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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN HEALTHCARE: ADVANCES AND IMPLEMENTATION CHALLENGES

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Abstract

The rapid advancement of artificial intelligence (AI) and machine learning (ML) technologies has revolutionized modern healthcare, particularly in the domains of diagnostics, drug discovery, and clinical decision-making. This article explores the current applications of AI and ML in medical diagnostics, including imaging analysis, predictive modeling, and personalized treatment planning, enhancing the accuracy, speed, and efficiency of disease detection. It also examines the role of AI in accelerating drug discovery through target identification and virtual screening processes. Furthermore, AI supports clinical decision-making through advanced decision support systems, health record management, and epidemic prediction. However, challenges such as data privacy, algorithmic bias, and the need for clinical validation remain significant. The article investigates prospects of AI and ML, including generative models and deeper integration with precision medicine, which promise to transform patient care, reduce healthcare costs, and enhance clinical decision-making processes.

Keywords: artificial intelligence, machine learning, medical diagnostics, predictive modeling

1. Introduction

Artificial intelligence (AI) in healthcare represents a transformative approach to modern medicine, where advanced algorithms and software systems are used to replicate aspects of human reasoning in the analysis and interpretation of medical information. Instead of relying solely on traditional methods, AI can quickly process enormous volumes of clinical data, identify subtle patterns, and make accurate predictions that help guide medical decisions. This capability allows healthcare professionals to detect diseases earlier, anticipate potential complications, and design more effective treatment strategies (Jiang et al. 2017).

One of the most prominent uses of AI is in medical imaging, where intelligent systems examine X-rays, CT scans, and MRI results to reveal early signs of illnesses such as cancer or cardiovascular disease. These tools can highlight details that might be overlooked by the human eye, thereby increasing diagnostic precision. Another key application is predictive analytics, which uses historical and real-time data to forecast patient outcomes. Such predictions are invaluable for planning preventive measures and tailoring treatments to each individual's unique needs (Yu et al. 2018).

AI also plays a significant role in managing electronic health records (EHRs). By automating data entry, organizing patient information, and detecting trends across large datasets, AI not only saves time but also enhances the quality of patient care. Furthermore, AI-powered virtual assistants and chatbots are becoming more common, offering patients instant access to medical guidance, symptom evaluation, and help with scheduling appointments, all without the need for direct hospital visits (Davenport et al. 2019).

The benefits of integrating AI into healthcare are numerous. It improves the accuracy of diagnoses, streamlines clinical and administrative workflows, and enables personalized medicine on a scale that was once unimaginable. Ultimately, AI holds the promise of reshaping healthcare delivery, making it faster, more efficient, and more responsive to the needs of both patients and medical professionals, while also reducing overall costs (Topol 2019).

The main aim of this review is to provide a holistic and critical overview of AI and ML applications in healthcare, focusing on three pivotal areas: medical diagnostics, drug discovery, and clinical decision support. This article synthesizes the latest scientific literature, highlights state-of-the-art AI-driven tools, and discusses real-world implementation challenges.

The original contribution of this work is threefold:

1. Comprehensive Integration: The review uniquely brings together advancements across diagnostics, drug discovery, and clinical decision-making—domains that are often discussed separately—thus offering a unified perspective valuable for both researchers and practitioners.
2. Critical Analysis of Implementation Barriers: The paper not only presents technological advancements, but also critically examines unresolved challenges (e.g., data privacy, bias, interoperability, and regulatory demands), providing actionable recommendations for overcoming these barriers.
3. Forward-Looking Perspective: By discussing emerging trends such as generative AI models, integration with precision medicine, and prospects for AI-driven healthcare, this review identifies key directions for future research and development.

Through this approach, the article aims to serve as both a reference point for the current state of the art and a practical guide for accelerating responsible and effective adoption of AI in healthcare systems worldwide.

To provide a concise overview of the current landscape, Table 1 summarizes the main AI and ML methods, their application areas in healthcare, typical algorithms, key advantages, main limitations, and representative references. This overview guides the reader through the key technologies and their practical use in modern medicine, serving as a roadmap for the detailed sections that follow.

