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Research Article

Artificial Intelligence for Medical Diagnostics in IoT-Based Healthcare Networks: Foundations and Future Trends

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ABSTRACT

AI is quickly transforming the landscape of medical diagnostics, leading to remarkable gains in accuracy, speed, and availability. We perform a systematic review on the fundamental strategies, tools, applications, and challenges of AI enabled diagnostic in medicine with focus on medical diagnostics in IoT-based healthcare networks. The paper presents the use of machine learning algorithms, deep learning models, including CNN, and NLP to interpret clinical documentation. It also investigates the usage of smart computing infrastructures such as edge systems and the Internet of Medical Things (IoMT) that facilitates real-time, data-driven clinical decision-making consistently matching or exceeding human-level perception, notably in medical imaging, pathology and biosignal analysis. Nevertheless, there exist great challenges, such as data heterogeneity, lack of high-quality labeled datasets, model interpretability and ethics, such as algorithmic bias and patient privacy. In addition, questions on standards, clinical confidence, and regulation are often considered less important than technical performance but are central to the effective deployment of AI within health systems. This paper presents the comparison of AI-combated diagnostic approaches with the traditional ones, a recent literature review and some research gaps for future work. The study seeks to underpin the need to advance AI systems that can be understood, are clinically applicable and ethically justifiable. It promotes interdisciplinary cooperation and uniformed evaluation methodologies for the safe, efficacious and equitable utilization of AI for healthcare diagnostics.

1. INTRODUCTION

The rise of big Data, IoT and Artificial Intelligence (AI) is transforming today¿s health care, especially in medical diagnosis where timely and accurate diagnosis is important to the patient. As the volume and complexity of clinical data including but not limited to medical imaging and genomic sequencing has been expanding, the drawbacks of conventional diagnostic models heavily relying on manual aggregation and rule-based heuristics have become apparent. Instead, AI-related solutions — made powerful by the extreme precision, efficiency and real-time decision-making that deep learning, machine learning and intelligent computation architecture now make possible — are transforming the field.

Recent advances have shown that AI approaches can achieve at least parity and sometimes even exceed that of experienced clinicians' performance in terms of diagnosis. Neural Networks, namely Convolutional Neural Networks (CNNs), have, for instance, reached dermatologist's performance in the classification of skin cancer [1] and sensitivity and specificity performance in the illuminations of diabetic retinopathy from retinal images [2]. In addition to medical imaging, AI is being used for biosignal analysis, digital pathology and unstructured clinical text (e.g., as in NLP), for a more opened and comprehensive diagnosis.

One of the major drivers of this development is the evolution of computational hardware and embedded intelligence. High-performance platforms like GPUs, FPGAs or ASICs are being embedded in medical devices and enable a real-time AI inference on the edge device. At the same time, the growth of Internet of Medical Things (IoMT) and edge computing is providing opportunities to deploy AI models on wearables, mobile health platforms, and remote monitoring systems, for real-time, low-latency and continuously patient assessment [3,4].

Figure 1 highlights the central position of AI in the diagnostic pipeline, encompassing the entire spectrum from data acquisition and automated detection to real-time clinical decision support. This includes various data sources (e.g., imaging,

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biosignals), AI methods (CNNs, NLP, etc.), and computational infra structures (cloud computing, edge devices, IoMT), that are converging to provide accurate, timely, and actionable diagnostic information

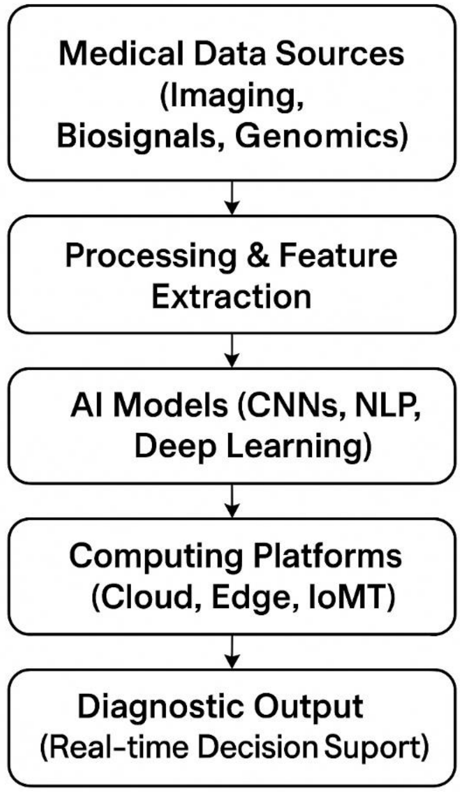

Fig. 1. AI-enabled diagnostic pipeline in IoT-based healthcare systems.

