Scientific Research Publishing

Open Journal of Applied Sciences, 2025, 15(12), 4110-4133
https://www.scirp.org/journal/ojapps
ISSN Online: 2165-3925
ISSN Print: 2165-3917

Artificial Intelligence in Healthcare Diagnostics: A Literature Review

Tony Bader

Rise Academy, Beirut, Lebanon
Email: bader.tony@gmail.com

How to cite this paper: Bader, T. (2025) Artificial Intelligence in Healthcare Diagnostics: A Literature Review. *Open Journal of Applied Sciences*, **15**, 4110-4133.
https://doi.org/10.4236/ojapps.2025.1512266

Received: November 20, 2025
Accepted: December 21, 2025
Published: December 24, 2025

Abstract

Artificial intelligence (AI) has rapidly become a central force in healthcare, particularly in diagnostic medicine, where it promises earlier disease detection, improved accuracy, and more personalized care. This structured narrative review synthesizes recent evidence on AI applications in healthcare diagnostics, focusing on methodological approaches, clinical performance, and the ethical and regulatory challenges that shape real-world adoption. A targeted search of PubMed, Scopus, IEEE Xplore, ScienceDirect, and Google Scholar identified 84 eligible articles published between 2020 and 2025. These studies covered medical imaging, predictive analytics, clinical decision support systems, real-time monitoring, implementation in low- and middle-income countries (LMICs), and cross-cutting issues related to fairness, explainability, and governance. Across imaging and predictive tasks, AI systems frequently achieved diagnostic performance comparable to, or exceeding, that of human experts, while also enhancing workflow efficiency and enabling continuous patient monitoring. However, the review also reveals substantial limitations, including dependence on high-quality and demographically diverse datasets, performance degradation when deployed across different institutions and populations, and persistent algorithmic bias that risks exacerbating health inequities. The black-box nature of many models, gaps in explainable AI (XAI), and fragmented regulatory frameworks further complicate safe and trustworthy deployment in clinical environments. To support more responsible integration of AI diagnostics, this review proposes a 6P framework that emphasizes Performance, Provenance, Population, Privacy, Practice integration, and Policy. These dimensions highlight the conditions under which AI can function as a genuinely supportive tool that augments, rather than replaces, clinician expertise. Overall, AI in diagnostic medicine holds considerable promise, but its benefits will only be realized equitably if technical, ethical, and infrastructure-related challenges are addressed through interdisciplinary collaboration and robust governance.

Keywords

Artificial Intelligence, Diagnostics, Medical Imaging, Clinical Decision Support, Explainable AI, Health Equity

1. Introduction

Artificial intelligence has emerged as a defining force in contemporary healthcare, initiating a paradigm shift in how diseases are detected, diagnosed, and managed [1]. The integration of machine learning, deep neural networks, and advanced data analytics is transforming clinical decision-making and operational efficiency by enabling systems that learn from large-scale medical datasets and emulate certain elements of human reasoning [2] [3]. These technologies process vast quantities of imaging studies, genomic sequences, electronic health records (EHRs), and physiological data to identify subtle diagnostic patterns that often elude human observation [4]. As a result, AI is contributing not only to enhanced diagnostic accuracy but also to more personalized, proactive, and data-driven models of care [5].

The rapid development of AI-driven diagnostic systems reflects a broader shift toward automation and precision in medical practice. AI methods such as deep learning, natural language processing, and pattern recognition algorithms are increasingly embedded in clinical workflows, where they support tasks ranging from disease classification and risk prediction to treatment selection and outbreak monitoring [6]. The capacity of AI systems to integrate multimodal data streams allows clinicians to refine complex diagnostic assessments, improve detection of early-stage disease, and reduce the cognitive burden associated with high-volume clinical environments [1] [3].

Despite this progress, the implementation of AI in diagnostic medicine is accompanied by significant challenges. Issues relating to algorithmic transparency, data quality, generalizability, interpretability, equity, and ethical governance remain central concerns for researchers, practitioners, and policymakers [6]-[8]. These challenges underscore the importance of evaluating both the technological potential and practical limitations of AI-driven diagnostic systems.

This literature review aims to provide a structured and comprehensive synthesis of contemporary research on the application of artificial intelligence in healthcare diagnostics. It examines key methodological approaches, evaluates evidence across clinical domains, and identifies persistent barriers to safe and effective deployment. By consolidating findings from diverse studies, this review seeks to answer the following research questions:

- What are the dominant AI methodologies currently used in healthcare diagnostics, and how do they perform across medical specialties?
- What methodological and ethical challenges limit the generalizability, reliability, and clinical adoption of AI diagnostic tools?

- What evidence-based trends, gaps, and future directions emerge from the current body of literature?

The overall objective is to clarify the state of AI-driven diagnostic systems, highlight the conditions necessary for their responsible clinical integration, and provide a conceptual foundation for future research and policy development.

While several recent reviews have examined AI in medical imaging, predictive analytics, or explainable AI, most remain narrowly focused on individual specialties or single methodological dimensions. Prior work often evaluates diagnostic performance in isolation, without integrating the interconnected issues of dataset provenance, demographic representativeness, workflow integration, or regulatory governance. This review extends earlier studies by synthesizing these domains together and by proposing a structured framework that links technical performance with ethical, institutional, and implementation considerations. In doing so, it positions AI diagnostics not only as a computational advance but as a system-level transformation requiring alignment across clinical, infrastructural, and policy layers.

2. Methodology

This study follows a structured narrative review methodology aimed at synthesizing current evidence regarding the use of artificial intelligence in healthcare diagnostics. The review emphasizes peer-reviewed literature published between 2020 and 2025, reflecting a period during which AI diagnostic systems experienced rapid methodological, computational, and clinical advancements. The approach incorporates systematic elements, including explicit inclusion and exclusion criteria, database-based searches, and thematic synthesis, but does not claim to be a full systematic review with formal meta-analysis.

2.1. Search Strategy

A comprehensive search was conducted across major academic databases, including:

- PubMed/Medline
- Scopus
- IEEE Xplore
- ScienceDirect
- Google Scholar (as supplementary)

Search terms included combinations of:

- “artificial intelligence”
- “machine learning”
- “deep learning”
- “healthcare diagnostics”
- “medical imaging AI”
- “predictive analytics”
- “clinical decision support”

- "diagnostic accuracy"
- "algorithmic bias"
- "data quality healthcare AI"

Boolean operators (AND, OR) were used to combine terms. Reference lists of included papers were scanned to identify additional relevant literature.

2.2. Inclusion and Exclusion Criteria

Inclusion criteria:

- Articles published between 2020 and 2025
- Peer-reviewed journal articles or reputable conference proceedings
- Studies focusing on AI applications in diagnosis, risk prediction, medical imaging, genomics, or clinical decision support
- Research that reports performance metrics, methodological details, or clinical validation
- Studies discussing data quality, bias, explainability, or ethical and regulatory issues in AI diagnostics

Exclusion criteria:

- Non-English publications
- Studies focusing exclusively on robotics, non-diagnostic administrative systems, or wearable hardware without a diagnostic context
- Opinion pieces or editorials lacking an empirical or methodological basis
- Articles without an available full text

2.3. Screening and Selection Process

The database search returned several hundred records. After removal of duplicates, titles and abstracts were screened for relevance to artificial intelligence in healthcare diagnostics. Articles that were clearly unrelated to diagnostic applications, not focused on healthcare, or lacking sufficient methodological detail were excluded at this stage.

Full-text versions of the remaining articles were then assessed against the predefined inclusion and exclusion criteria. Studies that did not address diagnostic use cases, did not report methodological or performance details, or were purely opinion-based without analytical grounding were excluded.

