

A Scoping Review on the Applications of Artificial Intelligence in Diagnostic Care

Anthony Vincent Razzano

School of Technology and Business, Massachusetts College of Pharmacy and Health Sciences, Worcester, United States.

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ABSTRACT

Background: Artificial intelligence (AI) is emerging as a promising tool to enhance diagnostic care processes throughout various clinical domains. The use of AI is enhancing diagnostic accuracy through advancements in machine learning and deep learning. Therefore, the aim of this scoping review is to assess the current utilization of AI in diagnostic healthcare services, aiming to identify prevalent themes, trends, and existing gaps in the literature.

Methodology: This scoping review uses a structured approach using the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA) Checklist. A systematic literature search was conducted on PubMed, utilizing keywords including “artificial intelligence,” “machine learning,” “deep learning,” “diagnostic healthcare,” “medical diagnostics,” “diagnostic accuracy,” “radiology,” and “pathology.” The review aims to answer the population, intervention, comparison, and outcome (PICO) question: “Do hospitals that implement artificial intelligence technologies during diagnostic service-line patient care processes experience quality care improvements compared to hospitals that do not use such technologies?”

Conclusion: The study draws conclusions based on evidence that reveals significant promise of AI improving diagnostic accuracy and prognostic predictions across various imaging applications. These findings highlight the evolving landscape of AI in diagnostic care, advocating for rigorous validation and interdisciplinary collaboration to ensure effective clinical integration and maximize quality care outcomes. Future research is needed monitor and effectively implement AI across various clinical settings.

Keywords: artificial intelligence, diagnostic care, scoping review

INTRODUCTION

Artificial intelligence (AI) is a subcategory of computer science that specializes in techniques to make machines intelligent by using machine and deep learning to train algorithms based on the desired application.^[1] Various AI systems have been developed since the mid-1950s, with rise of expert systems in the 1980s, and significant advances in deep learning techniques in the late 20th century.^[2] Machine learning

algorithms offer predictions by identifying complex patterns in data, which can be useful for organizations to make data-driven decisions.^[3] Deep learning is a subset of machine learning, which simulates the neural networks of the human brain, employing layers of artificial neurons to model complex relationships between input and output data, allowing for autonomous feature extraction from unstructured data.^[4]

Diagnostic care within the healthcare setting includes a wide range of medical services that use medical evaluations and tests to identify the presence of a disease. [5] Diagnostic imaging professionals are skilled in providing safe and high-quality radiographic diagnostic imaging care. [6] Diagnostic tests and imaging services range in scope and setting; Magnetic Resonance Imaging, for example, serves as a valuable diagnostic adjunct to ultrasound for identifying subtle brain anomalies, especially cortical disorders. [7] Limitations in access to diagnostic tools creates challenges for diagnostic professionals when reviewing heterogenous and nonspecific symptoms. [8] Misdiagnosis or delayed diagnosis negatively impacts patient outcomes due to the time-sensitive nature of providing early treatment options. [9] The applications of AI within the healthcare setting are useful in various clinical settings. Newly developed AI systems can complete many tasks for automation, including speech recognition, visual perception, and clinical support decision-making. [10] The growth of AI is advancing in healthcare through improvements in preoperative, intraoperative, and postoperative phases, driven by foundation model architectures, wearable technologies, and improved surgical data infrastructures. [11] While acknowledging the rapid progress of AI in healthcare, it is crucial to subject AI tools to rigorous evaluation to ensure their safe and equitable implementation. [12] Significant growth in AI adoption in healthcare occurred during the COVID-19 pandemic. [1] The potential for AI technologies is growing with capabilities for enhancing diagnosis and treatment of chronic health conditions, such as axSpA, based on the ability to offer a more precise, efficient, and personalized solution. [24] Within the United States, there are over 390 Food and Drug Administration cleared AI software devices. [13] The intent of this scoping review is to uncover the current state of AI applications in diagnostic are. The review uses the

population, intervention, comparison, and outcome (PICO) question framework. Developing PICO questions are essential for gathering evidence to allow researchers to build recommendations in addressing healthcare inadequacies. [14] The study question includes: “Do hospitals that implement AI technologies during diagnostic service-line patient care processes experience quality care improvements compared to hospitals that do not use such technologies?” Scoping reviews are useful to systematically evaluate existing literature for synthesis of results for addressing questions related to research questions.

