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The Role of Digital Technology and Artificial Intelligence in Diagnosing Medical Images: A Systematic Review

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Abstract

The provision of up-to-date medical information on digital technology and AI systems in journals, clinical practices, and textbooks informing radiologists about patient care has resulted in faster, more reliable, and cheaper image interpretation. This study reviews 27 articles regarding the application of digital technology and artificial intelligence (AI) in radiological scholarship, looking at the incorporation of electronic health system records, digital radiology imaging databases, IT environments, and machine learning—the latter of which has emerged as the most popular AI approach in modern medicine. This article examines the emerging picture surrounding archiving and communication systems in the implementation phase of AI technologies. It explores the most appropriate clinical requirements for the use of AI systems in practice. Continued development in the integration of automated systems, probing the use of information systems, databases, and records, should result in further progress in radiological theory and practice.

Keywords

Artificial Intelligence, Machine Learning, Radiology

1. Introduction

Providing diverse tools and strategies for radiologists has been described as being akin to supplying patients with a safety net, expert diagnostician, and gatekeeper combined [1]. Extensive advancements made through developments in both artificial intelligence (AI) and modern imaging techniques have overcome many challenges and responsibilities once faced by the radiologist. This progress has involved two main factors: image finding interpretation and medical imaging production [2]. The ability to recognize an image is an important prerequisite for various types of identification, and a traditional human intuitive capacity necessary for recognizing features that differentiate "normal" from "abnormal" images [3]. However, this focus on human interpretation is largely undesirable in medical practice, since image complexity can hinder the predictability of outcomes and render interpretation mistakes more likely [4].

The idea of using computers and AI for medical imaging stems backs at least to the 1960s [1]. Radiologists at this time exploited the abilities of the emerging computer for retaining large amounts of data [5]. The computer permitted an authentic and explicit quantitative assessment, and helped in the characterization of radiological findings [6]. However, the effectiveness and reliability of computerized image interpretation were only fully realized in recent years, and radiologists have began to adopt the technology. A large number of AI techniques have been used in the context of healthcare disciplines, which has led to various debates among doctors relating to the ethics of AI in various types of medicine, particularly in terms of the risk involved in replacing human physicians with machines [7] [8]. In the foreseeable future, machines may probably not replace human physicians, although machines will almost certainly increase the speed and efficiency of clinical assessments. This may permit more reliable and justifiable decision-making, and may even partially replace low-level human decision-making in specific functional areas of healthcare [9]. In practice, recent successful applications of AI in healthcare have been rigorously examined, owing to the widespread availability of digital data and the current ease in applying big data analytical methods [4]. Seminal AI techniques can explain hidden appropriate information that consequently informs clinical decision-making.

The achievements and advantages of AI and machine learning techniques in the context of healthcare, especially radiology have been widely discussed [2] [3] [8] [9]. Machine learning techniques can be used to extract various characteristics from an extensive data set, as well as to gather broad understanding for assisting clinical practice. Learning and self-correcting programs are equipped with algorithms that enhance accuracy based on continuous feedback. However, the provision of up-to-date information from medical journals, clinical practice, medical guidelines, and textbooks are necessary to result in appropriate patient care, and which may be more easily incorporated when using an AI system. Also, diagnostic and therapeutic errors can be reduced through AI, and relevant information can be extracted for developing real-time inferences toward predicting health outcomes and health risk alerts.

A method for quantifying the frequency and impact of human error in medicine was initially expounded as early as 1949, by Garland [10], where it was noted that radiologists are prone to errors. Indeed, presently, radiologists make approximately 40 million radiological errors per annum worldwide [11], of which, 9.3% are syntactic and semantic errors [12], averaging 1.23 errors per report [13]. In general, accurate diagnoses do not necessary indicate a successful radiological investigation. Lack of experience, time constrains, and technical difficulty in properly viewing huge imaging data may lead to misinterpretation. For instance, the occurrence of notorious laterality errors is a product of mistakes made by a physician about body orientation, or labelling errors by a radiologist. Indeed, errors made by a radiologist can lead to delays or missed diagnosis, which can cause unfavourable patient outcomes. Thus, the application of AI in radiology ensures faster, more reliable, and cheaper image interpretation, utilizing electronic health system records and digital imaging databases [14]. The present review aims to determine the role of AI and other technologies in the daily practice of radiologists, from historical and current perspectives to providing an overview for practicing radiologists, acting as type of roadmap for this technological territory and a provision that can aid practitioners in future advancements.