In total, 84 articles met the eligibility criteria and were included in the final synthesis. These studies covered a range of topics including medical imaging, predictive diagnostics, clinical decision support, explainable AI, ethical and regulatory issues, and implementation challenges in both high-income and low- and middle-income country (LMIC) settings.

2.4. Data Extraction and Synthesis

For each included study, the following variables were extracted when available:

- AI methodology used (for example, CNN, RNN, transformer models, NLP approaches)

- Dataset characteristics (size, imaging modality, demographic diversity)
- Ground truth definition and annotation process
- Validation strategy (train-test split, cross-validation, external validation)
- Diagnostic performance metrics (accuracy, AUC, sensitivity, specificity)
- Ethical or regulatory notes (privacy, consent, bias, explainability, liability)

Studies were grouped into thematic categories to support structured synthesis, including medical imaging, predictive analytics, decision support, real-time monitoring, LMIC implementation, and cross-cutting ethical and regulatory concerns.

2.5. Methodological Considerations in AI Diagnostic Research

2.5.1. Data Quality, Curation, and Preprocessing

High-quality datasets are essential for developing reliable AI diagnostic systems. Many studies emphasized challenges such as limited dataset diversity, missing or incomplete clinical values, inconsistent imaging protocols, variation in EHR structures, and the presence of artifacts or low-resolution images [8] [9]. Data preprocessing often requires cleaning and normalization, rigorous anonymization to comply with privacy laws such as HIPAA and GDPR [10] [11], reduction of noise and imaging artifacts, and balancing of class distributions. Poor-quality or non-representative datasets can propagate errors throughout the diagnostic pipeline and adversely affect model performance.

2.5.2. Annotation and Ground Truth Challenges

Developing labeled medical datasets is difficult and labor-intensive. It typically requires expert annotators such as radiologists and pathologists, and is subject to inter-observer variability [12] and is often underfunded in low-resource settings [13]. Multiple reviewers are frequently needed to ensure consistency. Several studies note the scarcity of well-annotated data as a major impediment to robust AI model development [14] [15].

2.5.3. Security Foundations: Fault Detection and Cryptographic Integrity

The security of embedded AI diagnostics, especially within IoT-enabled medical systems, increasingly depends on integrating robust fault detection mechanisms and cryptographic hardening to safeguard against adversarial manipulation and operational faults. Recent advances in side-channel-resistant cryptographic implementations, such as optimized Ed25519 architectures for constrained processors, demonstrate how lightweight yet robust cryptography can protect medical devices from leakage-based threats [16]. Furthermore, with the advent of post-quantum cryptography, implementations like Fast SIKE Round 3 on ARM Cortex-M4 highlight ongoing efforts to maintain cryptographic security in embedded medical devices against future quantum threats [17]. Equally important, hardware-level fault detection schemes, including those using Cyclic Redundancy Check for finite-field computations, help prevent fault-injection attacks that could alter model outputs or compromise diagnostic integrity [18]. Additionally, the development of fault detection architectures specifically designed for FPGA implemen-

tations involving finite-field operations further enhances the resilience of these systems [19]. Incorporating these techniques within AI-driven diagnostic pipelines strengthens the trustworthiness of medical inference processes and ensures that clinical decisions remain secure, verifiable, and resistant to tampering in real-world healthcare environments.

Beyond hardware-level fault detection, AI diagnostic pipelines must also address broader security threats documented in prior research. Early studies on systematic poisoning attacks in healthcare [20] demonstrate how corrupted training data can compromise model reliability, highlighting the need for robust data provenance safeguards. Likewise, advances in secure hardware implementations for EdDSA signatures (Ed25519/Ed448), FPGA-optimized SIKE architectures, and reliable hash functions such as ECHO and Fugue provide practical cryptographic pathways for strengthening integrity, authentication, and tamper-resistance in embedded medical AI systems.

2.5.4. Dataset Diversity and Generalizability

A major theme across the literature is that AI models trained on homogeneous datasets perform poorly on diverse populations. Contributing factors include data silos across institutions, geographic and ethnic underrepresentation, heterogeneous imaging protocols, and lack of national or global reference datasets [21]. Performance degradation of 15 - 20 percent across hospitals has been reported when models are evaluated on unseen data distributions [22] [23].

2.5.5. Ethical and Privacy Considerations in Data Handling

Ethical issues related to data handling include strict consent requirements, institutional review board approvals, the need to protect sensitive patient information through robust de-identification, restricted data access due to regulatory barriers, and the risk of systemic bias arising from skewed training datasets [8] [24]. Deep learning's black-box nature raises accountability concerns and underscores the need for transparent documentation and validation of model development processes.

2.5.6. Bias, Equity, and Fairness Challenges

AI tools often underperform in underrepresented demographic groups, leading to diagnostic disparities, unfair clinical outcomes, and amplification of existing health inequities [7] [25]. Suggested mitigation strategies include more diverse sampling, fairness-aware algorithms, subgroup performance reporting, and careful evaluation of heterogeneity in datasets [9] [26].

2.5.7. Data Access Barriers and Infrastructure Limitations

Many studies highlight difficulties accessing high-quality medical data, lack of standardized infrastructure, privacy restrictions between institutions, insufficient computational capacity in LMICs, and dependence on third-party annotation companies [27] [28]. These barriers limit the scalability and external validity of AI diagnostic models.

2.5.8. Importance of Ethical Oversight and Regulatory Compliance

Ethical oversight mechanisms, including written consent, review by ethics committees, rigorous data inspections, and adherence to local and international regulations, are critical for ensuring that AI diagnostic research respects patient rights and institutional responsibilities [12] [29] [30].

3. Results

This section presents the findings of the 84 studies included in this review, organized into major thematic categories corresponding to AI's demonstrated performance, domains of application, workflow contributions, and systemic limitations. The results summarize what the literature collectively reports, without adding interpretation or normative judgment.

3.1. Overview of Included Studies

A total of 84 studies were included. Although many publications addressed multiple aspects of AI in healthcare, their primary focus areas could be grouped into several broad categories. Approximately 12 studies (14.3 percent) concentrated mainly on medical imaging and computational pathology, including applications in radiology, oncology, and dermatology. Around 18 studies (21.4 percent) focused on diagnostic and predictive modeling, such as disease risk prediction, outcome forecasting, and AI-enabled personalized medicine.

A smaller subset of about 7 studies (8.3 percent) examined clinical decision support systems and AI-based diagnostic copilots, with an emphasis on workload reduction, triage, and integration into clinical workflows. Roughly 19 studies (22.6 percent) dealt primarily with ethical, regulatory, fairness, and explainability questions surrounding diagnostic AI, including algorithmic bias, transparency, and liability. Approximately 8 studies (9.5 percent) explored implementation, infrastructure, and context-specific challenges, particularly in LMICs and in real-world deployment settings.

The remaining 20 studies (23.8 percent) were broad narrative or scoping reviews that spanned multiple domains, simultaneously discussing diagnostic performance, clinical integration, ethical implications, and health system impacts.

3.2. Results: Thematic Findings from the Literature Review

3.2.1. AI in Medical Imaging and Advanced Pattern Recognition

Recent years have witnessed a profound acceleration in the development and application of artificial intelligence across engineering, computing, and particularly medical domains [31]. In healthcare, AI-driven technologies are reshaping diagnostic and therapeutic processes by enabling complex data analysis, enhancing clinical accuracy, and supporting personalized decision-making [2] [32]. This section synthesizes major thematic areas emerging from the literature review.

A dominant theme concerns the integration of AI into medical imaging. Deep learning and convolutional neural networks (CNNs) have demonstrated superior performance in detecting patterns and anomalies in X-rays, CT scans, MRIs, ul-

trasounds, and other imaging modalities [1] [33]. CNNs excel at segmentation, classification, and anomaly detection due to their capacity to learn hierarchical visual features with high precision [34].