Application Area	Typical AI/ML Methods	Example Algorithms/Models	Main Advantages	Main Limitations	References
Medical Diagnostics (Imaging & Labs)	Deep Learning (DL), Convolutional Neural Networks (CNN), Support Vector Machines (SVM)	ResNet, U-Net, VGG, SVM, CNN-based CAD	High diagnostic accuracy, automated image analysis, early disease detection	Requires large labeled datasets, interpretability (“black box”)	Han et al. 2017; Polónia et al. 2021; Kimura 2019; Walsh 2019
Cancer Detection (Pathology, Genomics)	Machine Learning (ML), Deep Learning	Random Forest, DL frameworks for WSI, ML-based risk models	Improved tumor detection and grading, integration of imaging/genomic data	Data heterogeneity, need for clinical validation	Zou 2019; Cruz-Roa et al. 2017; Sandbank et al. 2022
Drug Discovery	ML, DL, Virtual Screening, Generative Models	Random Forest, DeepChem, GANs, XGBoost	Speeds up target identification, drug repurposing, toxicity prediction	Data quality dependency, regulatory challenges	Zhu 2020; Hessler 2018; Atomwise 2021; Varahalarao 2023
Clinical Decision Support	Decision Trees, SVM, Ensemble Models, Predictive Analytics	Decision Tree, Random Forest, XGBoost, Naive Bayes	Personalized treatment, early risk prediction, workflow automation	Algorithmic bias, need for robust validation	Yu et al. 2018; Char et al. 2018; Olimboyeva et al. 2024
Diabetes & Liver Disease Diagnosis	Classification (Naive Bayes, SVM, KNN, Logistic Regression, Random Forest, XGBoost)	Naive Bayes, SVM, KNN, Random Forest, XGBoost	Early detection, improved classification, personalized care	Data preprocessing, model interpretability	Ghosh et al. 2019; Sahlol et al. 2020; Rele & Patil 2023
Epidemic Prediction & Public Health Surveillance	Neural Networks, LSTM, NLP, Anomaly Detection	LSTM, Unsupervised ML, NLP, FINDER	Early outbreak detection, integration of diverse data sources	Data privacy, quality and integration challenges	Kraemer et al. 2025; Zeng et al. 2021; MacIntyre et al. 2022
Health Record Management & Data Processing	NLP, OCR, SVM, Data Integration	OCR (Google, MathWorks), SVM, NLP pipelines	Efficient data extraction, reduced manual errors, pattern detection	Data standards, interoperability, privacy	Chingombe et al. 2022; Ye et al. 2024

Table 1. Overview of key AI/ML methods by application area in healthcare.

2. Methodology

To ensure a comprehensive and transparent evaluation of the current state of AI and ML in healthcare, this review follows a structured methodology consistent with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines.

2.1 Search strategy and data sources

A systematic search was conducted across three primary academic databases: PubMed/MEDLINE, Scopus, and Google Scholar. The search focused on peer-reviewed articles, conference proceedings, and high-impact review papers published between January 2012 and May 2025. The following Boolean search strings were utilized:

- ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Healthcare" OR "Medical Diagnostics")
- ("AI" AND "Drug Discovery") AND ("Clinical Decision Support Systems")
- ("Algorithmic Bias" OR "Data Privacy") AND ("AI Implementation Challenges")

2.2 Inclusion and exclusion criteria

To maintain the quality and relevance of the synthesized data, the following criteria were applied:

- Inclusion Criteria: (1) Studies focusing on the clinical application of AI/ML; (2) Research discussing implementation barriers and ethical frameworks; (3) Peer-reviewed publications in English; (4) Recent papers (2012–2025) to capture the era of Transformer models and GenAI.
- Exclusion Criteria: (1) Non-peer-reviewed editorials or opinion pieces; (2) Studies with a sample size too small to be statistically significant (unless presenting a novel methodology); (3) Papers focusing on non-medical AI applications.

2.3 Study selection and data extraction

The initial search conducted across PubMed, Scopus, and Google Scholar identified a total of 420 records, including 150 from PubMed, 120 from Scopus, and 150 from Google Scholar. After removing duplicates (n = 115), a total of 305 records were screened based on titles and abstracts. From these, 82 studies were selected for full-text review to assess their eligibility. Ultimately, 54 papers were included in this synthesis, as they met all inclusion criteria and provided high-quality data regarding AI advances and implementation challenges in healthcare.