Despite the remarkable progress in AI for diagnostics, several key challenges still prevent wide clinical deployment. These consist of the heterogeneity of medical data, the lack of abundant high-quality labeled data, ethical issues associated with model interpretability and fairness, algorithmic bias, and patient data privacy [5]. In addition, the AI systems will need to be integrated within current health systems while maintaining levels of interoperability, consideration for regulations and crucially, the trust of healthcare professionals – these are aspects typically overlooked in technically driven research.
In Table 1, we describe some frequently considered criteria (accuracy, speed, scalability and interpretability) to differentiate conventional and AI-powered diagnostic systems using selected, illustrative examples from the real world.

TABLE I. COMPARISON OF TRADITIONAL AND AI-BASED 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	Cloud/Edge Deployment	Telemedicine platforms
Interpretability	Transparent, Rule-Based	Often Black-Box; XAI efforts ongoing	Explainable AI (XAI) in diagnostics

2. LITERATURE REVIEW

Advancements in Artificial Intelligence (AI) have been successful in the field of medical diagnosis, because its algorithm unveils complicated patterns from clinical data. Early AI systems (such as expert systems) codified professional knowledge into decision systems and set the path forward for other methods in AI. Although such systems were transparent and interpretable, they were not scalable and had limited ability to accommodate unstructured or noisy clinical data[6].
The rapid advance of Machine Learning (ML) techniques has resulted in more accurate and efficient data- driven models, especially of supervised ML algorithms such as Support Vector Machines (SVMs) and Decision Trees. But these models mostly needed a lot of feature engineering, as well as domain-specific pre-processing[7].
Medical Imaging has been revolutionized by the advent of Deep Learning especially Convolutional Neural Networks (CNN)! CNNs have even achieved clinician-level performance in radiology, dermatology, and ophthalmology, surpassing

general physicians in projects such as skin lesion classification[6] and pneumonia detection from chest X-rays[8]. However, the "black-box" nature of DL models has impeded clinical confidence and acceptance. To tackle this, Explainable AI (XAI) tools such as attention maps and Layer-wise Relevance Propagation (LRP) have been employed in deep models to improve the interpretability and diagnostic transparency[9].
Consequently, Natural Language Processing (NLP) has become an essential method to process unstructured clinical text (e.g., discharge summaries, radiology reports). 2Related Work Pre-trained language representations such as BERT and BioBERT have achieved the state-of-theart in a variety of NLP applications including named entity recognition, and clinical text classification[10]. However, there still remain challenges resulting from the specific vocabulary and non-standard manifest formats in the domain, as well as lack of annotated training data. Current work is currently investigating domain adaptation, self-supervised learning, and continual fine-tuning to become robust to various healthcare environments[11].
Multi-modal diagnosis is also an important frontier, which includes combining imaging, genomics, electronic health records (EHRs, which are much less complete in most places), and biosignals to better reflect a real patient with a real biography and to provide more personalized diagnosis. However, problems of integration like format heterogeneity, temporal misalignment and sparseness of data are ubiquitous [12]. Further, model generaliza tion and fairness are attacked by demographic biases and small labeled datasets[13]. Possible solutions like synthetic data generation, and federated annotation pipelines are being investigated.
Recent deployment-oriented literature has concentrated on the shift toward point-of-care AI operating via use of edge computing and federated learning. These low-latency technologies that process data in a distributed way at the edge side on the medical devices would provide to also ensure its data privacy. However, real-time synchronization, model performance variability, and compliance with health-care laws such as HIPAA or GDPR are still challenging[14,15].
Despite the promise presented by technical innovations, many studies fail to consider important ethical and regulatory aspects—they fail to consider ethical concerns such as algorithmic bias, patient autonomy and the transparency of the model. Furthermore, the absence of prospective clinical trials prevents validation of AI systems to be deployed in clinical workflow and impedes implementation of AI technology into clinical practice[16]. To fight this gap interdisciplinary cooperation among computer scientists, clinicians, ethicists and policy makers is needed [17].
To summarize and compare results and the major contributions and limitations of most recent studies we list in Table 2 a comparative summary on the current AI applications on health care diagnostics.