3.2.2. Machine Learning for Clinical Data, Prediction, and Personalized Medicine

AI models have achieved diagnostic performance comparable to, and in some domains exceeding, expert clinicians. Examples include dermatology, where deep learning systems match specialist-level accuracy, and breast cancer screening, where AI reduces false positives and false negatives in mammography [6] [35]. AI-assisted imaging has been applied to earlier detection of cancers, cardiovascular irregularities, neurological lesions, and genetic disorders [36]. These systems support more accurate, timely, and cost-effective diagnostic pathways and can reduce unnecessary interventions and radiation exposure [37].

Beyond imaging, AI methods such as machine learning algorithms, ensemble models, and deep neural networks analyze heterogeneous clinical datasets, including laboratory results, vital signs, and genomic information, to identify disease trajectories and predict patient outcomes [2] [38]. These models process clinical histories, biochemical tests, genomic variants, and large-scale EHRs, uncovering nonlinear patterns indicative of disease progression or risk [39] [40].

In precision medicine, AI systems integrate patient-specific data to personalize therapeutic strategies, optimize drug choices, minimize adverse events, and support individualized care pathways [41] [42]. By leveraging big data analytics, AI shifts healthcare from reactive, symptom-based practice toward a more proactive and preventative paradigm [43].

3.2.3. AI in Clinical Decision Support Systems and Workflow Optimization

AI-powered decision support tools play a central role in reducing diagnostic errors and enhancing clinician performance. These systems synthesize complex patient data, generate differential diagnoses, reference medical literature and guidelines, and highlight risk factors and disease correlations [3] [6] [44]. They can reduce cognitive burden, mitigate human variability, and improve treatment pathways across specialties.

AI decision support systems also shorten diagnostic timelines by automating routine image analyses, filtering irrelevant information, and prioritizing critical findings [45] [46]. This is particularly valuable in high-pressure environments such as emergency medicine, oncology, and intensive care.

3.2.4. Real-Time Monitoring and Remote Diagnostic Capabilities

AI's utility extends to real-time health monitoring through data from wearable devices, mobile health applications, and remote sensors. These systems continuously track heart rate, glucose levels, oxygen saturation, movement patterns, and chronic disease markers [47]. Continuous, machine-generated physiological data allow AI to detect anomalies early and trigger rapid medical responses [48]. Such capabilities are critical for remote or underserved regions, supporting proactive

interventions and reducing hospitalizations.

3.2.5. Demonstrated Performance Advantages Over Human Diagnosis

Several studies show that AI surpasses human diagnostic accuracy in specific domains, including early tumor detection, retinal disease identification, dermatological lesion classification, and radiographic interpretation for breast cancer and lung disease [49]-[51]. These systems identify patterns that may be imperceptible due to clinician fatigue, high workloads, or subtle visual variations. Enhanced precision contributes directly to improved patient outcomes and reduced healthcare costs [52]. AI also supports differential diagnosis, automates labor-intensive tasks, and improves inter-observer consistency, thereby strengthening diagnostic reliability [44].

3.2.6. Cross-Specialty Applications Across Medicine

AI diagnostics now span a wide range of specialties, including radiology, cardiology, neurology, oncology, genetics, dermatology, pathology, and emergency medicine [34] [53] [54]. In each domain, AI contributes through image recognition, predictive analytics, automated classification, and treatment optimization. Its cross-disciplinary impact underscores AI's role as an integrative technology reshaping clinical diagnostics at a systemic level.

3.2.7. Challenges: Data Quality, Bias, and Generalizability

Despite its promise, the literature consistently identifies critical barriers to AI adoption in clinical diagnostics:

- Dataset quality and heterogeneity: AI performs best when processing objective, machine-generated information and may struggle with inconsistent or subjective inputs such as self-reported symptoms [55]. Challenges include missing values, inconsistent imaging parameters, heterogeneous EHR systems, unbalanced datasets, and poor annotation quality [8] [9].
- Bias and lack of demographic diversity: Models trained on narrow or homogeneous datasets risk underperforming in diverse populations, exacerbating diagnostic inequities [7] [14]. This problem is especially pronounced when datasets originate from high-income, majority populations.
- Limited access and infrastructure barriers: Data silos, privacy restrictions, limited infrastructure, and inadequate clinical computing capacity hinder model generalizability and scalability [28] [56] [57].
- Lack of standardization: Variability in imaging protocols and workflow processes may reduce diagnostic consistency by 15 - 20 percent across institutions [22] [23].
- Annotation and labor constraints: The creation of high-quality labeled datasets remains expensive, labor-intensive, and logistically difficult, especially in low-resource settings [13] [58].

3.2.8. AI in Low- and Middle-Income Countries (LMICs)

Studies focusing on LMICs highlight the transformative potential of AI in com-

pensating for specialist shortages and improving diagnostic access [59] [52]. AI-enabled tools can assist clinicians in remote or underserved regions by providing automated interpretations and decision support. However, LMICs face greater obstacles, including limited high-quality training data, infrastructure constraints, regulatory uncertainty, and a lack of interoperable systems [13] [60]. Addressing these barriers is essential to ensure that the benefits of AI diagnostics are equitably distributed.

3.2.9. Summary

Overall, the literature highlights significant advances in AI-enabled diagnostics across medical disciplines. AI systems demonstrate high accuracy, efficiency, and the ability to process multimodal data. However, persistent challenges, including dataset quality, fairness, interpretability, and infrastructure limitations, must be addressed to ensure responsible clinical adoption.

3.3. Diagnostic Accuracy and Performance Outcomes

3.3.1. Improvements in Imaging Diagnostics

The majority of imaging-focused studies reported that AI systems achieved high sensitivity and specificity in detecting abnormalities, with performance equal to or surpassing that of expert radiologists in tasks such as mammography, chest imaging, and dermatological lesion classification [6] [35] [49]. Enhanced detection of early-stage tumors, subtle lesions, and rare abnormalities was consistently documented.

3.3.2. Predictive Analytics Using Clinical Data

Studies leveraging clinical histories, laboratory results, genomic sequences, and biochemical indicators reported strong performance in predicting disease risk, progression, and clinical outcomes [2] [14] [38]. These models successfully identified subtle correlations within heterogeneous datasets, often outperforming traditional statistical methods.

3.3.3. Personalized and Precision Diagnostics

Several studies highlighted AI's capacity to generate individualized diagnostic insights by integrating multimodal data, leading to more precise stratification and tailored treatment recommendations [4] [41] [42]. These systems contributed to the early identification of high-risk patients and selection of optimized therapies.

3.4. Workflow Efficiency and Clinical Support

3.4.1. Enhanced Clinical Workflows

AI-supported systems improved diagnostic workflows by automating routine image analyses, prioritizing urgent cases, extracting actionable insights from EHRs, and shortening diagnostic turnaround times [45] [46]. Several studies reported measurable reductions in clinician workload and improved throughput in radiology and pathology departments.

3.4.2. Decision Support Performance

AI tools used as clinical decision support systems demonstrated improved diagnostic consistency, enhanced synthesis of data across modalities, and increased clinician confidence in complex cases [3] [6] [44]. Many systems provided accurate evidence-based recommendations and risk profiles that complemented human judgment.

3.5. Real-Time Monitoring and Remote Diagnostics

Studies employing wearable sensors and digital health platforms found that AI algorithms detected anomalies in real time, monitored chronic disease indicators, and produced reliable alerts for early intervention [47] [48]. Continuous, machine-generated data streams supported early warning capabilities and remote diagnosis, particularly where in-person access to specialists was limited.

