been shown to reach clinician-level performance in radiology, dermatology, and ophthalmology. CNNs showed better performance in classification of skin lesions [6] and pneumonia detection in chest X-rays [8] than general practioneers. Model interpretability, however, categorically referred to as the "black-box" problem, causes difficulties in clinical trust and acceptance. Recent studies attempt to combine explainable AI (XAI) such as [1] attention maps and layer-wise relevance propagation with the learning process to improve the transparency and diagnostic accuracy [9].

Simultaneously, natural language processing (NLP) has developed as a powerful tool in the analysis of unstructured clinical text, such as discharge summaries and radiology reports. Compound models such as: BERT, and BioBERT achieved competitive results in named entity recognition, relation extraction and clinical text classification tasks [10]. However, the medical domain has its own challenges in terms of considering specialized vocabulary, non-standard documentation style and insufficient annotated data. Domain adaptation, self-supervised learning and continual fine-tuning are a current focus of research towards enhancing NLP robustness across institutions and patient populations [11].

An other important line of research, multi-modal diagnostics, refers to a situation where AI extracts features from multiple sources, such as imaging, genomics, electronic health records (EHRs), and biosignals. This will open up the path to a more comprehensive and individualized diagnostic concept. But, integrating disparate data sources is difficult itself, such as format reconciliation, time mismatch and sparse data [12]. Besides, the lack of such genuinely labeled and demographically diverse datasets hampers the generalizability and fairness of diagnostic models [13]. To combat these issues, approaches, such as synthetic data generation and federated annotation pipelines are being investigated.

On the deployment side, there is also an emerging literature on how to deploy AI models at the point of care in an optimal way. Approaches to edge processing and federated learning make it possible to run AI-driven diagnostics directly on medical devices or local servers, minimizing latency and keeping patient information private [14]. Faster architectures have been proposed to address these limitations; however, those solutions add additional overhead in distributed training, real-time inference, and synchronization. Moreover, enforcing healthcare-specific policies—e.g., HIPAA or GDPR—within decentralized settings continue to be a key challenge [15].

Whilst advances have been made in technology, the existing literature remains far from reaching today's demands. Such ethical considerations — especially regarding algorithmic bias, equity, transparency, and patient autonomy — are also frequently overlooked in technical articles. In addition, there is a lack of prospective, clinical trials that have to support the use of AI models in everyday diagnostic pathways [16]. Interdisciplinary cooperation among computer engineers, physicians, law professionals, and ethicists is lacking but is key to translating AI advancements to clinically safe, ethically sustainable, and regulatory acceptable tools[17].

To summarize the main contribution, methodology and identified gaps over reviewed literature, Table 2 provides the comparison and focus on areas, techniques used, strengths, and limitations of some major studies to provide a synthesized view of the current state of AI-based healthcare diagnostic.

Table 2: Comparative Analysis of Key Literature on AI in Healthcare Diagnostics

Ref.	Study Focus	Techniques/ Models Used	Strengths	Limitations/Gaps
[6]	Rule-based expert systems in diagnostics	Knowledge-based systems	High interpretability; early integration in decision support	Poor scalability and adaptability to new data
[7]	Early machine learning in imaging diagnostics	Decision Trees, SVMs	Improved performance over rule-based systems	Heavy dependence on feature engineering
[8]	Deep learning in skin cancer classification	CNNs	Achieved dermatologist-level accuracy	Lack of explainability; risk of bias in datasets
[9]	Explainable AI (XAI) for medical imaging	Saliency maps, attention layers	Enhances interpretability of deep models	Still limited in clinical adoption due to complexity
[10]	NLP in biomedical literature and records	BERT, BioBERT	State-of-the-art clinical NLP performance	Requires large annotated corpora; domain-specific challenges
[11]	Clinical adaptation of NLP models	Clinical BERT	Better contextual understanding of clinical language	Limited generalization across institutions
[12]	Multi-modal data integration	EHRs, Imaging, Genomics	Supports personalized and holistic diagnostics	Data heterogeneity; alignment challenges
[13]	Big data analytics in healthcare	Cloud-based AI systems	Scalability and population-level insights	Privacy concerns; data siloing
[14]	Federated learning for privacy-preserving AI	Federated deep learning	Enables model training without central data sharing	Complex synchronization; performance variation
[15]	Edge computing in digital health	Edge AI architectures	Real-time inference and reduced latency	Hardware limitations; regulatory uncertainties
[16]	Ethical concerns and validation gaps	Conceptual frameworks	Highlights societal and regulatory implications	Underrepresentation in technical studies
[17]	AI's impact on clinical roles and collaboration	Review and analysis	Emphasizes interdisciplinary needs and clinician trust factors	Lack of concrete implementation strategies

