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Intelligent Expert Systems for Disease Diagnosis in Resource-Constrained Health Systems: A Systematic Review of Current Trends and Research Gaps.

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Abstract

Design and development of artificial intelligence (AI) has transformed many sectors, one of which is healthcare, through early disease prediction, improved diagnostic accuracy, and decision support systems. However, the potential of Artificial Intelligence has not been maximized for Africans. Most existing diagnostic tools use AI models developed with data from Western populations; this has therefore limited their reliability and effectiveness when applied in African contexts. This is due to differences in genetic makeup, demography, and infrastructure. Additionally, data policy, privacy, and security concerns remain some of the major challenges in adopting AI in healthcare across Africa. This research proposes the design and development of a secured multimodal AI system capable of integrating various medical data, including laboratory results, medical images, and textual health records, to support prognostic and diagnostic decisions for African patients. This AI model will be trained with African data, enabling it to handle local medical data variations and implement robust encryption and privacy mechanisms. By solving the challenges of both data security and data bias, this research aims to enhance the fairness, effectiveness, and reliability of AI-assisted medical diagnosis within African healthcare systems.

Keywords: Artificial Intelligence, Health, Diagnosis

Materials and Methods: This study is a systematic review of the application of Artificial Intelligence in health care research using PRISMA. This research analysis consist of string which are keywords to search to access scientific literature from the PubMed and Google Scholar database, and a set of inclusion and exclusion criteria were employed to screen retrieved studies for fit and review, these database were used due to the clinical depth.

Results and Conclusion: From the review done, we found that artificial intelligence approaches have served to uncover diagnosis and prognosis, this has aided in developing rapid and sensitive diagnostic.

I. INTRODUCTION

Artificial Intelligence (AI) is defined as the ability of a computer system to simulate human intelligence. Today, artificial intelligence has been incorporated into various fields, such as cinematography, engineering, finance, and health[49,52]. AI in many scenarios has been used for treatment, diagnosis, and prognosis, thereby drastically improving health outcomes[51,1,9].

There has been inadequate public health surveillance in Africa, which is due to various contributing factors; this has led to an increase in the burden of infectious diseases, and the traditional methods of disease surveillance have proven to be ineffective. Machine learning is used for easy identification of patterns, thereby leading to efficient healthcare delivery even in low-resource settings [10]. Disease diagnosis is crucial in the healthcare profession; despite being a major challenge in Africa, this is due to lack of access to state-of-the-art facilities [50,52]. Over the last decade, we have seen a tremendous increase in the use of artificial intelligence in various healthcare sectors, even beyond the African setting. There are various advantages of artificial intelligence in the health sector, ranging from automated diagnostic approaches that grant easy access to both urban and rural dwellers to reduction in diagnostic costs [45,50]. AI-driven healthcare diagnosis relies heavily on medical data; this could be in the form of images, text, speech, and genetic information. This helps the model make informed decisions based on data training and testing [48,32]. AI-driven healthcare seeks to revolutionize clinical practices by leveraging the capabilities of information technology. This represents a promising avenue for addressing critical disease diagnosis challenges[40,27]. Various data scientists, bioinformaticians, and medical practitioners have been involved in the collection of medical data, which is integrated into machine learning and artificial intelligence models that provide a standardized framework for the development and evaluation of medical prognosis and diagnostic algorithms [38,50].

II. METHODOLOGY

A. **Inclusion criteria and Exclusion Criteria** This provide details on the condition in which a publication was considered suitable for this systematic review.

Table 2.1 shows the search Term used to search for publication.

Table 2.1: Search Terms used to search for publication.

Major Terms	Search Terms
Artificial Intelligence	(AI OR Artificial Intelligence)
Machine Learning	OR (ML OR Machine Learning)
Healthcare	AND (Health OR Medical)

B. Information Sources

The sources of information for this review included online article databases from PubMed, Google, and Future Learn websites. The PubMed database was used because of its quality and comprehensive combination, which includes expertly curated abstracts and a citation database with enriched data and linked scholarly literature, while the websites provided supplementary materials.

C. Search Strategy

There were two query strings designed. The first search was made on the PubMed database; this comprised three keywords bound together by the "AND" operator. Two alternate keywords were bound together by the "OR" operator. Additionally, the second query string was applied to the website searches and contained two blocks bound together by the "AND" operator.