3.6. AI Contributions in Low- and Middle-Income Countries (LMICs)

Findings from LMIC-focused studies indicate strong potential for AI to compensate for specialist shortages, assist clinicians in rural and resource-limited contexts, and improve diagnostic speed and reliability through automated systems [13] [52] [59]. However, these studies also documented substantial challenges related to data scarcity, infrastructure gaps, and regulatory uncertainty.

3.7. Ethical, Data Quality, and Methodological Limitations in the Evidence Base

3.7.1. Data Quality and Structure

Most studies emphasized that AI diagnostic performance depends heavily on structured, machine-generated input, high-quality annotated datasets, and consistent imaging parameters [8] [55]. AI exhibited lower accuracy when processing subjective or unstructured data compared to objective physiological or imaging data.

3.7.2. Dataset Bias and Representativeness

Many studies highlighted underrepresentation of minority groups, limited geographic diversity, and skewed datasets from single institutions [7] [25]. These factors restricted the generalizability of diagnostic models and raised concerns about equitable performance.

3.7.3. Infrastructure and Data Access Gaps

Commonly reported challenges included restricted data sharing, heterogeneous EHR systems, lack of interoperable infrastructure, and insufficient computational resources in many regions [28] [56] [57].

3.7.4. Lack of Standardized Evaluation Frameworks

Substantial performance variability, sometimes up to a 20 percent reduction across sites, was reported due to inconsistent imaging protocols, annotation practices,

and validation methods [22] [23]. Few studies used standardized reporting guidelines.

3.7.5. Annotation Constraints

Several studies described limited availability of expert annotators, inconsistencies in ground truth labels, and high costs of generating large labeled datasets as major bottlenecks [13] [58].

3.8. Key Trends Identified Across the Literature

Across studies, several recurring trends emerged:

1) AI demonstrates consistently high diagnostic performance in imaging and predictive tasks.

2) Real-time monitoring applications are expanding rapidly, especially for chronic conditions.

3) AI improves workflow efficiency and supports clinical decision-making.

4) Generalizability remains a major challenge due to biased and limited datasets.

5) AI systems perform best when trained on large, objective, machine-generated data.

6) LMICs benefit significantly from AI tools but face heightened structural and regulatory limitations.

3.9. Summary

Overall, the reviewed studies demonstrate strong potential for AI to enhance diagnostic accuracy, accelerate clinical workflows, and provide personalized and real-time insights. At the same time, limitations related to dataset quality, bias, infrastructure, and methodological inconsistencies present ongoing barriers that must be addressed.

4. Discussion

The findings of this review highlight the transformative potential of artificial intelligence in healthcare diagnostics while revealing persistent limitations that must be overcome before widespread and equitable clinical adoption becomes feasible.

4.1. Diagnostic Benefits and Clinical Impact

AI systems show strong performance across imaging, predictive analytics, and decision support. Their ability to integrate diverse data modalities allows for the detection of subtle patterns that may elude human clinicians, enabling earlier diagnoses, more precise risk stratification, and improved clinical outcomes [1] [2]. AI tools reduce diagnostic variability, enhance consistency among practitioners, and support more personalized medicine through tailored risk profiles and treatment recommendations.

Workflow optimization is particularly notable. By automating repetitive analyses, triaging high-risk cases, and summarizing complex information, AI reduces cognitive load and frees clinicians to focus on nuanced decision-making and patient communication [45] [46]. Real-time monitoring adds another layer of benefit, especially for chronic disease and remote care, where continuous data streams support early detection of deterioration and timely intervention [47] [48].

4.2. Limited Generalizability and the Central Role of Data Quality

A central challenge emerging from the review is the limited generalizability of AI diagnostic models. Many systems perform impressively in controlled, single-center research settings but lose accuracy when deployed across different populations, institutions, imaging devices, or geographic regions [23]. Reported performance degradation of 15 - 20 percent across sites underscores how strongly AI tools depend on the structure, quality, and origin of their training data [22].

Models trained on homogeneous, institution-specific datasets are susceptible to overfitting and biased diagnostics, particularly when applied to underrepresented demographic groups. Without diverse, standardized, and well-annotated datasets, AI risks producing inequitable outcomes and reinforcing existing disparities [7] [25].

4.3. Algorithmic Bias and Equity

Bias is one of the most pressing concerns in AI diagnostics. Skewed or non-randomized datasets can create trends and assumptions that disadvantage underrepresented groups. When models learn primarily from dominant patterns, they may misclassify rare conditions or minority population variants, leading to unequal diagnostic accuracy, higher false negatives among vulnerable populations, and reinforcement of systemic inequities [8] [9].

Mitigating algorithmic bias requires both technical and structural interventions. Proposed strategies include balanced sampling, subgroup performance reporting, fairness-aware optimization objectives, and robust external validation on diverse cohorts [26] [30]. However, these techniques remain unevenly applied, and fairness considerations are often secondary to aggregate performance metrics

4.4. Interpretability, Transparency, and the Black Box Problem

Another major theme is the interpretability of AI models. Many high-performing models, particularly deep learning systems, function as black boxes, producing outputs without clear explanations of how conclusions were reached [47] [61]. This lack of transparency undermines clinician trust, complicates accountability, and poses challenges for regulatory approval.

Explainable AI has emerged as a critical area of research, with methods such as saliency maps, attention mechanisms, counterfactual explanations, and interpretable surrogate models proposed as solutions [62]-[64]. However, the literature indicates that current XAI techniques are not yet mature enough to provide con-

sistent, clinically validated explanations. Without robust interpretability frameworks, clinicians may hesitate to rely on AI-generated diagnoses in high-stakes contexts.

Current XAI approaches also face the fidelity-interpretability trade-off, where models that provide more comprehensible explanations often sacrifice accuracy, and no clinically validated metrics exist to assess whether an explanation is truly faithful to the diagnostic reasoning process.

4.5. Ethical and Regulatory Considerations

The ethical implications of AI integration are multifaceted. Recurrent issues include patient privacy and data governance, unclear accountability for AI-driven clinical errors, lack of consent transparency, insufficient regulatory oversight, and risks of misuse or unintended harm [12] [24] [29]. The review highlights the absence of a globally unified ethical or regulatory framework for AI in diagnostics [65]. Instead, fragmented national and institutional policies lead to inconsistent standards and variable safeguards.

Accountability is particularly problematic. Responsibility is shared among developers, who design and train models, healthcare institutions, which procure and deploy them, and clinicians, who interpret their outputs. Current liability frameworks do not clearly define responsibility when AI-related diagnostic errors occur, creating uncertainty and potential risk for practitioners [8] [27].

4.6. Infrastructure and Resource Constraints, Especially in LMICs

While AI shows promising results in LMICs and can help address specialist shortages, these settings face heightened challenges. Limited access to high-quality training data, inadequate computational infrastructure, fragmented EHR systems, insufficient funding for annotation and validation, and restrictive regulations on data sharing are frequently cited [13] [59] [60]. These barriers reduce the reliability and scalability of AI tools intended for global use and risk entrenching a digital divide in diagnostic capabilities.

4.7. Methodological Weaknesses in the Evidence Base

Several methodological limitations characterize the current evidence base:

- Inconsistent validation strategies and limited external validation
- Reliance on small or institution-specific datasets
- Limited reporting of demographic distributions and subgroup performance
- Absence of standardized outcome measures and reporting frameworks
- Rare inclusion of long-term, real-world evaluations of model impact on patient or system outcomes

These weaknesses limit the interpretability of performance claims and complicate cross-study comparisons.