2. Materials and Methods

A systematic review design based on PRISMA guidelines by Mohr, *et al.* [15] was used to examine the role of AI and other technologies for validating medical diagnosis in radiology. It looked at the current available state of the art to suggest advancements for future practice.

This review has restricted its search to English-language studies and on human subjects. However, no restriction on the initial timeline was selected, therefore, studies published before Dec 2020 were included, as this was the day last search was conducted. Medical images of various modalities, such as mammography or mastography, X-radiation (x-ray), Magnetic Resonnce Imaging (MRI), Ultrasound (US), and Computed tomography (CT), were all incorporated as radiological images. Studies examining AI that combine medical images and other types of clinical data were included. Articles based on clinical settings were included in this review, informing understanding about the use of AI in various radiological imaging and modality settings. No limits were placed on the target population, the intended context for using the model, or the disease outcome of interest. Editorials, letters, comments, conference abstracts and proceedings, and review articles were also included. This review has exhaustively searched PubMed, Cochrane, MEDLINE, and EMBASE databases to identify original research articles that examine the role of AI and machine learning in investigating medical images toward diagnostic decision-making. Also, owing to limited data on the topic, a grey literature search was conducted by incorporating a search through customizing the Google search engine. The complete list of inclusion and exclusion criteria is shown on **Table 1**. The keywords used were "Artificial Intelligence OR Machine learning OR Deep learning" AND "Medical Imaging OR radiological studies" AND "Diagnosis OR Accuracy OR Performance" (**Table 2**). Both published and unpublished studies were searched rigorously before conducted the review to prevent reviewer selection bias and publication bias.

Initially, after searching all databases, studies were deduplicated using RefWorks. After deduplication, the title and abstracts were read and screened (1st

Table 1. Inclusion and exclusion criteria.

	Inclusion Criteria	Exclusion Criteria
Population	Studies for all age groups and from all populations, including studies from all high-, middle- and low-income countries	Studies on animals or non-human object
Intervention	Medical images and images of different radiological modalities, such as mammography, x-ray, MRI, US, and CT	Studies with obsolete radiological technologies or modalities
Outcome	Studies examining AI that combine medical images and other types of clinical data.	Studies reporting patient experiences or narratives
Design	RCTs, clinical trials, Editorials, letters, comments, conference abstracts and proceedings, and review articles were also included.	Qualitative studies
Language	English	All other languages
Setting	Clinical settings	Studies that violated declaration of Helsinki
Time period	All studies	-

Table 2. Search queries using keywords.

Search number	Search Strategy
Search number	Searched Items
S1	Artificial intelligence OR Machine learning OR Deep learning OR Convolutional Network
S2	Diagnosis OR Diagnostic OR Diagnosing OR Accuracy OR Receiver operating OR Performance
S3	Radiological Studies OR Mammography OR CT OR CT Scan OR US OR Ultrasound OR MRI or Magnetic Resonance Imaging
S4	S1 AND S2 AND S3

screening) based on inclusion and exclusion criteria (Table 1). Full texts of the included articles were then obtained and screened (2nd screening) using the same criteria. The two independent reviewers assessed the eligibility criteria of the screened titles and abstracts and later the full text of the search results; non-consensus was resolved by a third reviewer. A Microsoft Excel Sheet was prepared to screen the included and excluded studies. Articles included after a 2nd screening were then screened (3rd screening) for quality analysis using the STROBE checklist [16]. Again, the screening was carried out by two independent reviewers to ensure that the included studies had internal and external validity. The article search procedure is shown on Table 3.

A pre-developed and standardized proforma was used during the data extraction process. First author name, year of publication, study type, methodology of the study and final outcome of the study were extracted and summarized in a table which was then used for data analysis. The outcomes of studies were based on complex mathematical and statistical AI models, which include deep learning

Table 3. Result for Search strategy in PubMed.

Search number	Search Strategy	Studies Found
S1	Artificial Intelligence or Machine learning or Deep learning	2401
S2	Medical Imaging or radiological studies	94,539
S3	Diagnosis or Accuracy or Performance	553,380
S4	S1 and S2 and S3	27,099
S6	Language Filter	24,246
S7	Study Design Filter	2032
S8	Species filter	2,032

algorithms that examine medical images, produce magnitudes of medical image data, and provide automated diagnoses of radiological findings. The development of the coding protocol helped to record important data from each screened study. Characteristics were added to the proforma when literature, patterns, or findings required inclusion. The coding was performed by the author, who controlled the inter-rater reliability.