MATERIALS & METHODS

A scoping review is a type of literature review that explores existing studies on a particular subject to uncover trends and gaps in knowledge. This review uses the PRISMA checklist to guide study process criteria through established and quality framework. The scoping review includes a literature review to systematically query PubMed for relevant evidence. PubMed provides access to a vast and comprehensive database of biomedical and life sciences literature, ensuring high-quality, peer-reviewed, and up-to-date research from reputable sources. [15]

The search strategy for this scoping review involved a comprehensive literature review on publicly available studies on PubMed. Articles with free full-text access were considered. A properly conducted literature review helps a researcher gain familiarity with existing work in the chosen area of research and allows for the expansion of knowledge based on this background. [16] All articles were published on PubMed in year 2023. Articles were available in the English language. Search keywords included “artificial intelligence,” “machine learning,” “deep learning,” “diagnostic healthcare,” “medical diagnostics,” “diagnostic accuracy,” “radiology,” and “pathology.” The eligibility of existing research synthesized within this scoping review is

based on the research inquiry criteria. Appropriately constructed research inquiry search criteria are crucial to not overly constrict results, while filtering results to obtain quality information. [17] Selection of eligible studies were at the discretion of the author screening titles and abstracts to ensure relevance to the study topic. Additionally, the author evaluated the

eligibility of the articles selected by reviewing the full text of each to ensure topic relevance in meeting search criteria. The PubMed search query returned 15 articles. The author reviewed the abstract of each article. From there, the author reviewed 5 full texts and selected 3 of the most appropriate studies for evidence.

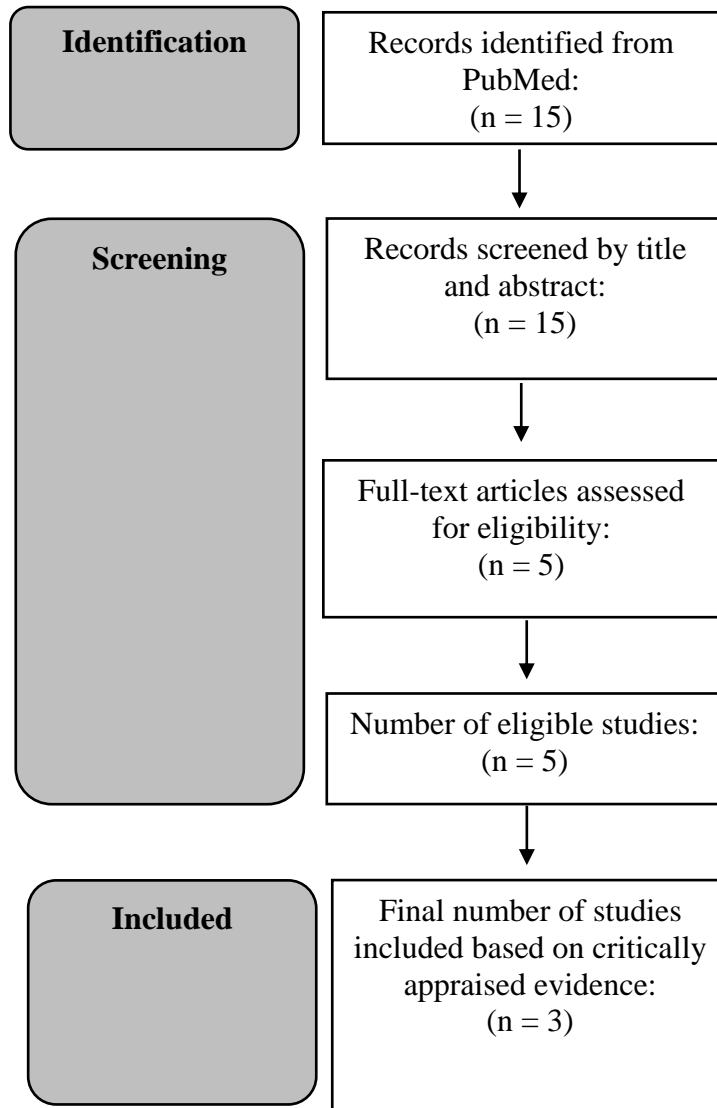


Figure 1: PRISMA Flow Diagram

RESULT

This scoping review uses the simple process of evaluating data from the studies reviewed and reorganizes such data into a summarized graph to help identify patterns and trends across each source. The scope, study design, population, and statistical

relevance are extracted. The scope establishes the general intent of the article, while noting the author and data published. The study design refers to the selected framework, methods, and processes used to collect data used within the study, which can help researchers assess the rigor and

limitations in design. [18] The study population refers to the group of individuals that the study is investigating. [19] Statistical relevance refers to the presence, impact, and reliability of study findings based on

statistical significance being applicable to the current study topic. [20] The evidence from the selected articles is presented in the table 1.