4.8. Limitations and Shortcomings

Despite the breadth of evidence reviewed, the current landscape of AI diagnostics

remains constrained by recurring methodological and structural shortcomings. Many studies rely on small, institution-specific datasets that limit external validity, while others use inconsistent validation strategies that make cross-study comparisons difficult. Additionally, gaps in demographic reporting, limited long-term evaluations, and the absence of standardized outcome measures weaken the strength of existing conclusions. These limitations underscore the need for more rigorous, transparent, and harmonized research practices to support reliable clinical adoption.

4.9. Implications for Research, Practice, and Policy

For research, the findings underscore the need for robust, diverse, multi-institutional datasets; stronger emphasis on explainable and transparent AI; and longitudinal, real-world clinical studies that assess not only accuracy but also safety, equity, and system-level impact [66] [67].

For clinical practice, AI should be implemented as an augmentation to, not a replacement for, clinician judgment. Successful integration requires clinician training, workflow adaptation, and continuous monitoring of model performance, including post-deployment drift and bias.

For policy-making, comprehensive regulatory frameworks are needed to address validation, accountability, fairness, and data governance. Investment in interoperable infrastructure and standard-setting for evaluation and reporting will be crucial.

Although the discussion above outlines the major themes identified in the literature, it is also important to acknowledge the inherent limitations of the reviewed evidence. Many studies relied on small, institution-specific datasets and lacked standardized validation methods, which restricts the generalizability of their findings. A large portion of the literature reported only aggregate performance metrics without subgroup analysis, making it difficult to assess equity across demographic groups. Furthermore, few studies examined the long-term clinical impact of AI deployment in real settings, and most evaluations occurred in controlled environments rather than routine clinical workflows. These shortcomings collectively indicate that the current evidence base remains uneven and fragmented, and that stronger methodological standards will be necessary to support robust clinical adoption. These concerns are consistent with broader findings that emphasize the persistent gap between AI success in controlled clinical trials and its limited translation into real-world healthcare settings, underscoring the need for stronger implementation pathways [68].

AI-driven diagnostic systems also face security-specific risks that arise from adversarial interference. Prior work has demonstrated how systematic poisoning attacks in healthcare datasets can degrade or redirect model outputs, highlighting the need for robust data provenance and monitoring [20]. In parallel, advances in hardware-secure EdDSA signatures (Ed25519 and Ed448), post-quantum schemes such as SIKE implemented on FPGA, and fault-tolerant hash functions like ECHO

and Fugue provide concrete pathways for strengthening the integrity, authenticity, and tamper-resilience of AI diagnostic pipelines. These developments underscore the importance of integrating cryptographic and hardware-level safeguards into the clinical deployment lifecycle.

Emerging technologies such as multimodal foundation models and generative AI may significantly reshape diagnostic pathways by integrating imaging, clinical notes, genomics, and sensor data into unified reasoning systems. Early demonstrations, including foundation-model-based chest X-ray triage tools and large-vision-language architectures adapted for LMIC radiology units, suggest substantial potential for scalable deployment even in resource-constrained environments. However, these systems also introduce new risks related to hallucination, data provenance, and opaque reasoning chains, requiring more rigorous validation pipelines before clinical integration.

Recent analyses of generalist multimodal models further demonstrate significant limitations in diagnostic reliability and error interpretability, reinforcing the need for cautious, rigorously monitored deployment of such systems in clinical environments [69].

5. A 6P Framework for Responsible AI Diagnostics

To translate the reviewed evidence into a practical lens for evaluating and deploying AI in diagnostics, this review proposes a 6P framework that brings together technical, ethical, and organizational dimensions.

1) Performance

AI systems must demonstrate robust, reproducible diagnostic performance using clinically meaningful metrics such as sensitivity, specificity, AUC, and calibration, with rigorous internal and external validation.

2) Provenance

Models should be trained and tested on well-documented datasets with clear information about data sources, annotation procedures, and curation processes. Provenance also includes transparency about versioning, updates, and retraining.

3) Population

Training and evaluation must reflect the demographic and clinical diversity of target populations. Subgroup performance should be reported, and strategies for bias detection and mitigation should be embedded from the outset.

4) Privacy

Data handling must comply with applicable regulations (for example, HIPAA, GDPR) and reflect best practices for de-identification, access control, and secure data sharing.

5) Practice Integration

AI tools must be designed for realistic clinical workflows, with attention to usability, interoperability with existing systems, clinician training, and mechanisms for human oversight and override.

6) Policy

Deployment should be guided by clear policies on accountability, liability, procurement, and lifecycle management, including pathways for regulatory approval and periodic re-evaluation.

This 6P framework synthesizes the main themes identified in the literature into a structured perspective that can guide future research, product development, and governance of AI diagnostics.

Unlike existing AI ethics guidelines or implementation-science frameworks, the 6P model consolidates technical robustness, data provenance, demographic equity, workflow integration, and policy considerations into a single, diagnostic-specific structure. Its contribution lies in bridging technical and clinical perspectives, offering a more operational and healthcare-oriented synthesis than broader frameworks such as the EU Trustworthy AI Principles or traditional digital-health implementation models.

6. Limitations of This Review

This review has several limitations. First, although the search strategy covered major databases and applied explicit inclusion criteria, it is not a full systematic review, and some relevant studies may have been missed. Second, the review is limited to English-language publications, which may introduce language bias. Third, no formal quality appraisal tool such as QUADAS-2 was systematically applied to all included studies, so the strength of evidence across domains may be uneven.

Fourth, the categorization of studies into thematic areas required interpretive judgement, and some articles could reasonably fit multiple categories. Fifth, the review did not perform a quantitative meta-analysis, which limits the ability to derive pooled effect estimates or formally compare performance across models and clinical settings. Finally, the field is evolving rapidly, and newer studies may further refine or challenge some of the conclusions presented here.

7. Conclusions

Artificial intelligence has become a central force in the evolution of diagnostic medicine, demonstrating substantial potential to enhance accuracy, efficiency, and personalization in clinical decision-making. Through advanced pattern recognition, multimodal data integration, and predictive analytics, AI systems have shown the capacity to identify early-stage disease, support real-time monitoring, and inform precision treatment strategies. The evidence reviewed in this study underscores AI's growing role as a complementary tool that augments clinician expertise and strengthens diagnostic workflows across diverse medical specialties.

At the same time, the findings highlight critical challenges that must be addressed before AI can be safely and equitably integrated into routine clinical practice. The most pressing limitations concern data quality, demographic representativeness, annotation consistency, and generalizability. Many AI systems continue to rely on datasets that are narrow in scope, insufficiently diverse, or inconsistently curated, resulting in diagnostic disparities and unreliable performance across pop-

ulations. These shortcomings underscore the need for standardized benchmarks, high-quality reference datasets, and rigorous evaluation protocols that accurately reflect real-world clinical complexity.

Transparency and interpretability remain significant obstacles as well. The black-box nature of many deep learning models reduces clinician trust and complicates accountability for diagnostic errors. The integration of explainable AI will be essential for enhancing transparency, improving clinician confidence, and meeting regulatory requirements. Future advancements in interpretable model design, such as attention mechanisms, visual saliency tools, and counterfactual reasoning, represent promising directions for making AI insights more accessible and clinically meaningful [62] [63].

The ethical and regulatory implications of AI deployment are equally critical. Issues surrounding data privacy, algorithmic fairness, patient consent, and liability require robust governance structures. At present, the absence of a unified global ethical framework creates inconsistencies that hinder responsible adoption [29] [65]. Clearer definitions of accountability among developers, institutions, and clinicians are necessary to ensure that AI technologies reinforce, rather than undermine, equitable care and patient safety.

Recent scholarship also highlights that ensuring fairness and transparency in medical AI requires not only technical safeguards but organizational and behavioral change within institutions, emphasizing the multidimensional nature of responsible AI adoption [70].