The percentages of incorporated studies were calculated to perform external validation. The proportions of studies, including diagnostic cohort designs, prospective data collection, and inclusion of multiple institutions, were identified for external validation.

3. Results and Discussions

3.1. Search Results

A total of 4348 studies were yielded from the search process, as shown on the PRISMA flow diagram (**Figure 1**). After deduplication, the yield was reduced to 3109 articles. Following screening of title and abstract this was further decreased to 787 articles, and after going through the 2nd stage of the screening process, 31 articles remained. The removal of 756 studies was based on the following criteria: the studies did not report the desired outcome, the radiological aspect was not adequately discussed, or the setting was not clinical. Following a quality analysis, 27 articles were finally included in the review. The data extraction from these articles is shown on **Table 4**.

3.2. Inception of AI in Radiology

In the recent past, digital images and advanced imaging processing techniques were not readily available, even though significant outcomes were accomplished using unique applications of early computers [17]. A type of paradigm shift occurred in computer science during the 1980s, through the invention of the microchip, which allowed scientists to develop systems that can support radiologists in ways previously unimaginable [5]. Following this development, various approaches have been proposed, some having widespread success, such as hypertext, rule-based and case-based reasoning, Bayesian networks [8], and artificial neural networks (ANNs).

Table 4. Data extraction for included studies.

Name of Author	Year of Publication	Study Type	Study Methods	Final outcomes
Atkinson [1]	2016	Descriptive Report	Discussing myths around AI and its role in hijacking jobs in radiology	The activation of AI technologies was found to be one of the most crucial challenges for the user in the initial phases
Wong *et al.* [2]	2019	Descriptive study	Discussion on recent developments in medicine using AI	Collaborations for use of AI with radiological assessment are incorporated which can reduce workload of clinical radiologists
Mesko [3]	2017	Editorial	Discussing role of AI in precision medicine	AI system can be updated by personalized expert knowledge, where both individual observations and images can be utilized as inputs for ANNs
Kahn [5]	1994	Review Article	Reviewed AI techniques and its application in radiology	Invention of microchips have advanced radiological assessment of medical images
Honsy *et al.* [6]	2018	Opinion Article	Discuss multiple facets of radiology	AI methods (deep learning) automatically recognizes complicated patterns in clinical images and provide qualitative assessment.
Fazal *et al.* [7]	2018	Descriptive study	Discussing benefits of AI in radiology	Errors in report assessment can be reduced by using AI
Schmidt *et al.* [8]	2000	Descriptive studies	Case-based reasoning was applied in making knowledge-based reasoning	Knowledge based system in medical sciences is advanced by hypertext, rule-based and case-based reasoning
Brady [11]	2017	Review article	It outlined the errors and discrepancies in radiology, and categorized them to help understand, and contribute, both human- and system-based radiology	Humans are not able to account for the many wide-ranging qualitative characteristics in routine medical imaging examinations
Ringler *et al.* [12]	2017	Retrospective study	Reports generated by Syntactic and semantic errors in radiology which were signed by 147 different radiologists from 3 January 2011 through 16 April 2014 were analyzed	Extensive medical data is required for moderate ease of retrieval and access in radiology
Motyer *et al.* [13]	2016	Retrospective study	Audit of 378 finalized radiology reports	Automation using AI and leveraging big data incorporates a large number of quantitative aspects collaboratively, using an iterative technique
Grayev [17]	2019	Editorial Paper	Descriptive	Even though significant outcomes were accomplished from the various unique applications of early computers AI has been more advanced in recent years.
Daniel *et al.* [18]	2018	Descriptive study	On use of AI (deep learning) in image based medical diagnosis	(AI) can classify retinal images from optical coherence tomography for early diagnosis of retinal diseases
Blumke [19]	2018	Editorial Paper	Revision of radiology criteria	The weighting of each connection as well as each neuron is used to represent the knowledge base of the system which activates other neurons
Pravedello [20]	2019	Original study	The study annotated and adjudicated dataset of chest radiographs to make them publicly available	AI learning can train ANNs, based on generic techniques such as clustering, anomaly detection, and association, which are enhanced with each case to assure authentic diagnoses