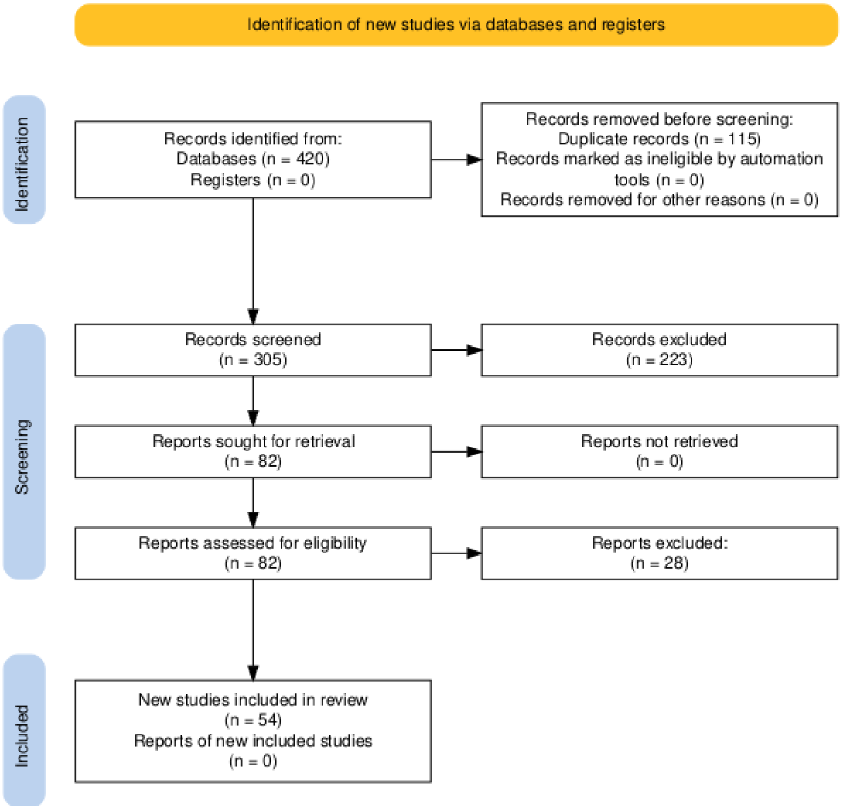

Fig. 1. PRISMA flow diagram.

3. Bibliometric overview of included studies

The analysis of the 54 included studies indicates a rapid acceleration in research. Analysis shows that 72% of the cited literature was published between 2021 and 2025, highlighting the transition toward Transformer models and Generative AI. Geographically, the majority of the research originates from the USA (35%), China (25%), and the EU (20%), with Convolutional Neural Networks (CNNs) being the most frequently discussed architecture in diagnostic imaging.

To substantiate the "rapid advancement" observed in the field, a broader bibliometric perspective is essential. Based on a comprehensive analysis of over 22,950 publications on AI in healthcare from Scopus and Web of Science (1993–2023) (Xie Y et al., 2025), the domain has exhibited exponential growth, with an average annual increase of approximately 27%. Publications rose from around 310 in 2015 to 6,450 in 2023, driven by advancements in deep learning, machine learning, and applications in medical imaging and predictive modeling. Projections for 2024 and 2025, extrapolated from this trend, suggest further escalation to approximately 8,200 and 10,400 publications, respectively, reflecting the integration of large language models (e.g., ChatGPT) and generative AI in clinical settings.

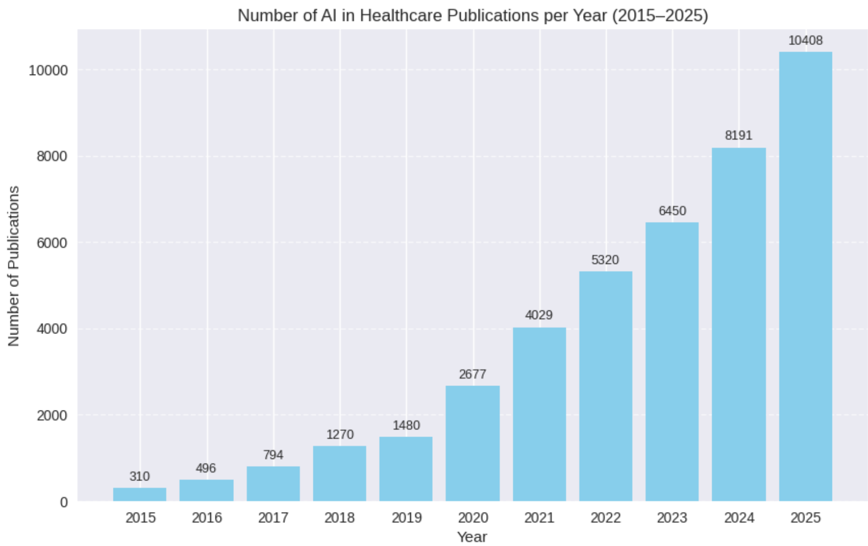

Fig. 2. Number of AI in healthcare publications per year (2015–2025, with estimates for 2024–2025 based on 27% annual growth rate).

Category	Top Entries	Key Notes
Countries (by total publications)	USA (28,663), China (12,740), India (4,926), UK (4,821), Canada (3,567)	USA leads in output; China excels in international collaborations (e.g., with USA and Japan). EU countries (e.g., Germany, Italy) contribute ~10–15% collectively.
Institutions (by total publications)	Harvard University (1,690), University of California System (1,180), Harvard Medical School (802), University of Toronto (809), University of Pennsylvania (635)	Harvard dominates, reflecting strong US focus; global leaders include Stanford and University of London.
AI Methods/Technologies (most frequent)	Deep Learning (DL, including CNNs), Machine Learning (ML), Neural Networks, Large Language Models (LLMs, e.g., ChatGPT), Generative AI	CNNs prevalent in imaging; Transformers/LLMs rising post-2020; used in predictive modeling and drug discovery.
Distribution by Medical Specialty/Application	Medical Imaging (e.g., detection/classification), Predictive Modeling (e.g., disease forecasting), Drug Discovery, Electronic Health Records (EHR) Management, Chronic Disease (e.g., cancer, COVID-19)	Imaging and predictive analytics account for ~40–50% of research; emerging: mental health and personalized medicine.