3. Techniques an d Tools Used in AI for Diagnostics

AI methods in healthcare diagnostics are diverse, as they are drawn from a variety of machine learning ML and deep learning (DL) algorithms developed for specific diagnostic tasks. Classical ML models, including Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF), have been shown to have good performance in structuring data classification tasks and risk stratification [18]. But the wave of success for DL models, especially CNNs and RNNs, has consequently changed the paradigm to process image-based and sequential data [19].

The Natural Language Processing (NLP) tools like BERT, BioBERT, and ClinicalBERT the diagnostic information can be extracted from the unstructured clinical texts, Electronic Health Record (EHR), etc., and it could be served as a serious help in decision-making process [20]. Furthermore, AI toolkits and platforms such as TensorFlow, PyTorch, and Scikit-learn establish interfaces for AI algorithm development and deployment.

The adoption of AI in healthcare diagnostics is also facilitated by highperformance hardware platforms like GPUs and TPUs [19] and edge computing infrastructure, which enables online processing on medical devices [21]. Advances in Internet of Medical Things (IoMT) brought diagnostic models closer to the patient bed by operating in decentralized settings, enabling the use of intelligent diagnostic tools in remote or poor resource areas [22].

This flowchart describes the technology ecosystem of AI in healthcare diagnostics, presenting how the different ML and DL methods are mainstreamed into diagnostic workflow. It starts with classic models including Support Vector Machines (SVMs) and Decision Trees (DTs) and further develops to more general deep learning (DL) methods. These methods are used to structured (e.g., images and sequential) and unstructured data (e.g., clinical text) for models such as Convolutional Neural Networks (CNNs). NLP models are crucial for deriving actionable knowledge from unstructured documents such as EHRs. Frameworks such as TensorFlow, PyTorch and Scikit-learn are enabling the development and deployment of these models. Last but not least, hardware support (such as those from GPUs and TPUs) and edge and cloud-based infrastructures allow real-time and decentralized diagnostics applications. Figure 2 Framework of AI Techniques and Infrastructure in Healthcare Diagnostics Figure 2 shows Framework of AI Techniques and Infrastructure in Healthcare Diagnostics

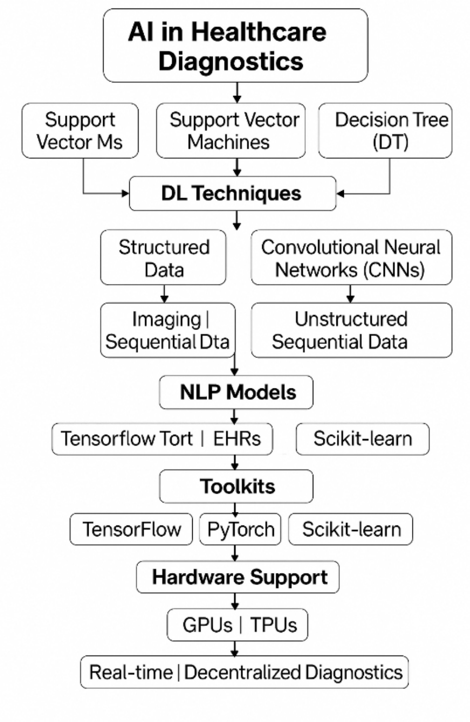

Figure 2: Framework of AI Techniques and Infrastructure in Healthcare Diagnostics

4. Applications of AI in Healthcare Diagnostics

AI in health diagnostics span across range of fields such as medical imaging, biosignal processing, genomics and clinical decision support. In the field of imaging diagnostics, CNN based systems have reached the performance of a dermatologist for skin cancer detection and high sensitivity for diabetic retinopathy (from retinal scans.) [23] Automated pattern recognition techniques have also made significant contributions to pathology and radiology, greatly decreasing the manual burden and diagnostic variation.