TABLE II. COMPARATIVE ANALYSIS OF KEY LITERATURE ON AI IN HEALTHCARE DIAGNOSTICS

Ref.	Study Focus	Techniques/Models Used	Strengths	Limitations/Gaps
[6]	Rule-based expert systems	Knowledge-based systems	High interpretability; early use in decision support	Limited scalability; poor handling of unstructured data
[7]	Early ML in imaging diagnostics	Decision Trees, SVMs	Improved accuracy over rule-based models	Dependency on handcrafted features
[8]	Deep learning in skin cancer detection	CNNs	Clinician-level accuracy	Black-box nature; dataset bias
[9]	Explainable AI for imaging	Saliency maps, attention	Improved transparency of deep models	Limited clinical adoption due to complexity
[10]	NLP in biomedical records	BERT, BioBERT	Advanced clinical text analysis	Needs large annotated datasets
[11]	Domain-specific NLP adaptation	Clinical BERT	Better contextual understanding	Limited transferability across institutions
[12]	Multi-modal diagnostics	EHRs, Imaging, Genomics	Personalized, comprehensive diagnosis	Data alignment, heterogeneity issues
[13]	Big data and cloud AI in healthcare	Cloud AI Systems	Scalability; population-wide insights	Data privacy; siloed datasets
[14]	Federated learning for medical AI	Federated deep learning	Data privacy; no central data sharing	Synchronization complexity; uneven performance
[15]	Edge AI for point-of-care diagnostics	Edge AI systems	Real-time inference; reduced cloud dependency	Hardware limitations; regulation uncertainty
[16]	Ethical and regulatory gaps in AI diagnostics	Conceptual frameworks	Raises awareness on societal implications	Underrepresentation in AI research
[17]	Interdisciplinary collaboration in AI deployment	Literature review	Emphasizes clinician trust and ethical alignment	Lacks detailed implementation strategies

3. TECHNIQUES AND TOOLS USED IN AI FOR DIAGNOSTICS

It is critically important to evaluate the performance of AI models vs standard diagnostic technique on real-world implications and clinical significance. Several submission measures—such as accuracy, specificity, sensitivity, interpretability, and efficiency—are commonly used for evaluating AI methods versus the state-of-the-art in diagnostics.

There is now relatively new data to show that for some applications of health AI – notably deep learning – it also delivers performance that can outpace traditional diagnostic systems in terms of speed and scale and sometimes in diagnostic accuracy for some cases [27]. Such as, AI algorithms can rapidly review big data subsets, uncovering patterns in medical imaging and biosignals beyond those of human discriminators. Though the AI models obtain promising predictive performance, the interpretability of the AI models is quite limited, especially for deep learning networks, which can question trust and clinical validation.
In fact this might even still be a clear advantage regarding traceability and explainability as compared to these classical rulebased systems, due to their logical processing the decision paths can be directly tracked. In order to bridge the gap, hybrid models, such as one that hybridizes rule-based reasoning with datadriven learning and prediction, have gained popularity, since they offer a balance between desirable performance and interpretability [28].
Another critical aspect is validation. While classic algorithms can have established recipes for combinatorial generating potential countermeasures, AI approaches require re-validated applicability in many new clinical contexts as they arise over time. This calls for a commitment to integrating AI into clinical work flow with deep clinical engagement, and with a commitment to regulation and standards [29]. Table 3 A comparative overview of differences between AI based diagnostic methodologies versus conventional diagnostic method.