Continued

Deyer *et al.* [21]	2019	Editorial	Discussing application of AI to radiology	ANN process allows the continuous progression of the system, learning in a similar way that corresponds with the human brain, but with the benefit of a permanent memory function
Schier [22]	2018	Opinion	Providing an alternative view on radiology practice and AI	The accuracy rates of ANNs currently surpass human radiologists in narrow-based tasks, such as detecting lung nodule features
Stivaros *et al.* [23]	2010	Review article	Reviews role of decision support systems in radiological assessment	Machine learning permits reliable automated detection of lung nodules in CT scans, and pneumonia in chest x-rays
Porto Pazos [24]	2008	Book	Use of biological process application in advancement of AI	The behaviour of pre-cancerous lesions on CT scans is predicted by means of modeling, or regression, and prevents superfluous invasive examinations, such as biopsy
Pesapane *et al.* [25]	2018	Narrative review	Discusses the role of practicing radiologist in promoting AI in radiology	AI will help radiologists in being a multidisciplinary team, be more on forefront with patients and add value to tasks
Kamar [26]	2016	Review paper	Considering Human intelligence in AI	Electronic health records could improve the success rate of radiologists
Fieschi [27]	2013	Book	Discusses expert systems of AI in medicne	Radiologists can distinguish themselves by creating AI that does hybrid work through collective intelligence software
Danforth *et al.* [28]	2009	Project writing	Developed a virtual patient simulations system that will help in medical education	Intelligence augmentation in radiology is where higher levels of accuracy in diagnosis are achieved through the amalgamation of human radiologists and AI to form hybrid intelligence
Thrall *et al.* [29]	2018	Descriptive study	Discusses opportunities and challenges faced by AI in radiology	Value created by AI will measure its role in radiology *i.e.*, by increasing diagnostic certainty, quicker turnaround, improved patient outcomes, and for radiologists a better quality of work life
Gillies *et al.* [30]	2016	Special report	Describes the process of radiomics, its potential power to facilitate better clinical decision making and its challenges; especially in cancer patients	It is important to consider aspects such as picture archiving and communication system (PACS), electronic health records, IT environments, and radiology information systems in the implementation phase of AI
Prevedello *et al.* [31]	2017	Retrospective study	AI algorithm performance was tested on a separate dataset containing 35 with noncritical findings, 15 with suspected acute infarct findings, and 50 with hemorrhage, mass effect, or hydrocephalus findings	AI (deep learning) is promising for detecting noncontrast-enhanced head CT, whereas, to detect suspected acute infarction required dedicated algorithm. Detection of suspected acute infarct had lower sensitivity compared to hemorrhage, mass effect, or hydrocephalus detection, but showed reasonable performance
Hanson [32]	2001	Review article	Databases were searched for articles regarding application of AI in radiographs used in intensive care units	Unsupervised learning is one approach that allows automated data curation
Kulikowski [33]	1988	Review article	A brief history of articles before 1988 on the use of AI in medicine is reviewed in a systematic way	Recent developments in unsupervised learning include different auto-encoders and generative adversarial networks, which are highly effective, where discriminated aspects are learned despite a lack of comprehensive labelling