Looking ahead, future research must prioritize:

- the development of diverse, large-scale, and multi-institutional datasets
- longitudinal evaluations of AI performance in real clinical environments
- standardized validation frameworks for algorithmic transparency, safety, and fairness
- robust methods for continuous learning and adaptation to evolving medical knowledge
- interdisciplinary collaboration among clinicians, AI researchers, ethicists, and policymakers

Addressing these areas will be essential for creating diagnostic systems that are accurate, explainable, equitable, and clinically trusted. Ultimately, AI should not replace the human clinician but instead serve as a powerful augmentation, enhancing diagnostic capabilities, informing treatment pathways, and expanding access to high-quality care. With careful governance, responsible innovation, and sustained investment in methodological integrity, AI has the potential to reshape diagnostic medicine and contribute meaningfully to a more precise, ethical, and patient-centered healthcare future.

Compared to previous reviews that primarily emphasized accuracy gains or model architectures, this study provides broader contextualization by incorporating evidence on bias, generalizability, cryptographic and security concerns, and LMIC-specific deployment challenges. Earlier works rarely addressed these issues

collectively or linked them to a practical implementation lens. The 6P framework proposed here contributes to the literature by offering an integrated, cross-domain perspective that situates AI diagnostics within the realities of clinical workflows, population diversity, and evolving regulatory landscapes. This comparative positioning demonstrates how the present review builds upon and extends earlier scholarship while identifying key gaps that future research must address.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

[1] Alhur, A.A., Alhur, A.A., Hamdan Alghamdi, S.J., Asiri, Z.I., Saeed Alzamil, S.K., Alfateih, S., *et al.* (2023) Advancing the Frontiers of Artificial Intelligence in Transforming Healthcare: A Comprehensive Literature Review. *Journal of Population Therapeutics and Clinical Pharmacology*, **30**, 2107-2112. https://doi.org/10.53555/jptcp.v30i19.4744

[2] Faiyazuddin, M., Rahman, S.J.Q., Anand, G., Siddiqui, R.K., Mehta, R., Khatib, M.N., *et al.* (2025) The Impact of Artificial Intelligence on Healthcare: A Comprehensive Review of Advancements in Diagnostics, Treatment, and Operational Efficiency. *Health Science Reports*, **8**, e70312. https://doi.org/10.1002/hsr2.70312

[3] Aamir, A., Iqbal, A., Jawed, F., Ashfaque, F., Hafsa, H., Anas, Z., *et al.* (2024) Exploring the Current and Prospective Role of Artificial Intelligence in Disease Diagnosis. *Annals of Medicine & Surgery*, **86**, 943-949. https://doi.org/10.1097/ms9.0000000000001700

[4] Udegbe, F.C., Ebulue, O.R., Ebulue, C.C. and Ekesiobi, C.S. (2024) The Role of Artificial Intelligence in Healthcare: A Systematic Review of Applications and Challenges. *International Medical Science Research Journal*, **4**, 500-508. https://doi.org/10.51594/imsrj.v4i4.1052

[5] Sharma, R. (2020) Artificial Intelligence in Healthcare: A Review. *Turkish Journal of Computer and Mathematics Education* (*TURCOMAT*), **11**, 1663-1667. https://doi.org/10.61841/turcomat.v11i1.14628

[6] Egon, A., Broklyn, P. and Gracias, A. (2024) AI-Driven Decision Support Systems for Healthcare Diagnosis. Research Square.

[7] Reddy, S. and Shaikh, S. (2025) The Long Road Ahead: Navigating Obstacles and Building Bridges for Clinical Integration of Artificial Intelligence Technologies. *Journal of Medical Artificial Intelligence*, **8**, 7-7. https://doi.org/10.21037/jmai-24-148

[8] Li, Y., Yi, X., Fu, J., Yang, Y., Duan, C. and Wang, J. (2025) Reducing Misdiagnosis in AI-Driven Medical Diagnostics: A Multidimensional Framework for Technical, Ethical, and Policy Solutions. *Frontiers in Medicine*, **12**, Article ID: 1594450. https://doi.org/10.3389/fmed.2025.1594450

[9] Koçak, B., Ponsiglione, A., Stanzione, A., Bluethgen, C., Santinha, J., Ugga, L., *et al.* (2024) Bias in Artificial Intelligence for Medical Imaging: Fundamentals, Detection, Avoidance, Mitigation, Challenges, Ethics, and Prospects. *Diagnostic and Interventional Radiology*, **31**, 75-88. https://doi.org/10.4274/dir.2024.242854

[10] Yousaf Gill, A., Saeed, A., Rasool, S., Husnain, A. and Khawar Hussain, H. (2023) Revolutionizing Healthcare: How Machine Learning Is Transforming Patient Diagnoses—A Comprehensive Review of Ai's Impact on Medical Diagnosis. *Journal of*

World Science, **2**, 1638-1652. https://doi.org/10.58344/jws.v2i10.449

[11] Bin Akhtar, Z. (2025) Artificial Intelligence within Medical Diagnostics: A Multi-Disease Perspective. *Artificial Intelligence in Health*, **2**, 44-62. https://doi.org/10.36922/aih.5173

[12] Jha, D., Durak, G., Sharma, V., Keles, E., Cicek, V., Zhang, Z., *et al.* (2023) A Conceptual Algorithm for Applying Ethical Principles of AI to Medical Practice. arXiv:2304.11530.

[13] del Valle, A.C. (2025) Leveraging Digital Pathology and AI to Transform Clinical Diagnosis in Developing Countries. *Frontiers in Medicine*, **12**, Article ID: 1657679. https://doi.org/10.3389/fmed.2025.1657679

[14] Zhang, M., Chu, R., Liu, C., Zhang, S. and Ren, X. (2025) Navigating the AI Tide: Challenges, Opportunities, and Future Directions for Early-Career Dermatologists. *Frontiers in Medicine*, **12**, Article ID: 1684035. https://doi.org/10.3389/fmed.2025.1684035

[15] Stacke, K. (2022) Deep Learning for Digital Pathology in Limited Data Scenarios. Linköping University Electronic Press. https://doi.org/10.3384/9789179294748

[16] Owens, D., Khatib, R.E., Bisheh-Niasar, M., Azarderakhsh, R. and Kermani, M.M. (2024) Efficient and Side-Channel Resistant Ed25519 on ARM Cortex-M4. *IEEE Transactions on Circuits and Systems I: Regular Papers*, **71**, 2674-2686. https://doi.org/10.1109/tcsi.2024.3384414

[17] Anastasova, M., Azarderakhsh, R. and Kermani, M.M. (2021) Fast Strategies for the Implementation of SIKE Round 3 on ARM Cortex-M4. *IEEE Transactions on Circuits and Systems I: Regular Papers*, **68**, 4129-4141. https://doi.org/10.1109/tcsi.2021.3096916

[18] Canto, A.C., Mozaffari-Kermani, M. and Azarderakhsh, R. (2021) Reliable CRC-Based Error Detection Constructions for Finite Field Multipliers with Applications in Cryptography. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, **29**, 232-236. https://doi.org/10.1109/tvlsi.2020.3031170

[19] Sarker, A., Kermani, M.M. and Azarderakhsh, R. (2021) Fault Detection Architectures for Inverted Binary Ring-LWE Construction Benchmarked on FPGA. *IEEE Transactions on Circuits and Systems II: Express Briefs*, **68**, 1403-1407. https://doi.org/10.1109/tcsii.2020.3025857

[20] Jagielski, M., Oprea, A. and Rosenberg, E. (2014) Systematic Poisoning Attacks on and Defenses for Machine Learning in Healthcare. *Advances in Neural Information Processing Systems*, **31**, 19-35.