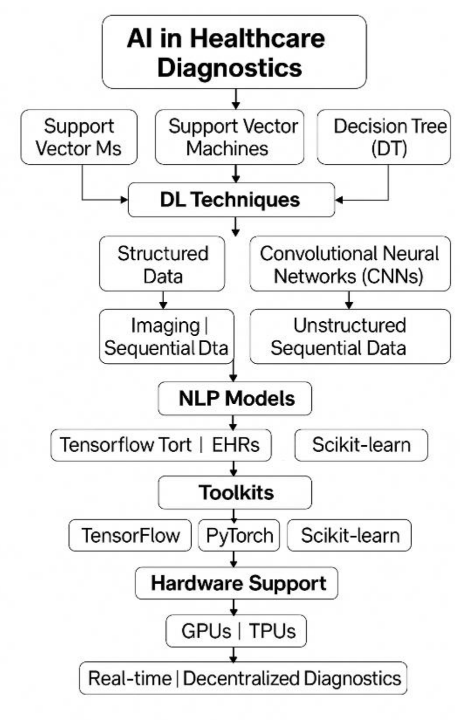

Fig. 2. Framework of AI Techniques and Infrastructure in Healthcare Diagnostics

4. APPLICATIONS OF AI IN HEALTHCARE DIAGNOSTICS

Medical imaging, biosignal analysis, genomic data interpretation and clinical decision support systems (CDSS), are some of the healthcare diagnostic fields in which the potential of artificial intelligence (AI) has proven to be revolutionary. Not only are they improving diagnostic accuracy, they are also helping to optimize efficiency, consistency, and availability of medical care.

4.1 Medical Imaging

Regarding medical image analysis, Convolutional Neural Networks (CNNs) have received considerable attention in tasks like skin lesion classification and elicitation of retinal diseases. For example, CNN-based diagnostic models have achieved dermatologist-level performance for detecting skin cancer, as well as sensitivities across patients from retinal fundus images with diabetic retinopathy[23]. Automated pattern recognition has been applied for the radiology and pathology thereby reducing human workload, inter-observer variation and faster diagnosis.

4.2 Biosignal Analysis

AI has also been widely used in biosignal-based diagnostics, with the use of recurrent neural network (RNN) and attention mechanism in analyzing dynamic signals such as ECGs, electroencephalograms (EEGs), and other physiological signals. The early real-time detection of cardiac arrhythmias, epileptic seizures and neurological conditions is facilitated using such models to real-time analyze streaming data and detect subtle, time-dependent anomalies which would be difficult for humans to identify[24].

4.3 Genomic Diagnostics

In genomics, AI algorithms help translate complex genetic information derived from sequence technologies. Applications range from variant classification to mutation prediction as well as finding disease susceptibility markers in patterns in DNA and RNA sequences given in [25]. These functions are important for personalized medicine, which is a treatment customized using personal genetics information.

4.4 Clinical Decision Support System (CDSS)

As computers with AI are being widely used in clinical practice, there is a highly potential role for diagnosis tool and treatment assistant based on AI. Such systems combine patient data with clinical guidelines and latest literature to produce evidence-based recommendations. By assisting the clinician in complicated or ambiguous situations, CDSS improve diagnostic consistency, decrease errors, and improve patient outcomes [26]. Their wide application indicates the increasing acceptance of AI as an adjunct to clinical knowledge.

5. COMPARATIVE ANALYSIS OF AI APPROACHS

Comparative examination is of utmost importance to assess the performance of AI systems as compared to standard diagnostic methods for its real-world implication and clinical importance. A number of submission metrics—including accuracy, specificity, sensitivity, ease of interpretation, and efficiency—are typically applied to assess AI practices relative to state-of-the-art in diagnostics.

Relatively recent work has demonstrated that for certain applications of health AI—primarily deep learning—performance can exceed that of traditional diagnostic systems both in speed and scale as well as diagnostic accuracy in some cases [27]. For example, AI algorithms are able to quickly analyze large subsets of data, discover patterns within medical images and biosignals that are beyond the discrimination of human observers. Even though these AI models show promising performance, AI models (especially deep learning networks) usually have poor interpretability and hence challenge the trust and clinical validation.