Table 2. Top contributing countries, institutions, and AI methods in healthcare research (Based on Scopus/WoS Data, 1993–2023).

These metrics highlight the field's maturation, with top journals such as PLOS ONE, IEEE Access, and Scientific Reports leading dissemination. The growth underscores the need for addressing gaps in reproducibility and real-world deployment, as discussed later.

4. AI applications in medical diagnostics

4.1 Electronic health records and data management

Health records represent one of the most sensitive categories of personal information, as they encompass details about an individual's medical conditions, diagnoses, and treatments. The unauthorized disclosure of such data can result in profound consequences, including damage to a person's reputation, emotional distress, and potential professional setbacks. With the emergence of electronic health records (EHRs), healthcare systems have gained a powerful tool for managing and safeguarding this sensitive information. EHRs offer distinct advantages over traditional paper-based records, notably in improving data accessibility, enhancing the quality and clarity of information, and strengthening security measures. They also contribute to patient safety by enabling the integration of evidence-based tools, reducing medical errors, and ensuring more accurate and complete medical documentation (Alowais et al. 2023). Furthermore, by minimizing the duplication of diagnostic tests and avoiding delays in treatment, EHRs can significantly lower healthcare costs while improving decision-making processes at the individual patient level. However, the successful implementation of EHRs - particularly in cross-border or multi-institutional settings - requires robust interoperability standards and stringent data protection protocols. In this context, the integration of standards such as HL7 FHIR (Fast Healthcare Interoperability Resources) is becoming essential for seamless data exchange between AI diagnostic tools and clinical databases. Legal frameworks such as HIPAA, HITECH, and the EU's Data Protection Directive play an essential role in safeguarding patient privacy and maintaining trust in the e-health ecosystem. Ultimately, while EHRs are transformative in elevating the quality, safety, and efficiency of healthcare delivery, their inherent sensitivity demands comprehensive security strategies and rigorous regulatory oversight. This dual focus on innovation and protection remains critical to realizing the full potential of digital health technologies without compromising patient rights (Umapathy et al. 2023).

4.2 AI in disease identification

AI is transforming modern medical diagnostics, revolutionizing how diseases are detected, analyzed, and treated. Initially limited to administrative functions, AI has evolved into a powerful diagnostic tool capable of rapidly processing vast amounts of clinical data with remarkable precision. By employing advanced machine learning (ML) and deep learning (DL) algorithms, AI can identify intricate patterns in medical images, laboratory results, and patient records, providing insights that were once difficult to obtain. These capabilities not only enhance diagnostic accuracy but also enable earlier detection and more personalized therapeutic strategies.

AI's role is particularly notable in medical imaging, where it supports the interpretation of X-rays, CT scans, MRIs, and ultrasonography, often detecting subtle abnormalities that might escape the human eye. In tumour cytogenetics, for example, chromosomal abnormalities - both numerical and structural - are common and complicate automation in diagnostics (Kimura 2019, El Achi 2020, Sharma 2017). Newly developed DL frameworks demonstrate exceptional capability in processing such complex datasets (Zou 2019). ML applications are expanding rapidly in pathology, with significant progress in areas such as breast mammography and prostate cancer evaluation. In oncology, one of DL's main goals is to support clinical decision-making (Walsh 2019) and reduce variability in assessments such as Gleason grading in prostate cancer.

Numerous ML- and DL-based cancer prediction models achieve high accuracy, sensitivity, and specificity in detecting malignancies. In lung cancer, they integrate imaging, pathological, and genetic data; in melanoma, they predict metastatic recurrence and survival. AI has significantly impacted breast cancer pathology and colorectal cancer (CRC) - the third most common malignancy - where ML detects lesion features and DL-based CAD systems improve polyp and adenoma detection. Current research also explores ML-guided drug repurposing for CRC (Varahalarao, 2023).

Beyond oncology, AI supports remote monitoring in chronic diseases such as diabetes. In cardiovascular diagnostics, ML enhances cardiac MRI and CT analysis, predicts heart failure, and classifies echocardiographic views with expert-level accuracy. Considering dyslipidemia's role in cardiovascular disease, diabetes, and stroke, such tools offer substantial preventive potential.