Biosignal-based diagnosis using RNNs and attention mechanism to translate ECGs, EEGs, and other human physiologies in real-time, for early screening of cardiac arrhythmia and neuro-disease detection [24]. In genomics, AI is utilized for prediction of mutations, classification of variants, and identification of susceptibility to disease based on sequencing data [25].

AI-based Clinical decision and support systems Conventional Clinical Decision Support Systems (CDSS) that utilize AI technology, incorporate information from the patient, medical standards and immediate analysis to offer evidence-based advice and suggestions. Such systems both improve the diagnostic consistency and the patient outcome in challenging or equivocal clinical cases [26]. The broad usage of such tools indicates the desire of AI in enhancing human expertise across many diagnostic areas.

5. Comparative Analysis of AI Approaches

For the assessment of the effectiveness of AI systems with the conventional diagnostic strategies of pathology, there a few metrics accuracy, specificity, sensitivity and the time efficiency are taken into account. Table

Overview of main comparative findings for selected studies Table Key comparative insights from selected studies, AI out-performs in speed and scale and adds more value by not missing or improving on diagnostic performance [27].

Even though AI has exhibited its performance advantages, interpretability remains a notable aspect where conventional techniques still have advantages. There are transparent logical trails in the rule based expert systems, while deep learning models are “black-box”. Rule-based reasoning and data-driven learning hybrid models are becoming popular as a middle solution [28].

In addition, unlike established diagnostics based on sound validated protocols, AI would need to be revalidated constantly using new data to remain valid. The comparison highlights the importance of appropriately training AI into clinical workflow with regulation and clinician involvement in mind [29]. Table 3 summarize comparison between AI based diagnostic systems and conventional diagnostic systems.

Table 3: Key Differences Between AI-Driven and Conventional Diagnostic Approaches

Criteria	AI-Based Diagnostic Systems	Traditional Diagnostic Methods
Accuracy	Often equal to or higher than experts in image/text-based diagnosis [27]	Generally high, but may vary with human factors
Specificity & Sensitivity	High, especially in imaging and biosignal interpretation	Dependent on practitioner skill and standardized protocols
Time Efficiency	Real-time or near-real-time; scalable across large datasets	Time-consuming; manual processes
Interpretability	Often limited ("black box" models like deep learning)	High (transparent logic in rule-based systems)
Adaptability	Continuously improves with data; supports personalization	Rigid protocols; less adaptive to individual variation
Scalability	Easily deployed across cloud, edge, and IoMT devices	Limited to facility-based, manual workflows
Transparency	Requires explainable AI tools (e.g., SHAP, LIME)	Inherent transparency in logic-based systems
Regulatory & Validation	Requires ongoing validation and regulatory adaptation	Built upon well-established clinical guidelines
Hybrid Model Potential	High: Combines rule-based logic with learning capabilities for improved performance [28]	Low: Limited capacity to integrate learning mechanisms
Clinician Involvement	Requires trust-building, human-in-the-loop systems [29]	High involvement; clinicians are decision-makers

6. Challenges and Issues

There are many challenges associated with the use of AI i:n diagnostics. First is heterogeneity of data—health data differs across institutions, patient populations and modalities, making the generalizability of AI models challenging

[30]. Moreover, the scarce availabilities of large, annotated datasets prevent the training of cumbersome models, in particular for rare diseases categories.

Another issue is the interpretability of the model. Practitioners are typically wary of opaque algorithms, especially without detailed transparency on critical diagnostic calls. Explainable AI (XAI) frameworks are expected to mitigate this challenge by introducing model decisions in visual or rule-based forms, but their usage has been so far quite confined [31].

Algorithmic bias carries ethical and legal hazards. For example, if the training data is not diverse, models could perform poorly for particular demographic groups, which could subsequently worsen health disparities. The issue of fairness in AI would need to be carefully considered to include representative datasets and bias correction in decision making algorithms [32].

7. Limitations of Existing Research

Methods and practical constraints pose challenges in the AI diagnosis research. Most of the studies are retrospective, based on selected datasets, and do not represent clinical heterogeneity. Back in China, multi-center prospective trials will be required to prove AI systems are reliable under different operational circumstances [33].

The lack of common benchmarks is also a limitation in terms of the performance assessment. Comparison with other models is difficult since different datasets, metrics and evaluation procedures are used. Adoption of standardised datasets and challenge structures would facilitate this, enabling fair comparisons and progress to be made [34].