Actually, compared to these traditional rule-based systems a clear advantage might still be transparency and traceability, because of their logical processing the actual decision paths can be directly followed. To fill this gap, hybrid models that combine rule-based reasoning and data-driven learning approaches are becoming popular, as they provide a compromise between good performance and interpretability [28].

Another critical aspect is validation. Whereas conventional algorithms rely on time-honored protocols for combinatorial generation of potential countermeasures, AI models need perpetually renewed validation to be useful in different emerging clinical contexts. This necessitates the active integration of AI in the clinical workflow with deep clinical involvement and adherence to regulations and standards [29]. Table 3 provides a comparative summary of the differences between AI driven diagnostic approaches and traditional diagnostic method:

TABLE III. KEY DIFFERENCES BETWEEN AI-DRIVEN AND CONVENTIONAL DIAGNOSTIC APPROACHES

Criteria	AI-Based Diagnostic Systems	Traditional Diagnostic Methods
Accuracy	Often equal to or exceeds expert-level performance in imaging/text diagnostics [27]	Generally high but susceptible to human error
Specificity & Sensitivity	High, especially in image and biosignal analysis	Variable; depends on practitioner expertise and protocol adherence
Time Efficiency	Real-time or near real-time; scalable across large datasets	Time-intensive; manual interpretation processes
Interpretability	Limited (especially with deep learning "black-box" models)	High (transparent logic in rule-based systems)
Adaptability	Continuously improves with data; supports personalized care	Less flexible; relies on fixed protocols
Scalability	Easily deployable across cloud, edge, and IoMT platforms	Typically constrained to physical facility-based workflows
Transparency	Requires explainable AI (e.g., SHAP, LIME) for model understanding	Inherent due to rule-based decision-making
Regulatory & Validation	Requires ongoing updates and regulatory adaptation	Established under clinical guidelines with clear validation
Hybrid Model Potential	High: Enables combination of rule-based and data-driven logic [28]	Low: Limited capacity for self-adaptation
Clinician Involvement	Requires trust-building and human-in-the-loop integration [29]	High involvement; direct clinical decision-making

This comparative analysis emphasizes that while AI holds immense potential to revolutionize diagnostics, its successful integration into clinical practice must address interpretability, trust, regulatory compliance, and validation challenges. The hybridization of AI with conventional logic-based models may represent a promising path forward, combining the strengths of both paradigms.

6. CHALLENGES AND ISSUES

The adoption of artificial intelligence (AI) in diagnoses has a great potential to transform the field of health; however, it comes with various technical, ethical and practical hurdles that need to be addressed prior to its clinical deployment.

1. Heterogeneity and Scarcity of Data: One of the most challenging obstacles is the heterogeneity of health care data. Diagnostic data are significantly heterogeneous in different institutions, patients, and medical devices, as well as clinical scenarios, challenging attempts to build AI models that are general and robust across different environments[30]. Furthermore, the scarcity of large and annotated datasets — especially with rare diseases — also hinders the use deep learning models with a high capacity. This scarcity of high-quality data is a major challenge to achieve reliable diagnostic performance.
2. Interpretable: The interpretability has also been a major concern as AI models, in particular deep learning models, are frequently deemed as black box models. Understandably, a concern of clinicians is the dependence on systems that do not provide a rationale for their diagnostic decisions. Although Explainable AI (XAI) methodologies including saliency maps or attention mechanism, as well as rul-based visualisation, have been proposed in order to improve transparent model, their application in reality is still in its infant stage and strictly context dependent [31]. Lack of interpretability is a major obstacle for clinical trust and regulatory approval.

Algorithmic Bias and Fairness: AI bias raises serious ethical and legal considerations. When insufficient diversity is represented in the training dataset, models may perform worse for underrepresented groups, thereby contributing to inequitable healthcare. But AI models trained on data sets heavily comprising samples of a single race or ethnic group might make poor predictions for other races, contributing to rather than narrowing healthcare disparities. Rectifying this requires demographically representative data sets, and the application of processes to identify and mitigate bias across the entire lifecycle of AI model development [32].

7. LIMITATIONS OF EXISTING RESEARCH

Although AI-assisted diagnostics have developed promptly, current studies are confronted with some methodological and practical restrictions that might prevent clinical translation and widespread application.