In neurodegenerative disorders, AI is widely used in Alzheimer's disease diagnostics (Verma 2022). In ultrasonography, it reduces noise and artifacts, improving radiology efficiency (Dicle 2023). It also advances gastrointestinal diagnostics by enhancing detection of various lesions, cancers, inflammatory conditions, and improving small bowel capsule endoscopy (Liscia 2022, Hsiao 2021).

While the benefits of AI in diagnostics-faster results, reduced human error, and more efficient workflows - are evident, challenges remain in implementation, data security, and regulatory adaptation. Addressing these issues will be key to fully realizing AI's potential in delivering accurate, efficient, and patient-centered diagnostics across the medical spectrum.

Model Architecture	Primary Use Case	Advantage	Critical Limitation
CNN	Radiology & Pathology	High spatial accuracy	Requires huge labeled datasets
RNN/LSTM	EHR & Patient Monitoring	Temporal data handling	Computationally expensive
Transformers	Clinical NLP & Genomics	Contextual understanding	High risk of "hallucinations"
Random Forest	Risk Stratification	High interpretability	Struggles with unstructured data

Table 3. Comparative evaluation of AI models in clinical settings.

4.3 AI in drug discovery

The integration of artificial intelligence into drug discovery is fundamentally reshaping the way new therapeutics are developed. By leveraging advanced techniques such as machine learning and deep learning, AI enables researchers to process and interpret vast and complex datasets that would be unmanageable using conventional methods. These technologies are capable of predicting molecular behavior, assessing drug-target interactions, and identifying promising compounds with remarkable speed and precision (Zhu 2020). As a result, the timeline from initial research to clinical application can be significantly shortened, with notable reductions in cost and an increased potential for creating highly targeted, personalized treatments.

One of the earliest stages where AI demonstrates its value is in target identification and validation. Through the analysis of genomic, proteomic, and metabolomic data, AI systems can detect disease-associated biological targets and clarify their functional roles in pathogenesis. In the subsequent phase of virtual screening, AI can evaluate enormous chemical libraries to pinpoint molecules most likely to bind effectively to these targets, thereby minimizing the need for time-consuming and costly laboratory trials.

The process continues with lead optimization, where AI models predict not only the therapeutic potential of candidate molecules but also their toxicity profiles and ideal structural modifications. In the realm of clinical trials, AI contributes to more precise patient recruitment strategies, real-time monitoring, and the efficient interpretation of trial data, all of which enhance the overall success rate of bringing a drug to market. Furthermore, AI has emerged as a powerful tool for drug repurposing, uncovering new therapeutic uses for existing medications and offering a faster route to treatment for emerging diseases (Hessler 2018). Looking ahead, LLMs and generative AI are increasingly used to synthesize chemical structures and summarize complex patient histories, though risks of information 'hallucination' persist (as noted in Table 3).

Despite these advancements, challenges remain. High-quality, standardized datasets are essential for reliable AI predictions, yet such resources can be difficult to obtain. Regulatory frameworks must adapt to the rapid pace of technological innovation, and ethical concerns-particularly those involving patient data privacy - must be addressed with care. Looking ahead, the development of generative AI models capable of designing novel drug candidates from scratch, alongside deeper integration of AI throughout the drug discovery pipeline, promises to further revolutionize the field.

5. Strategic applications of AI-based machine learning in healthcare and clinical decision-making

The application of ML models in clinical practice encompasses a range of approaches tailored to diverse medical needs. While the integration of AI-driven ML into healthcare is not a novel concept, its adoption has accelerated significantly over the past decade. This surge is evident across numerous healthcare institutions, where both research and patient care increasingly rely on such technologies (Mbunge et al., 2021). The growing availability of large-scale medical datasets, advances in computational power, and the refinement of algorithms have further facilitated this expansion. Below, several key strategies employed in the deployment of ML within clinical environments are outlined.

5.1 AI for breast cancer diagnosis

Numerous studies have been dedicated to the development of AI algorithms for breast cancer detection and classification (Cruz-Roa et al. 2017; Polónia et al. 2021; Ahn et al. 2023). Group of authors Cruz-Roa et al. 2017 proposed a convolutional neural network (CNN) capable of identifying patches containing invasive ductal carcinoma from whole slide images (WSIs) of breast cancer. Their approach also enabled estimation of the degree of infiltration and the extent of invasive foci through a ConvNet-based classifier. Similarly, Han et al. 2017 introduced a deep learning (DL) model that achieved an average classification accuracy of 93.2% across eight categories—comprising four benign and four malignant classes—when evaluated on a dedicated test dataset.