Scope	Type of study	Population	Statistical relevance
Developing and evaluating a deep learning model for rotator cuff tear detection on shoulder MRI scans. [21]	Retrospective	Sample size of 11,925 MRI scans, subset used for model development (11,405) and final testing (520).	High area under the curve values (0.93 for supraspinatus, 0.89 for infraspinatus, and 0.90 for subscapularis tendon tears), indicating comparable diagnostic accuracy to clinical readers for detecting and classifying rotator cuff tears.
Developing and validating a deep-learning (DL) model to predict mortality, intensive care unit admission, and intubation in COVID-19 patients using three-dimensional chest CT images and clinical data. [22]	Multicentric cohort	Sample of 1051 patients across multiple centers, with separate groups for training, internal validation, and external validation	High predictive accuracy for mortality (91.7% accuracy, 90.5% sensitivity, 92.4% specificity, receiver operating characteristic 95%), intubation (91.3% accuracy, 91.5% sensitivity, 89.8% specificity, receiver operating characteristic 95%), and ICU admission (89.6% accuracy, 90.2% sensitivity, 86.5% specificity, receiver operating characteristic 94%), with decreased performance in an external validation cohort, highlighting challenges in generalizability across different patient populations and imaging technologies.
Developing and validating a deep learning (DL) approach to predict tumor mutation status in diffuse midline gliomas (DMG) using T2-weighted MRI images. [23]	Retrospective, prospective	341 patients with diffuse midline brain gliomas from Center-1, 42 patients from Center-2, and 133 patients with diffuse spinal cord gliomas from Center-1.	High Dice coefficients for tumor segmentation (0.87 for brain gliomas, 0.81 for spinal cord gliomas) and strong diagnostic performance in internal testing (92.1% for brain gliomas, 85.4% for spinal cord gliomas) highlight effective prediction of tumor, H3 K27M, mutation status using T2-weighted MRI images.

Table 1

DISCUSSION

The reviewed articles exemplify the transformative potential of deep learning (DL) in medical imaging and predictive analytics, particularly in enhancing diagnostic accuracy and prognostic predictions across different clinical scenarios.

The first study focused on DL models for detecting and classifying rotator cuff tears using shoulder MRI. [21] This research showcased robust diagnostic performance, with DL achieving accuracy comparable to subspecialty-trained radiologists. The models effectively differentiated between tear types—no tear, partial-thickness tear, and full-thickness tear—highlighting DL's

ability to handle complex image data from multiple sequences. This capability is crucial for improving clinical decision-making in musculoskeletal radiology. However, the study highlights that while DL offers promising accuracy, its clinical integration requires careful consideration of workflow integration and validation in real-world settings to ensure consistent performance. [21]

The second study applied DL to predict adverse outcomes in COVID-19 patients based on 3D chest CT images acquired at hospital admission. [22] The model demonstrated high accuracy, sensitivity, and specificity in predicting mortality, intubation, and ICU admission within the

internal validation cohort. This highlights DL's potential in aiding resource allocation and patient management during public health emergencies. However, the study mentions the decrease in performance observed during external validation, which highlights challenges in model generalizability across diverse patient populations and healthcare settings. Addressing these challenges is critical for deploying DL effectively in pandemic response and clinical decision support. [22]

The third study explored DL's role in predicting H3 K27M mutation status in diffuse midline gliomas using T2-weighted MRI. [21] The DL model exhibited strong performance metrics, achieving high accuracy and sensitivity in identifying genetic mutations critical for prognostic assessment in neuro-oncology. This capability highlights DL's potential to noninvasively stratify patient subgroups and guide personalized treatment strategies. The study mentions the model's consistency across different patient cohorts and institutions highlights its robustness and clinical relevance in oncological imaging. [23]

Interpreting these results reveals DL's significant contributions to advancing precision medicine and improving patient care outcomes. By harnessing DL's capacity to assess vast amounts of imaging and clinical data, healthcare providers can enhance diagnostic certainty, tailor treatment strategies, and optimize resource allocation. However, translating DL models from research settings to routine clinical practice requires addressing several challenges. These include ensuring model robustness across diverse patient populations, integrating DL seamlessly into clinical workflows, and adhering to ethical guidelines regarding data privacy and algorithm transparency.

CONCLUSION

The studies highlighted AI's capability to enhance diagnostic accuracy and prognostic predictions in musculoskeletal imaging,

COVID-19 patient management based on chest CT scans, and genetic mutation prediction in neuro-oncology using MRI. [21-23] While demonstrating promising results, challenges such as model generalizability and ethical considerations remain. Standardizing validation methods, fostering interdisciplinary collaboration, and promoting AI competency among healthcare professionals are crucial for realizing AI's potential to transform healthcare delivery. Future research should prioritize rigorous validation across diverse patient populations to ensure robust and reliable clinical integration of AI technologies.

Moving forward, future research should prioritize large-scale validation studies across multiple platforms to enhance DL's reliability and generalizability. Standardizing validation methodologies and promoting interdisciplinary collaborations between clinicians, data scientists, and regulatory bodies will be essential in navigating these challenges. Moreover, continued investment in nursing informatics and AI competency education will empower healthcare professionals to leverage DL technologies effectively in clinical settings.

Declaration by Authors

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