7.1 Retrospective and Non-Generalizable Studies

A large body of current literature is based on retrospective datasets, many of them hand-picked to work well and lacking in clinical heterogeneity. These data sets do not sufficiently characterize the heterogeneity observed in real-life healthcare environments, especially across different institutions and patient populations. For instance, research performed in China has highlighted that albeit promising, multi-center prospective clinical trials are essential for an adequate performance characterization and reliability evaluation of AI systems across different operational settings[33].

7.2 Absence of Standardized Benchmarks

Another significant limitation is the absence of uniform evaluation measures. Due to the variety of datasets, performance metrics, evaluation methods used in research, it is hard to compare AI models or sense the progress around the field. Fair and reproducible comparisons are possible, however, only when standardized datasets, common evaluation protocols, and open benchmarking competitions are available[34].

7.3 Focused in the Clinic and Limitations for Clinical Deployment

Algorithms are often demonstrated to achieve high accuracies in the academic setting, but are seldom successfully deployed in the wild. These range from challenges to existing hospital systems integration to UX for clinicians to regulatory compliance. The implementation of the clinical integration requires multidisciplinary expertise (software engineers, healthcare professionals and regulatory specialists) such as is not regularly addressed in the current literature.[35].

7.4 Reproducibility and Transparency Challenges

Even for AI models that are available, often they are trained using proprietary or nonpublic data, as well as code, which raise concern about reproducibility. The eccentricity in test rigs also introduces significant complexity into the validation of models, provoking resistance against best practices. In order to isolve these, there's an increasing demand for open source codebases, transparent model reports, and shared validation pipelines in an attempt to increase reproducibility and robutness.

7.5 Academic-Industry Disconnection

The majority of AI diagnostic research to-date has been performed in academia, where studies are typically disconnected from clinical practice and commercial application. This silos strategy obviously restricts chances for real-world validation and degree. It is key to prompt academia, healthcare and industry to collaborate, as to develop strong and actionable AI solutions that satisfy clinical and regulatory requirements.
To highlight present methodological and practical limitations in AI-oriented diagnostic research and development, Table 4 provides a compiled overview of the main limitations with potential solutions, which could provide a link between successful experimental studies and clinical implementation.

TABLE IV. CATEGORIZED LIMITATIONS OF CURRENT AI DIAGNOSTICS RESEARCH AND RECOMMENDED SOLUTIONS

Limitation Category	Description	Proposed Solution / Need
Data Limitations	Use of retrospective, curated datasets that lack clinical diversity [33]	Conduct prospective, multi-center studies reflecting real-world scenarios
Evaluation Inconsistency	Lack of standardized benchmarks and inconsistent evaluation metrics [34]	Develop standardized datasets, public challenge frameworks, and evaluation protocols
Clinical Integration Gap	Limited focus on deployment challenges such as UX, interoperability, and regulations [35]	Emphasize real-world deployment, clinician collaboration, and regulatory compliance
Reproducibility Issues	Model comparisons often not reproducible due to differing methodologies	Mandate transparent reporting, open-source code, and common testing frameworks
Academic Silos	Minimal collaboration between academia, hospitals, and industry	Promote partnerships among research institutions, healthcare providers, and commercial firms

8. SURVEY INSIGHTS AND RESEARCH GAPS

This review seeks to delineate the prevailing trajectories and persistent lacunae in the current AI-based diagnostic healthcare application landscape. On the one hand, Convolutional Neural Networks (CNNs) are still the workhorses for image-centric tasks, and transformer-based architectures such as BERT and its derivatives are being more and more employed for textual and multimodal processing. Yet even with these advances, use of holistic multimodal integration that includes both imaging and biosignals, along with clinical free text data are not often explored [36].
Moreover, the emergence of real-time AI deployment and edge computing, fueled by advances in Internet of Medical Things (IoMT), has brought diagnostics to near point-of-care. However, the design of trade-offs between latency, accuracy and power efficiency remains an engineering challenge [36]. Also, equity issues at the global scale remain: regions with fewer resources and with less represented languages are frequently being left out of training data, impacting the applicability of diagnostic models [37].
While explainability and fairness (XAI) are becoming increasingly popular the practical implementation of these methods is nascent within healthcare. The bridge between technical performance and clinical utility will have to be crossed by a multi-disciplinary effort including clinicians, researcher scientists in AI and bioethicists [38]. Table 5 To summarize these observations, Table 5 presents the key trends, limitations and directions remain to be explored.