In addition, the majority of the research is carried out in the university environment and little attention is paid to the integration into the clinic.

Deployment into the real world must confront interoperability, user experience, and regulatory approval problems, which are rarely touched upon in technical papers [35]. Table 4 summarizes the main methodological and practical challenges of current AI diagnostics studies.

Table 4: Limitations of Current Methodologies in AI Diagnostics and Proposed Solutions

Limitation Category	Description	Proposed Solution / Need
Data Limitations	Most studies use retrospective, curated datasets that lack clinical diversity [33]	Conduct prospective, multi-center studies that reflect real-world scenarios
Evaluation Inconsistency	Lack of standardized benchmarks and inconsistent metrics across studies [34]	Develop standardized datasets, evaluation protocols, and public challenge frameworks
Clinical Integration Gap	Research often lacks consideration for real-world implementation (interoperability, UX, regulation) [35]	Emphasize deployment feasibility, clinician involvement, and regulatory compliance
Reproducibility Issues	Model comparisons are often non-reproducible due to diverse experimental setups	Require transparent reporting, shared code, and common testing standards
Academic Silos	Dominance of academic-led research with limited collaboration with hospitals and industry	Foster academia-clinic-industry partnerships to bridge research and real deployment

8. Survey Insights and Research Gaps

This review indicates leading trends and growing voids in AI diagnostics research. CNNs are widely used in imaging tasks, and recently transformer-based architectures have gained popularity in both textual and multimodal domains. Yet, the holistic integration of multimodal data (including imaging, signals, clinical text data) lacks clear exploration [36].

Real-time and edge AI implementation is an increasing trend, due to the evolution in IoMT. However, balancing the trade-offs between latency, accuracy and power consumption requires careful engineering. Moreover, the sparse inclusion of low resource languages and regions in the generation of language data sets also reflects on a worldwide equity issue [37].

Although XAI and fairness have increased in relevance, concrete methodologies for their application in the clinical practice are evolving. Multidisciplinary models with clinicians and data scientists and ethicists can help bridge a gap between what AI can do and what is needed [38]. So we can see what are the key trends and gaps and future directions for AI diagnostics research from Table 5.

Table 5: Emerging Trends and Unaddressed Gaps in AI Diagnostics Research

Category	Current Trends	Identified Gaps / Needs
Model Usage	CNNs widely used for imaging; transformers gaining momentum in text and multimodal tasks [36]	Holistic multimodal integration (imaging + biosignals + text) is underexplored
Deployment Platforms	Increasing focus on real-time AI and edge computing through IoMT [36]	Engineering trade-offs: latency, accuracy, and power constraints require optimization
Equity in Datasets	Research mostly focuses on high-resource regions and major global languages [37]	Underrepresentation of low-resource languages/regions limits model generalizability
Explainability & Fairness (XAI)	Growing interest in fairness and explainability tools [38]	Lack of mature, deployable strategies in clinical practice; need for clinician engagement
Collaboration & Integration	Cross-disciplinary collaboration is recognized as important [38]	More structured frameworks involving clinicians, ethicists, and engineers are needed

9. Future Research Directions

As the integration of Artificial Intelligence (AI) in healthcare diagnostics continues to evolve, several key areas warrant focused research to ensure effective, ethical, and sustainable implementation. Future investigations should aim to address current limitations, improve system performance, and align AI tools with clinical needs and societal values. Key research directions include:

a) Develop generalizable models for reliable performance across populations and settings.
b) Create federated learning frameworks for collaborative training without data centralization.
c) Enhance explainability and clinician-AI collaboration.
d) Design user-friendly interfaces and decision pathways.
e) Integrate AI education into medical training for ease of adoption.
f) Evolve regulatory frameworks for continuous validation and post-deployment monitoring.
g) Prioritize cross-disciplinary studies for effective and socially responsible AI tools.