Table 2a shows the Inclusion and exclusion criteria for publications

Table 2a: Inclusion and exclusion criteria for publications

Ref.	Criteria
Inclusion Criteria	
IC1	Eligible studies should focus on artificial intelligence and / or machine learning, healthcare approaches, stand-alone subjects or as they are applied to healthcare.
IC2	Eligible studies should be written in the English language
IC3	Eligible studies must have available full texts.
Exclusion Criteria	
EC1	Studies not available in full-text forms.
EC2	Studies that had no component of AI / ML with a focus on health or medical care.
EC3	Studies published in languages other than the English Language.
EC3	Before the year 2016

Figure 1: PRISMA flow diagram of study selection

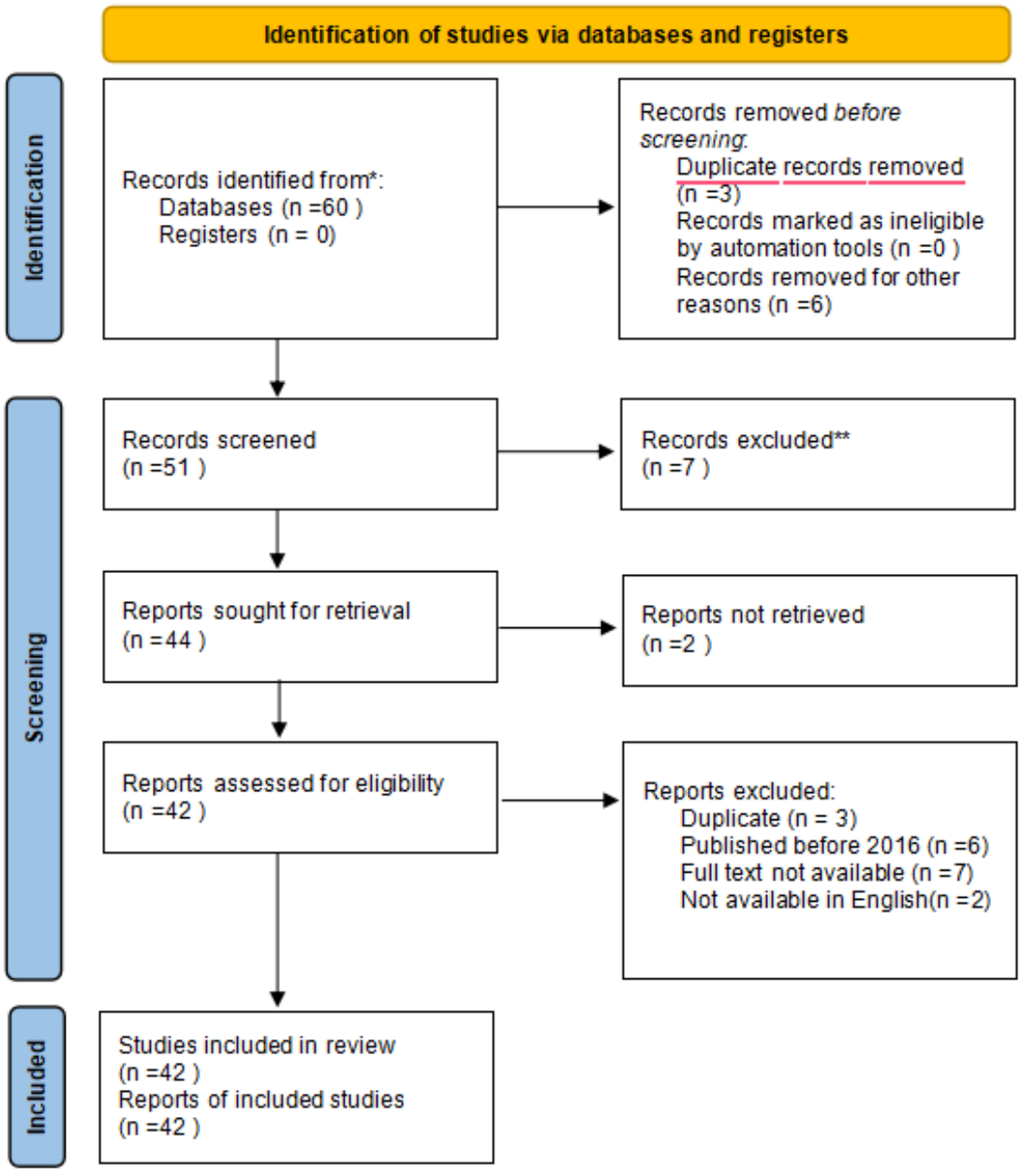


Table 2.1: Chronological Evolution of AI in Healthcare

Year	Author(s) and Reference number	Study Type	AI/ML Methodology	Clinical / Health Domain	Primary Contribution / Impact
2016	Gulshan et al. **[16]**	Validation study	CNN (deep learning)	Ophthalmology	First large-scale clinical validation of AI diagnosis
2016	Obermeyer & Emanuel **[30]**	Policy analysis	Predictive ML	Clinical medicine	Early articulation of ML-driven prediction and ethical considerations
2016	Miotto et al. **[25]**	Representation learning	Unsupervised DL	EHR analytics	Long-term disease prediction from EHR data
2016	Escobar et al.**[14]**	Pilot implementation	Predictive ML	Inpatient care	Early-warning systems for clinical deterioration
2017	Heinsfeld et al.**[17]**	Classification study	DL	Neurodevelopment	Autism spectrum disorder detection using DL
2017	Esteva et al. **[15]**	Diagnostic accuracy study	CNN	Dermatology	Dermatologist-level skin cancer classification
2017	Jiang et al. **[20]**	Historical review	ML & AI	Vascular medicine	Early synthesis of healthcare AI research