TABLE V. 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	Growing interest in fairness and explainability tools [38]	Lack of mature, deployable strategies in clinical practice; need for clinician engagement

This comparative analysis highlights that while AI in healthcare diagnostics is progressing rapidly, significant research and operational challenges remain. Future studies must focus on robust, interpretable, and inclusive AI systems that are not only technically sound but also clinically viable and socially responsible.

9. FUTURE RESEARCH DIRECTIONS

With the acceleration of AI into health care diagnostics, we must steer its direction toward ethical, equitable, and clinically relevant applications. Engaging with future directions and mitigating world-clinical context constraints in future will be key. The next future research directions are suggested to pave the way for the further development of AI-based diagnostic systems:

1. Development of Generalizable Models: Any future models should perform robustly over diverse patient populations, healthcare facilities, and data modalities. Methods that enable trustworthy and more generalizable models such as domain adaptation, transfer learning, and robust validation pipelines are critical.
2. Federated and Privacy-Preserving Learning: Model architectures that implement federated learning will enable AI models to be trained across institutions alike, but without exposing patient data, thereby preserving patient privacy and security, thereby boosting the diversity of the training.
3. Explanation and Human-AI Interaction: Explainable AI (XAI) Approaches need to be integrated into clinical processes to allow clinicians to comprehend, trust, and validate AI outputs. Emphasize Human-AI Interaction In situations where critical and high-stakes decision-making is involved, human-AI collaboration frameworks need to matter the most.
4. Clinician-Centered Interface Design: In the future, it's crucial to focus research on the development of an intuitive user interface and a transparent diagnostic decision pathway that are consistent with present clinical workflow for enhanced usability and integration in the daily practice.
5. AI Training in Medical Curricula: Adoption will be sustained if healthcare professionals are trained in AI principles. AI literacy, with learning objectives oriented toward ethics and when to apply AI, should also be included in medical curricula, enabling a cohort of AI-conscious clinicians.
6. Adaptive Regulatory and Monitoring Systems: Regulatory authorities require to come up with dynamic protocols that enable real-time validation, post-deployment audit, and performance monitoring of AI tools in real-world applications to ensure long-term safety and compliance.
7. Facilitate Cross-Disciplinary Collaboration: Clinicians, data scientists, engineers and ethicist need to come together and work in synergy to develop effective and socially responsible AI systems. Models of interdisciplinary research and co-development are needed to ensure that AI capabilities are integrated and aligned with not only human needs, but also healthcare goals.

10. CONCLUSION

Artificial intelligence (AI) as a new technological revolution in healthcare diagnosis has been shown to improve the accuracy, the speed and accessibility of diagnosis in healthcare. By combining machine learning (ML), deep learning (DL), and natural language processing (NLP) in areas ranging from medical imaging, biosignal analysis, and genomics, AI facilitates faster and accurate diagnostic decisions made by healthcare staff. As edge computing and the Internet of Medical Things (IoMT) become more widespread, AI systems are increasingly available for real-time clinical decision control, particularly in resource-limited or remote environments. Notwithstanding these advances, there remains barriers to large-scale clinical implementation of AI, including limitations on high-quality annotated data, unexplained "black box" deep learning models, and ethical considerations such as algorithmic bias and privacy. These challenges need to be tackled by the next step of research, which needs to focus on explainability, fairness, standardization and seamless interfacing with clinical processes. This requires a multidisciplinary response across clinicians, data scientists, engineers, ethicists and politicians to ensure the AI tools are not just technically effective, but are ethical, trusted, and equitable. Success of AI in healthcare diagnostics in the future will rely on development and deployment of transparent, inclusive, human-centered systems that improve diagnostic quality and make a real difference in promotion of global health equity.

Conflict of Interest

The authors declare that there is no conflict of interest.

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