10. Conclusion

Artificial Intelligence (AI) has become a game changer for healthcare diagnostics with dramatic enhancement in accuracy, speed and accessibility. Through the wide-spread application of AI techniques such as deep learning, machine learning, and natural language processing (NLP) in various diagnostic realms, including medical imaging, genomics and biosignal analysis, healthcare professionals are able to provide more accurate and timely diagnostic results. With growing potential in edge computing and real-time data interpretation, AI systems can now assist with clinical decision-making at point-of-care to improve patient management. Nevertheless, despite these tremendous developments, there are several obstacles currently preventing the extensive implementation of AI in health-related diagnostics. However data quality and availability are major concerns and AI requires significant amount of high quality labeled data to be trained well. Moreover, the black-box property associated with the majority of deep learning models, limiting interpretability, may prevent clinicians from trusting and accepting AI-based decisions. There are also lingering ethical considerations around things like algorithmic bias and patient privacy, as AI models may inadvertently reinforce inequities in health outcomes. Despite the promise, to fully harness the power of AI in healthcare diagnostics, future research must focus on enhancing model interpretability, fairness, and adoption mechanisms that can seamlessly package AI into clinical workflows. Here we advocate for a multidisciplinary, collaborative framework that brings together clinicians, data scientists, ethicists, and policymakers to ensure that the development of AI systems is ethical, complies with regulations, and is trustworthy in real-world clinical settings. At the end of the day, the eventual fate of AI in healthcare diagnostics will come down to building reliable, democratic and open models that don't just improve diagnostic accuracy, but also advance health equity and improve patient outcomes all over the world.

References

[1]. A. Esteva *et al.*, “Dermatologist-level classification of skin cancer with deep neural networks,” Nature, vol. 542, pp. 115–118, Feb. 2017.

[2]. V. Gulshan *et al.*, “Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs,” JAMA, vol. 316, no. 22, pp. 2402–2410, 2016.

[3]. M. S. Hossain and G. Muhammad, “Cloud-assisted Industrial Internet of Things (IIoT)–enabled framework for health monitoring,” IEEE Internet of Things Journal, vol. 6, no. 5, pp. 8085–8093, Oct. 2019.

[4]. A. Yazdinejad *et al.*, “Real-time remote health monitoring via intelligent edge computing: A systematic review,” IEEE Access, vol. 9, pp. 57005–57021, 2021.

[5]. J. D. Power *et al.*, “Ethical considerations in artificial intelligence applications in clinical diagnosis,” IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 5, pp. 1335–1343, May 2020.

[6]. E. H. Shortliffe and B. G. Buchanan, "A model of inexact reasoning in medicine," *Mathematical Biosciences*, vol. 23, no. 3–4, pp. 351–379, 1975.

[7]. [K. Doi, "Computer-aided diagnosis in medical imaging: Historical review, current status and future potential," *Computerized Medical Imaging and Graphics*, vol. 31, no. 4–5, pp. 198–211, Jun. 2007.

[8]. A. Esteva *et al.*, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, Feb. 2017.

[9]. M. Tjoa and C. Guan, "A Survey on Explainable Artificial Intelligence (XAI): Toward Medical XAI," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 11, pp. 4793–4813, Nov. 2021.

[10]. J. Lee *et al.*, "BioBERT: A pre-trained biomedical language representation model for biomedical text mining," *Bioinformatics*, vol. 36, no. 4, pp. 1234–1240, Feb. 2020.

[11]. A. Alsentzer *et al.*, "Publicly Available Clinical BERT Embeddings," in *Proc. 2nd Clinical NLP Workshop*, Florence, Italy, Aug. 2019, pp. 72–78.

[12]. H. Rajkomar *et al.*, "Machine learning in medicine," *New England Journal of Medicine*, vol. 380, no. 14, pp. 1347–1358, Apr. 2019.

[13]. M. Chen *et al.*, "Big Data Analytics for Personalized Healthcare," *IEEE Transactions on Emerging Topics in Computing*, vol. 2, no. 3, pp. 166–173, Sept. 2014.

[14]. Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated Machine Learning: Concept and Applications," *ACM Transactions on Intelligent Systems and Technology*, vol. 10, no. 2, pp. 1–19, Feb. 2019.

[15]. N. Rieke *et al.*, "The future of digital health with federated learning," *NPJ Digital Medicine*, vol. 3, no. 119, pp. 1–7, Sept. 2020.

[16]. B. A. Yu, A. Beam, and I. S. Kohane, "Artificial intelligence in healthcare," *Nature Biomedical Engineering*, vol. 2, no. 10, pp. 719–731, Oct. 2018.

[17]. M. J. van der Schaar *et al.*, "How artificial intelligence is changing the role of the doctor," *BMJ*, vol. 363, p. k3797, Oct. 2018.

[18]. J. D. Kelleher, *Machine Learning: A Concise Introduction*, MIT Press, 2019.