Year	Author(s) and Reference number	Study Type	AI/ML Methodology	Clinical / Health Domain	Primary Contribution / Impact
2017	Bejnordi et al.**[8]**	Comparative trial	Deep learning	Pathology	Human–AI collaboration in cancer detection
2018	Shickel et al.**[39]**	Survey	DL for EHR	Health informatics	Consolidation of DL techniques for EHRs
2018	Beam & Kohane **[7]**	Commentary	Big data ML	Healthcare analytics	Shift from rule-based to data-driven healthcare
2018	Panch et al. **[32]**	Systems analysis	Health AI policy	Global health	AI integration into health systems
2018	De Fauw et al.**[13]**	Clinical deployment	Two-stage DL	Ophthalmology	End-to-end clinically deployable AI system
2018	Rajkomar et al.**[35]**	Scalability study	Deep neural networks	Hospital medicine	Demonstrated large-scale ML deployment
2018	Miotto et al.**[26]**	Technical review	Deep learning	Multispecialty	Foundations, challenges, and opportunities of DL in health

Year	Author(s) and Reference number	Study Type	AI/ML Methodology	Clinical / Health Domain	Primary Contribution / Impact
2018	Ting et al. **[42]**	Perspective	Imaging AI	Radiology	Research agenda for imaging AI
2018	Johnson & Mark **[21]**	Review	ICU ML systems	Critical care	ML-based ICU monitoring
2019	Komorowski et al. **[23]**	RL study	Reinforcement learning	Intensive care	AI-guided sepsis treatment strategies
2019	Topol **[43]**	Perspective	Human–AI collaboration	Precision medicine	Introduced high-performance medicine concept
2019	Rajkomar et al. **[34]**	Review	Deep neural networks	Clinical workflows	ML integration into real-world care
2019	Liu et al. **[24]**	Meta-analysis	DL vs clinicians	Medical imaging	Quantified parity between AI and clinicians
2019	Wang et al. **[48]**	Randomized trial	Real-time DL	Gastroenterology	Improved adenoma detection rates
2019	National Academy of Medicine **[28]**	Consensus report	Policy framework	Health systems	Governance, ethics, and regulation of AI