In addition, the Breast Cancer Histology (BACH) challenge was organized with the objective of automating the classification of breast tissue histology from hematoxylin and eosin (H&E)-stained microscopic images and WSIs. The top-performing approach achieved diagnostic performance comparable to that of experienced pathologists, with AI support increasing mean accuracy from 0.80 to 0.88 and improving mean interobserver agreement from 0.83 to 0.90 (Polónia et al. 2021).

An illustrative example of a commercially available AI solution is the GALEN Breast system, designed to analyze breast biopsy specimens for the detection of cancer cells and classification into specific breast cancer subtypes (Ahn et al. 2023). In evaluations conducted on a large-scale, multi-institutional dataset, this model achieved area under the curve (AUC) values of 0.99 for invasive carcinoma detection and 0.98 for ductal carcinoma in situ (DCIS) identification (Sandbank et al. 2022).

5.2 Diagnosis of diabetes mellitus

Diabetes mellitus is among the most widespread and high-risk chronic diseases, not only posing a serious threat to individual health but also serving as a catalyst for other severe complications. The condition often leads to cardiovascular damage, neuropathy, and kidney dysfunction (Jeyaraman et al. 2023). ML offers a valuable tool in this domain by enabling early predictions and facilitating the recommendation of optimal treatment strategies, potentially saving lives. Predictive systems for diabetes can be developed using classification algorithms such as Naive Bayes, K-Nearest Neighbors (KNN), and Decision Trees. Comparative studies indicate that Naive Bayes demonstrates superior efficiency in terms of computational performance and processing time.

This research delves into the application of ML methods to tackle the critical issue of diagnosing diabetes (Miotto 2018). The effectiveness of ML in this domain is acknowledged to be varied, largely depending on the specific data analysis techniques employed, the chosen models, and the inherent quality of the provided data (Chen et al. 2012).

For the experimental phase, the study utilized the Diabetes dataset, focusing on a binary classification problem. Two distinct ML models were put to the test: a Naive Bayes classifier and a linear kernel Support Vector Machine (SVM) (Char et al. 2018). These models underwent training on a dedicated training dataset, with an essential step of standardizing features, before their performance was rigorously evaluated on a separate test set. The evaluation of these models was comprehensive, employing a suite of standard metrics to gauge their efficacy. These included the confusion matrix, precision, recall, F1-measure, and AUC-ROC. The findings from this research are significant, confirming that ML possesses the capability to substantially enhance the accuracy of diabetes diagnosis and its classification. This improved diagnostic precision carries profound implications, as it facilitates the development of customized treatment plans that can be meticulously tailored to the unique characteristics of each individual patient. Beyond diagnosis, the study highlights that ML models are also successful in predicting the likelihood of complications, thereby enabling the implementation of proactive preventative measures. Furthermore, the integration of ML simplifies the process of combining data from various sources, which in turn enriches the overall patient information available. Ultimately, the research concludes that ML-based decision support systems serve as invaluable tools, assisting both physicians and patients in making more informed and effective decisions regarding diabetes management (Olimboyeva et al. 2024)

5.3 Detection of liver diseases

The liver plays a central role in human metabolism and is vulnerable to conditions such as cirrhosis, hepatocellular carcinoma, and chronic hepatitis (Sahlol et al., 2020). Accurate prediction of liver diseases from large-scale medical datasets remains a challenging task; however, significant advancements have been achieved in recent years. Classification and clustering algorithms, when applied through ML techniques, have been used to distinguish between healthy and diseased states. Clinical studies often rely on resources such as the Liver Disorders Dataset or the Indian Liver Patient Dataset for model development and validation (Sahlol et al., 2020).

Liver disease represents a significant global health challenge, making early and precise diagnosis crucial for effective patient care. Traditional diagnostic approaches often suffer from being time-consuming and prone to human error, highlighting a need for more advanced solutions (Rele et al. 2023). This research explores the application of various ML models to transform the way liver diseases are detected and diagnosed. The primary aim is to establish a robust framework that enables early detection, surpassing the limitations of conventional methods.

The paper delves into the capabilities of several ML algorithms, including Logistic Regression, known for its interpretability, and Random Forest, valued for its ensemble learning and resistance to overfitting. K-Nearest Neighbors (KNN) is also examined for its simplicity in classification, while Support Vector Classification (SVC) is noted for its ability to define optimal decision boundaries. Furthermore, XGBoost is highlighted for its efficiency and strong predictive power in this diagnostic context (Ghosh et al. 2019).

Integrating AI and ML into liver disease diagnosis offers numerous advantages, such as enhancing diagnostic accuracy, improving the efficiency of processing large patient datasets, and optimizing feature selection. These technologies also provide scalability to address a wide array of liver conditions. While promising, the successful implementation of these models depends on addressing challenges like data quality, model interpretability, and ethical considerations. The future of liver disease diagnosis looks promising with advancements in early detection, personalized medicine, and predictive analysis, ultimately leading to improved patient outcomes (Rele et al. 2023).