[21] Grimm, J., Kiessling, F. and Pichler, B.J. (2020) *Quo Vadis*, Molecular Imaging? *Journal of Nuclear Medicine*, **61**, 1428-1434. https://doi.org/10.2967/jnumed.120.241984

[22] Wang, Q., Yin, J., Zhang, X., Ou, H., Li, F., Zhang, Y., *et al.* (2025) Applications of Artificial Intelligence in Early Childhood Health Management: A Systematic Review from Fetal to Pediatric Periods. *Frontiers in Pediatrics*, **13**, Article ID: 1613150. https://doi.org/10.3389/fped.2025.1613150

[23] Yang, J., Dung, N.T., Thach, P.N., Phong, N.T., Phu, V.D., Phu, K.D., *et al.* (2024) Generalizability Assessment of AI Models across Hospitals in a Low-Middle and High Income Country. *Nature Communications*, **15**, Article No. 8270. https://doi.org/10.1038/s41467-024-52618-6

[24] Olorunsogo, T., Adenyi, A.O., Okolo, C.A. and Babawarun, O. (2024) Ethical Considerations in AI-Enhanced Medical Decision Support Systems: A Review. *World Journal of Advanced Engineering Technology and Sciences*, **11**, 329-336. https://doi.org/10.30574/wjaets.2024.11.1.0061

[25] Chinta, S.V., Wang, Z., Palikhe, A., Zhang, X., Kashif, A., Smith, M.A., *et al.* (2025) Ai-driven Healthcare: A Review on Ensuring Fairness and Mitigating Bias. *PLOS Digital Health*, **4**, e0000864. https://doi.org/10.1371/journal.pdig.0000864

[26] Shafik, W., Hidayatullah, A.F., Kalinaki, K., Gul, H., Zakari, R.Y. and Tufail, A. (2024) A Systematic Literature Review on Transparency and Interpretability of AI Models in Healthcare. Research Square.

[27] Mashar, M., Chawla, S., Chen, F., Lubwama, B., Patel, K., Kelshiker, M.A., *et al.* (2023) Artificial Intelligence Algorithms in Health Care: Is the Current Food and Drug Administration Regulation Sufficient? *JMIR AI*, **2**, e42940. https://doi.org/10.2196/42940

[28] Staunton, C., Biasiotto, R., Tschigg, K. and Mascalzoni, D. (2024) Artificial Intelligence Needs Data: Challenges Accessing Italian Databases to Train AI. *Asian Bioethics Review*, **16**, 423-435. https://doi.org/10.1007/s41649-024-00282-9

[29] Li, P., Williams, R., Gilbert, S. and Anderson, S. (2023) Regulating Artificial Intelligence and Machine Learning-Enabled Medical Devices in Europe and the United Kingdom. *Law, Technology and Humans*, **5**, 94-113. https://doi.org/10.5204/lthj.3073

[30] Sabet, C.J., Tamirisa, K., Bitterman, D.S. and Celi, L.A. (2025) Regulating Medical AI before Midnight Strikes: Addressing Bias, Data Fidelity, and Implementation Challenges. *PLOS Digital Health*, **4**, e0000986. https://doi.org/10.1371/journal.pdig.0000986

[31] Tian, M., Shen, Z., Wu, X., Wei, K. and Liu, Y. (2023) The Application of Artificial Intelligence in Medical Diagnostics: A New Frontier. *Academic Journal of Science and Technology*, **8**, 57-61. https://doi.org/10.54097/ajst.v8i2.14945

[32] Sarkar, A. (2023) The Impact and Potential of Artificial Intelligence in Healthcare: A Critical Review of Current Applications and Future Directions. *International Journal for Research in Applied Science and Engineering Technology*, **11**, 2089-2091. https://doi.org/10.22214/ijraset.2023.55537

[33] Zeb, S., Fnu, N., Abbasi, N. and Fahad, M. (2024) AI in Healthcare: Revolutionizing Diagnosis and Therapy. *International Journal of Multidisciplinary Sciences and Arts*, **3**, 118-128. https://doi.org/10.47709/ijmdsa.v3i3.4546

[34] Fahim, Y.A., Hasani, I.W., Kabba, S. and Ragab, W.M. (2025) Artificial Intelligence in Healthcare and Medicine: Clinical Applications, Therapeutic Advances, and Future Perspectives. *European Journal of Medical Research*, **30**, Article No. 848. https://doi.org/10.1186/s40001-025-03196-w

[35] Korkmaz, S. (2024) Artificial Intelligence in Healthcare: A Revolutionary Ally or an Ethical Dilemma. *Balkan Medical Journal*, **41**, 87-88. https://doi.org/10.4274/balkanmedj.galenos.2024.2024-250124

[36] Soni, D.G. (2025) The Future of Artificial Intelligence in Medical Treatment. *International Journal for Research in Applied Science and Engineering Technology*, **13**, 2196-2200. https://doi.org/10.22214/ijraset.2025.74379

[37] Bhagat, I.A., Wankhede, K.G., Kopawar, N.A. and Sananse, D.A. (2024) Artificial Intelligence in Healthcare: A Review. *International Journal of Scientific Research in Science, Engineering and Technology*, **11**, 133-138. https://doi.org/10.32628/ijsrset24114107

[38] Anyanwu, E.C., Okongwu, C.C., Olorunsogo, T.O., Ayo-Farai, O., Osasona, F. and Daraojimba, O.D. (2024) Artificial Intelligence in Healthcare: A Review of Ethical Dilemmas and Practical Applications. *International Medical Science Research Jour-*

nal, **4**, 126-140. https://doi.org/10.51594/imsrj.v4i2.755

[39] Chatterjee, I., Ghosh, R., Sarkar, S., Das, K. and Kundu, M. (2024) Revolutionizing Innovations and Impact of Artificial Intelligence in Healthcare. *International Journal for Multidisciplinary Research*, **6**, 1-16. https://doi.org/10.36948/ijfmr.2024.v06i03.19333

[40] Shaheen, M.Y. (2021) AI in Healthcare: Medical and Socio-Economic Benefits and Challenges. *ScienceOpen Preprints*.

[41] Zartashea, Z. (2024) AI-Driven Personalized Medicine: Leveraging Machine Learning for Precision Treatment Plans. *Global Journal of Engineering and Technology Advances*, **20**, 232-241. https://doi.org/10.30574/gjeta.2024.20.2.0141

[42] Javanmard, S. (2024) Revolutionizing Medical Practice: The Impact of Artificial Intelligence (AI) on Healthcare. *Open Access Journal of Applied Science and Technology*, **2**, 1-16.