[19]. A. Esteva *et al.*, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, 2017.

[20]. J. Lee *et al.*, "BioBERT: a pre-trained biomedical language representation model for biomedical text mining," *Bioinformatics*, vol. 36, no. 4, pp. 1234–1240, 2020.

[21]. M. Abadi *et al.*, "TensorFlow: A System for Large-Scale Machine Learning," in *Proc. 12th USENIX Conf. Oper. Syst. Design Implement.*, 2016, pp. 265–283.

[22]. P. Gope and B. H. Kim, "A Survey on Security and Privacy Issues in Modern Healthcare Systems: Attacks and Defenses," *IEEE Access*, vol. 7, pp. 88521–88599, 2019.

[23]. V. Gulshan *et al.*, "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs," *JAMA*, vol. 316, no. 22, pp. 2402–2410, 2016.

[24]. P. Rajpurkar *et al.*, "Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks," *Nature Medicine*, vol. 25, no. 1, pp. 65–69, 2019.

[25]. D. Libbrecht and W. S. Noble, "Machine Learning Applications in Genetics and Genomics," *Nature Reviews Genetics*, vol. 16, pp. 321–332, 2015.

[26]. H. J. Topol, *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again*, Basic Books, 2019.

[27]. M. T. Ribeiro, S. Singh, and C. Guestrin, "Why Should I Trust You?" Explaining the Predictions of Any Classifier," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, 2016, pp. 1135–1144.

[28]. S. Holzinger *et al.*, "What Do We Need to Build Explainable AI Systems for the Medical Domain?" *arXiv preprint arXiv:1712.09923*, 2017.

[29]. D. R. Harder *et al.*, "Towards Clinically Applicable Explainable AI Models in Healthcare," *npj Digit. Med.*, vol. 4, no. 1, pp. 1–6, 2021.

[30]. E. Choi *et al.*, "RETAIN: An Interpretable Predictive Model for Healthcare Using Reverse Time Attention Mechanism," in *Proc. NIPS*, 2016, pp. 3504–3512.

[31]. S. Obermeyer *et al.*, “Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations,” *Science*, vol. 366, no. 6464, pp. 447–453, 2019.

[32]. A. Mehrabi, F. Morstatter, N. Saxena, K. Lerman, and A. Galstyan, “A Survey on Bias and Fairness in Machine Learning,” *ACM Comput. Surv.*, vol. 54, no. 6, pp. 1–35, 2021.

[33]. M. Zech *et al.*, “Variable Generalization Performance of a Deep Learning Model to Detect Pneumonia in Chest Radiographs: A Cross-Sectional Study,” *PLoS Med.*, vol. 15, no. 11, e1002683, 2018.

[34]. S. Irvin *et al.*, “CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison,” in *Proc. AAAI*, vol. 33, no. 1, pp. 590–597, 2019.

[35]. D. B. Saria, “Individualized Sepsis Treatment Using Reinforcement Learning,” *Nature Medicine*, vol. 25, pp. 1436–1445, 2019.

[36]. W. Xie *et al.*, “Multimodal Learning for Healthcare: A Review,” *IEEE Trans. Artif. Intell.*, vol. 2, no. 4, pp. 446–460, 2021.

[37]. A. Joshi *et al.*, “Machine Learning for Global Health: Lessons from COVID-19 and Beyond,” *Lancet Digit. Health*, vol. 3, no. 6, pp. e340–e341, 2021.

[38]. L. Morley *et al.*, “The Ethics of AI in Health Care: A Mapping Review,” *J. Med. Internet Res.*, vol. 22, no. 8, e16228, 2020.

[39]. Q. Yang, Y. Liu, T. Chen, and Y. Tong, “Federated Machine Learning: Concept and Applications,” *ACM Trans. Intell. Syst. Technol.*, vol. 10, no. 2, pp. 1–19, 2019.

[40]. B. Sendak *et al.*, “A Path for Translation of Machine Learning Products into Healthcare Delivery,” *NPJ Digit. Med.*, vol. 3, no. 1, pp. 1–10, 2020.

[41]. S. Wiens *et al.*, “The Future of AI in Healthcare: A Review of the Regulatory Landscape,” *IEEE J. Biomed. Health Inform.*, vol. 25, no. 4, pp. 1022–1029, 2021.