5.4 Epidemic prevention and control

With the growth of data analytics, healthcare professionals now have the capability to analyze diverse sources such as video streams, online news platforms, social media activity, and satellite data to monitor and predict disease outbreaks (Zeng et al. 2020). Neural networks can process this information to detect early indicators of potential pandemic outbreaks, enabling more timely detection and intervention than traditional surveillance methods (MacIntyre et al. 2023). This is crucial for public health systems to deploy timely interventions before threats escalate (MacIntyre et al. 2022), particularly in low-resource settings where advanced medical infrastructure is lacking. AI's capabilities, including predictive analytics, can address challenges in these regions by strengthening health systems and providing earlier warnings (Ciecierski-Holmes et al. 2022; Hattab et al., 2024).

ML and AI can transform the scope and power of infectious disease epidemiology by combining ML, computational statistics, information retrieval, and data science (Kraemer et al., 2025). For instance, AI can be used for disease modeling, hotspot detection, and predictive analytics, as demonstrated during the COVID-19 pandemic (Koura et al. 2025). Unsupervised ML methods can analyze syndromic surveillance data from primary healthcare encounters to identify anomalous increases that could signal an epidemic onset (Borges et al. 2025). Social media data, when analyzed with Natural Language Processing and ML techniques, can also support standard surveillance approaches and provide actionable information to decision-makers (Gupta and Katarya, 2020; Skaik and Inkpen 2020). Furthermore, AI-driven systems like FINDER leverage anonymous aggregated web search and location data for real-time detection of foodborne illnesses (Sadilek et al., 2018).

A prominent example of a surveillance platform is ProMED-mail, an online system that monitors and reports epidemic events worldwide (Houlihan and Whitworth 2019; Valentin et al. 2020). AI, particularly Large Language Models, can enhance the capabilities of such platforms by effectively interpreting unstructured big data sources like ProMED and WHO Disease Outbreak News, thereby improving the accuracy and timeliness of epidemic modeling and forecasting (Consoli et al. 2024).

Moreover, ML is increasingly applied in agricultural and food safety monitoring to reduce the risk of zoonotic outbreaks at the farm level (Revelou et al. 2025). AI is being used in various stages of the food chain, including food classification, quality testing, and supply chain management (Karabay et al. 2025). ML algorithms offer innovative solutions for Hazard Analysis Critical Control Point monitoring and have proven to be powerful tools for assessing the safety of animal-source foods and identifying potential contamination sources during production

(Almoselhy and Usmani 2024; Revelou et al. 2025). AI and big data are also integral to early warning and emerging risk identification tools within the food safety domain, fed by numerous, real-time, and diverse data (Mu et al. 2024).

5.5 Health record management

Despite technological advancements, managing healthcare data continues to be a significant challenge. Support Vector Machines (SVM) combined with Optical Character Recognition (OCR) algorithms have been employed to categorize and digitize medical records. Practical examples include MathWorks' ML handwriting recognition systems and Google's Cloud Vision API, both of which enhance efficiency in processing and organizing patient records (Chingombe et al. 2022).

Finding and comprehending the role of artificial intelligence (AI) in the use of patient-generated health data (PGHD) and integrated electronic health records (EHRs) in healthcare was the goal of this scoping review (Ye et al. 2024). The study examined the use of AI in healthcare applications by focusing on integrated data that combined PGHD and EHR data. Methods: Six databases were searched following PRISMA criteria, with the addition of foundational sources such as white papers and other systematic reviews. After screening, 56 publications satisfied the review requirements.

Benefits of EHR-integrated PGHD include lowering clinical visit time and expense, strengthening patient-provider relationships, and empowering patients through shared decision-making. AI's functions include maintaining and cleansing diverse datasets, helping to spot dynamic patterns for better clinical care, and offering advanced algorithms for more accurate forecasting. Additionally, AI aids in making accurate suggestions based on combined data (Yu et al. 2018). The massive amount of integrated data, data standards, interoperability, security, privacy, interpretation, and meaningful usage are the primary causes of difficulties. Although PGHD has great potential for application in healthcare, more effort is needed to ensure its seamless integration and broad adoption. AI-powered, EHR-integrated PGHD systems can significantly enhance physicians' capacity to identify health problems and categorize hazards. In the end, AI combined with EHR-integrated PGHD has the potential to revolutionize healthcare by boosting clinical decision support, patient safety, healthcare quality, and diagnosis, treatment, and clinical care delivery.