[43] Fatima, I., Grover, V., Raza Khan, I., Ahmad, N. and Yadav, A. (2023) Artificial Intelligence in Medical Filed. *EAI Endorsed Transactions on Pervasive Health and Technology*, **9**, 1-5. https://doi.org/10.4108/eetpht.9.4713

[44] Carrasco Ramírez, J.G. (2024) AI in Healthcare: Revolutionizing Patient Care with Predictive Analytics and Decision Support Systems. *Journal of Artificial Intelligence General Science*, **1**, 31-37. https://doi.org/10.60087/jaigs.v1i1.p37

[45] Jeong, J., Kim, S., Pan, L., Hwang, D., Kim, D., Choi, J., *et al.* (2025) Reducing the Workload of Medical Diagnosis through Artificial Intelligence: A Narrative Review. *Medicine*, **104**, e41470. https://doi.org/10.1097/md.0000000000041470

[46] Hossain, M.D., Rahman, M.H. and Hossan, K.M.R. (2025) Artificial Intelligence in Healthcare: Transformative Applications, Ethical Challenges, and Future Directions in Medical Diagnostics and Personalized Medicine. *International Journal of Science and Research Archive*, **15**, 381-390. https://doi.org/10.30574/ijsra.2025.15.1.0954

[47] Wang, J. (2023) The Power of AI-Assisted Diagnosis. *EAI Endorsed Transactions on E-Learning*, **8**, e3. https://doi.org/10.4108/eetel.3772

[48] Khan, A. (2023) Transforming Healthcare through AI: Unleashing the Power of Personalized Medicine. *International Journal of Multidisciplinary Sciences and Arts*, **2**, 67-77. https://doi.org/10.47709/ijmdsa.v2i1.2424

[49] Deorukhkar, U. (2023) Transforming Healthcare System through AI Sustainability: Chatbots and Emergency Assistance. *International Journal for Research in Applied Science and Engineering Technology*, **11**, 3195-3203. https://doi.org/10.22214/ijraset.2023.54247

[50] Mehta, V. (2023) Artificial Intelligence in Medicine: Revolutionizing Healthcare for Improved Patient Outcomes. *Journal of Medical Research and Innovation*, **7**, e000292. https://doi.org/10.32892/jmri.292

[51] Musthafa, M.M., Mahesh, T.R., Kumar, V.V. and Guluwadi, S. (2024) Enhancing Brain Tumor Detection in MRI Images through Explainable AI Using Grad-Cam with Resnet 50. *BMC Medical Imaging*, **24**, Article No. 107. https://doi.org/10.1186/s12880-024-01292-7

[52] Zuhair, V., Babar, A., Ali, R., Oduoye, M.O., Noor, Z., Chris, K., *et al.* (2024) Exploring the Impact of Artificial Intelligence on Global Health and Enhancing Healthcare in Developing Nations. *Journal of Primary Care & Community Health*, **15**, 1-10. https://doi.org/10.1177/21501319241245847

[53] Quazi, F., Mohammed, PhD, A.S. and Gorrepati, N. (2024) Transforming Treatment and Diagnosis in Healthcare through AI. *International Journal of Global Innovations*

and Solutions (*IJGIS*). https://doi.org/10.21428/e90189c8.072ffbe8

[54] Shahrukh Irfan, Prasanta Kumar Parida, Aakanksha Bajpai, S.D.M.N.J.D. (2023) Advancing Healthcare through Artificial Intelligence: Innovations at the Intersection of AI and Medicine. *Tuijin Jishu/Journal of Propulsion Technology*, **44**, 152-160. https://doi.org/10.52783/tjjpt.v44.i2.131

[55] Bhandari, G. (2025) Artificial Intelligence in Diagnostic Medicine: Literature Review Contrasting Differential Accuracy from Test Reports Versus Self-Reported Symptoms and Implications on Medical Specialties. *International Journal of Medical Sciences*, **3**, 47-62. https://doi.org/10.34218/ijms_03_01_003

[56] Ahmed, H., Michael, D.O. and Samaila, B. (2023) Current Challenges of the State-of-the-Art of AI Techniques for Diagnosing Brain Tumor. *Material Science & Engineering International Journal*, **7**, 196-208. https://doi.org/10.15406/mseij.2023.07.00224

[57] Lokaj, B., Pugliese, M., Kinkel, K., Lovis, C. and Schmid, J. (2023) Barriers and Facilitators of Artificial Intelligence Conception and Implementation for Breast Imaging Diagnosis in Clinical Practice: A Scoping Review. *European Radiology*, **34**, 2096-2109. https://doi.org/10.1007/s00330-023-10181-6

[58] Abir, S.I., Shoha, S., Shiam, S.A.A., Dolon, M.S.A., Shimanto, A.H., Zakaria, R. and Mamun, M.A.I. (2024) Deep Neural Networks in Medical Imaging: Advances, Challenges, and Future Directions for Precision Healthcare. *Journal of Computer Science and Technology Studies*, **6**, 94-112. https://doi.org/10.32996/jcsts.2024.6.5.9

[59] Babarinde, A.O., Ayo-Farai, O., Maduka, C.P., Okongwu, C.C., Ogundairo, O. and Sodamade, O.T. (2023) Review of AI Applications in Healthcare: Comparative Insights from the USA and Africa. *International Medical Science Research Journal*, **3**, 92-107. https://doi.org/10.51594/imsrj.v3i3.641

[60] Loku, A. and Malsia, E. (2024) Artificial Intelligence in Enhancing the Kosovo Health Information System. *Academic Journal of Interdisciplinary Studies*, **13**, Article 12. https://doi.org/10.36941/ajis-2024-0062

[61] Mandala, S.K. (2023) XAI Renaissance: Redefining Interpretability in Medical Diagnostic Models. arXiv:2306.01668.

[62] Agrawal, R., Gupta, T., Gupta, S., Chauhan, S., Patel, P. and Hamdare, S. (2025) Fostering Trust and Interpretability: Integrating Explainable AI (XAI) with Machine Learning for Enhanced Disease Prediction and Decision Transparency. *Diagnostic Pathology*, **20**, Article No. 105. https://doi.org/10.1186/s13000-025-01686-3

[63] Olumuyiwa, B.I., Han, T.A. and Shamszaman, Z.U. (2024) Enhancing Cancer Diagnosis with Explainable and Trustworthy Deep Learning Models. arXiv:2412.17527.

[64] Kaczmarzyk, J., Saltz, J.H. and Koo, P.K. (2024) Explainable AI for Computational Pathology Identifies Model Limitations and Tissue Biomarkers. arXiv:2409.03080. http://arxiv.org/abs/2409.03080

[65] Gong, J., Zhao, Z., Niu, X., Ji, Y., Sun, H., Shen, Y., *et al.* (2025) AI Reshaping Life Sciences: Intelligent Transformation, Application Challenges, and Future Convergence in Neuroscience, Biology, and Medicine. *Frontiers in Digital Health*, **7**, Article ID: 1666415. https://doi.org/10.3389/fdgth.2025.1666415

[66] Jeong, H., Jabbour, S., Yang, Y., Thapta, R., Mozannar, H., Han, W., *et al.* (2024) Recent Advances, Applications, and Open Challenges in Machine Learning for Health: Reflections from Research Roundtables at ML4H 2023 Symposium. arXiv:2403.01628.

[67] Zając, H.D. (2024) It Takes a Village to Raise Clinical AI: Towards Clinical Usefulness of AI in Healthcare. University of Copenhagen Research Portal. https://local.forskningsportal.dk/local/dki-cgi/ws/cris-link?src=ku&id=ku-7255b7dc-0047-4c0c-8d28-6987acf98680

[68] El Arab, R.A., Abu-Mahfouz, M.S., Abuadas, F.H., Alzghoul, H., Almari, M., Ghannam, A., *et al.* (2025) Bridging the Gap: From AI Success in Clinical Trials to Real-World Healthcare Implementation—A Narrative Review. *Healthcare*, **13**, Article 701. https://doi.org/10.3390/healthcare13070701

[69] Liu, M., Wu, J., Fang, Y., Li, H., Wang, W., Zhang, S. and Wang, Z. (2024) Exploring the Feasibility of Multimodal Chatbot AI as Copilot in Pathology Diagnostics: Generalist Model's Pitfall. arXiv:2409.15291.

[70] Liefgreen, A., Weinstein, N., Wachter, S. and Mittelstadt, B. (2023) Beyond Ideals: Why the (Medical) AI Industry Needs to Motivate Behavioural Change in Line with Fairness and Transparency Values, and How It Can Do It. *AI & SOCIETY*, **39**, 2183-2199. https://doi.org/10.1007/s00146-023-01684-3