Year	Author(s) and Reference number	Study Type	AI/ML Methodology	Clinical / Health Domain	Primary Contribution / Impact
2019	Parvaneh et al. **[33]**	Review	DL for ECG	Cardiology	Benchmarks for arrhythmia detection
2019	Nguyen et al. **[29]**	Prediction study	Deep learning	Radiation oncology	Personalized radiation therapy planning
2019	Kelly et al.**[22]**	Translational review	Clinical AI	Health systems	Identified barriers to clinical impact
2019	Obermeyer et al.**[31]**	Algorithm audit	Bias analysis	Population health	Exposed racial bias in health algorithms
2020	Topol **[44]**	Perspective	Precision AI	Personalized medicine	Individualized AI-driven care
2021	Hossain et al. **[19]**	Review	ML & DL	COVID-19	Pandemic-driven acceleration of health AI
2021	Suresh & Guttag **[41]**	Conceptual framework	Bias taxonomy	Ethical AI	Framework for unintended ML harms

Year	Author(s) and Reference number	Study Type	AI/ML Methodology	Clinical / Health Domain	Primary Contribution / Impact
2021	Choudhury et al. **[12]**	Review	ML	Geriatrics	AI applications in aging populations
2022	Scobie et al. **[37]**	Workflow analysis	Multimodal DL	Radiology	Multimodal AI-enabled radiology workflows
2023	Chakraborty et al.**[11]**	Comparative review	ML, DL	Medical informatics	Paradigm shift toward deep learning
2023	Al Kuwaiti et al.**[2]**	Scoping review	ML, DL, NLP	Healthcare systems	Classification of AI healthcare use cases
2023	Alowais et al.**[4]**	Mixed-methods	Clinical AI	Medical education	AI in clinical training and practice
2024	Younis et al.**[51]**	Systematic review & meta-analysis	Mixed AI models	Multidomain medicine	Quantitative synthesis of AI effectiveness
2024	Hirani et al.**[18]**	Narrative review	Conceptual synthesis	General healthcare	Historical evolution and future directions
2024	Schouten et al.**[36]**	Conceptual review	Multimodal AI	General medicine	Integration of multimodal data

Year	Author(s) and Reference number	Study Type	AI/ML Methodology	Clinical / Health Domain	Primary Contribution / Impact
2024	Ayorinde et al.**[6]**	Qualitative study	User-centered AI	Clinical workforce	Clinician experience and trust
2025	AI in Health Care Service Quality**[47]**	Systematic review	ML analytics	Health services	AI impact on care quality
2025	Ullah & Ali**[46]**	Systematic review	Mixed AI methods	Healthcare delivery	Adoption barriers and readiness
2025	AI for Medical History & Triage**[5]**	Scoping review	NLP, decision trees	Clinical intake	Automation of history taking
2025	Al-Nafjan et al.**[3]**	Systematic review	Predictive ML	Predictive healthcare	Risk stratification and forecasting

III. RESEARCH GAPS AND DISCUSSION

Machine learning today goes beyond diagnosis alone; it predicts labeled data based on algorithms such as support vector machines, LASSO regression, linear regression, Naive Bayes classifier, decision trees, and K-Nearest Neighbor. Unsupervised machine learning models can be used for fraud or anomaly detection. While machine learning has gained tremendous attention over the past ten years , a major research gap is data bias, specifically regarding genetic and geographical data, as African data has been constantly underrepresented.

IV. RECOMMENDATION

Today, machine learning is being used to manage heart failure and is applied in medical imaging, cancer, and tuberculosis detection, to name a few. Due to its level of accuracy and effectiveness, it is believed that machine learning in the near future will not only help in diagnosis and treatment but also in the prevention of various illnesses. This makes it important to balance both genetic and geographic data, thereby making medical AI reliable , and to expand data collection to local contexts. African AI policy should also consider frameworks that encourage the development of more medical AI.

V. CONCLUSION

Artificial intelligence in healthcare has been transformative, especially in early diagnosis and detection. There has been an increase in artificial intelligence in medical diagnostics and public health surveillance over the past ten years, with every sector in healthcare utilizing the potential of machine learning.

VI. ABBRIVIATION

DL: Deep Learning

NLP: Natural Language Processing

ML: Machine Learning

VII. DECLARATION

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Availability of Data and Material: Availability of data and materials: All data analyzed during this study are included in this published article. The specific literature search results and the list of studies screened are available from the corresponding author on reasonable request.

Competing interests: The authors declare that they have no competing interests.

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