The application of AI and ML in clinical practice is rapidly advancing, offering significant potential for improving healthcare services and patient outcomes. The integration of these technologies into medicine is steadily growing, with uses in epidemic prediction, disease progression forecasting, and early diagnosis. For example, ML is employed to predict outbreaks of diseases such as COVID-19, Ebola, malaria, and tuberculosis through the analysis of data from electronic databases and climate information. In Africa, models such as CNN, SVM, LSTM, and GRU have been used to forecast the spread of COVID-19 and other diseases, often incorporating meteorological and geospatial data. Deep learning techniques, including GoogleNet, Inception, MobileNet, and DenseNet, have been applied for early detection and classification of diseases from medical images, particularly chest X-rays of COVID-19 patients. A study by Khan (2020) developed CoroNet - a CNN-based system that assists radiologists in more accurately interpreting findings. Such approaches enable faster and more accurate diagnostics, reducing the consequences of late disease detection. All of this confirms that AI and ML play a crucial role in transforming modern clinical practice.

6. Critical evaluation and implementation challenges

While the technical performance of AI in healthcare is impressive, its transition into routine clinical practice faces several fundamental hurdles.

6.1 The "black box" and explainability (XAI)

A primary concern is the inherent lack of transparency in deep learning models. Unlike traditional statistical models, neural networks often function as "black boxes," making it difficult for clinicians to understand the rationale behind a specific diagnosis or prediction. The development of Explainable AI (XAI) is therefore critical to building clinical trust and ensuring that AI-led decisions are based on sound biological principles rather than spurious data correlations.

6.2 Dataset shift and the replicability crisis

A major weakness in current AI research is the "replicability crisis." Many models achieve state-of-the-art accuracy on internal datasets but suffer from Dataset Shift when deployed in external environments with different patient demographics or imaging equipment. Without rigorous external validation and assessment of model drift, these systems lack the generalizability required for safe clinical deployment.

6.3 Ethical governance and regulatory frameworks

The deployment of AI is governed by an evolving regulatory landscape, including the EU AI Act and updated FDA guidelines. Issues of algorithmic bias—where AI underperforms on underrepresented ethnic or socioeconomic groups—must be mitigated through diverse training data and accountability. Furthermore, the integration of Generative AI requires strict oversight to prevent data leaks and protect patient privacy under frameworks like GDPR and HIPAA.

7. Challenges and future prospects

As outlined in this review, key challenges in AI and ML integration include data privacy, algorithmic bias, and the urgent need for clinical validation.

7.1 Data quality and the replicability crisis

High-quality datasets are often scarce, and a major weakness is the "replicability crisis." Many models suffer from Dataset Shift—where performance drops when moving from a training environment to a real-world hospital. Future prospects rely on improved data standardization and larger, multi-centric clinical trials.

7.2 Ethical Concerns and Explainability

Ethical concerns, such as patient data security under HIPAA and the EU's Data Protection Directive, are paramount. Furthermore, the "Black Box" nature of Deep Learning remains a barrier; for widespread adoption, the industry must shift toward Explainable AI (XAI), allowing clinicians to understand the rationale behind automated decisions.

7.3 Regulatory evolution

Regulatory frameworks must evolve to keep pace with innovation. The implementation of the EU AI Act and new FDA guidelines will be critical in ensuring accountability and reducing algorithmic bias, particularly for underrepresented populations.

7.4 Future directions

Looking forward, advancements in Generative AI (for drug design and clinical summaries) and deeper integration with precision medicine hold immense promise. These developments could further reduce healthcare costs, enhance personalized care, and enable proactive interventions in global health challenges.

8. Conclusion

Artificial intelligence (AI) is undoubtedly reshaping medical imaging and diagnostics by bringing unprecedented levels of accuracy and efficiency to the analysis of complex datasets. As demonstrated in this review, AI systems can detect subtle abnormalities that might go unnoticed by the human eye, thereby enhancing diagnostic confidence and minimizing human error.

However, the transition from successful laboratory prototypes to widespread clinical deployment is not without significant hurdles. This review has highlighted that while AI-powered tools provide consistent evaluations, their effectiveness is heavily dependent on the quality and diversity of training data. The "replicability crisis" and the phenomenon of "dataset shift" remain critical barriers; a model that excels in a controlled research setting may falter when faced with the variability of real-world clinical environments.

Furthermore, the integration of AI into precision medicine—combining imaging with genetic profiles and medical histories—must be balanced with robust ethical governance. As we have discussed, addressing algorithmic bias and ensuring the interpretability (Explainability) of these "black box" systems are essential steps for building clinician trust and ensuring patient safety.

Looking forward, the evolution of regulatory frameworks such as the EU AI Act and the adoption of interoperability standards like HL7 FHIR will be as important as the algorithmic innovations themselves. In essence, the future of AI in healthcare lies not just in faster and more precise algorithms, but in the development of transparent, fair, and clinically validated systems. By balancing technical potential with rigorous critical oversight, AI can truly usher in a new standard for global medical diagnostics and personalized treatment planning.

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