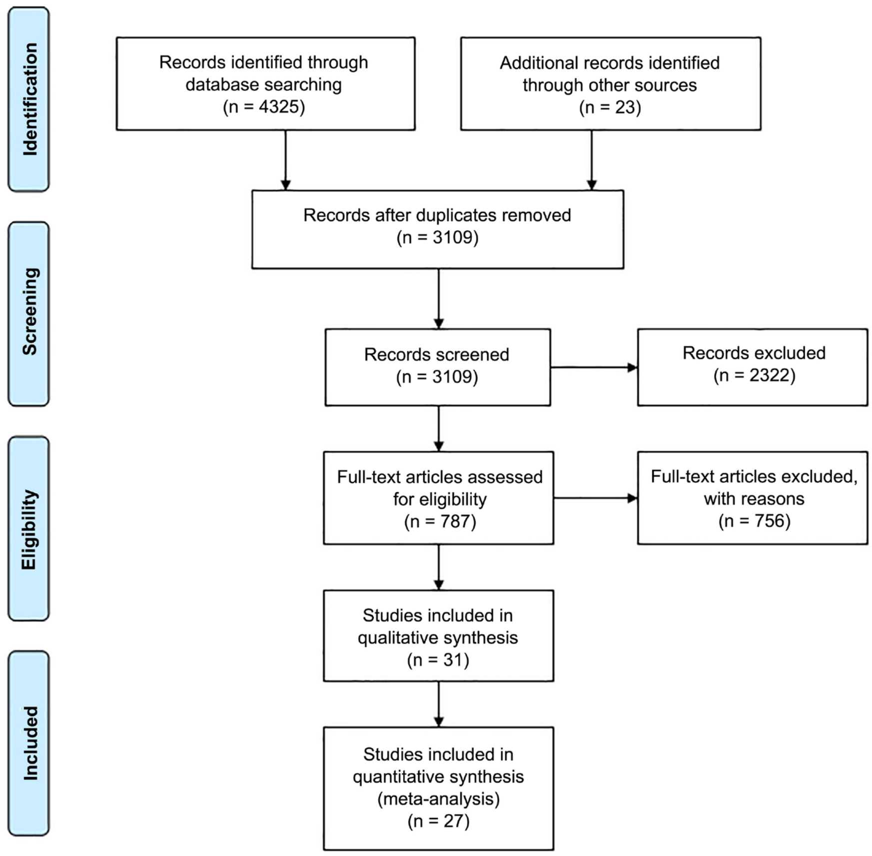

Figure 1. Search strategy for PubMed database.

Since 1943, ANNs have held a dominant position among AI techniques used in modern medicine [18]. The incorporation of ANNs has been one of the most effective and prolific applications of AI in radiological history [6]. ANNs are analogues of neurons in the human brain, comprising an amassed network of highly interconnected computer procedures, which perform parallel computations for data processing, with weighted connections between each node of the network [2]. This weighting results in the activation of other artificial neurons in the network, based on mathematical formulas [19]. The combined weighting of connections, as a product of the whole artificial neuronal structure, is used to represent the knowledge base of the system.

Supervised learning can be used to train ANNs, through a comparison of expected and actual outcomes. Unsupervised or semi-supervised learning can also train ANNs, based on generic techniques, such as clustering, anomaly detection, and association, which are enhanced with each case to assure authentic diagnoses [20]. ANNs are capable of extrapolating the input data of simple cases to handle more difficult scenarios. Additionally, a system can be updated by personalized expert knowledge, where both individual observations and images can be utilized as inputs [2] [3]. This process allows the continuous progression of a system, learning in a similar way that corresponds with human cognitive developmnet, but with the benefit of a permanent memory function [21]. AI-based computer-aided detected (CAD) programs are the most common application of ANNs in medical imaging. Images are investigated using ANN software to emphasize areas of risk, stimulating additional investigation by a radiologist. ANNs have been successfully applied to the characterization of cancerous tissue, leading to an increase in reading sensitivity, specificity, and accuracy in the detection of cancerous lesions and the recurrence of such phenomena.

3.3. Evolution of AI in Radiology: Current Concepts

The segmentation, staging, and diagnosis of disease are covered within the term "characterization" [18]. These activities are achieved by quantifying the radiological aspects of an abnormality, which include gathering data about internal texture and the size and extent of findings. Humans are not generally able to account for the many wide-ranging qualitative characteristics found in routine medical imaging examinations [11]. This is exacerbated by the inevitable differences between individual interpretations and patient characteristics. By contrast, AI leverages big data that processes a large number of quantitative aspects collaboratively, using iterative techniques [13].

In the past decade, there have been a number of significant innovations in medical imaging using deep learning techniques for image classification. Deep learning involves computational models that learn data characteristics rapidly from multiple levels. The dominance of deep learning in medical imaging studies has increased as the amount of data available has improved, largely the result of the powerful hardware in current computers. Indeed, the accuracy rates of ANNs now surpass human radiologist performance in narrow-based tasks, such as detecting lung nodule features [22]. Also, machine learning permits reliable automated detection of lung nodules in CT scans and pneumonia in chest x-rays [23]. The behavior of pre-cancerous lesions on CT scans is predicted by means of modeling, or regression, and prevents superfluous invasive examinations, such as biopsy [24]. This has significant potential in population screening for cancer, especially in countries where radiologists may be overworked or lack specialized training.

The demonstration of technological capabilities and the identification of novel systems in radiology is the first step in devising a strategy for practice, but which, however, may pose a threat to practitioners of other disciplines. For example, other medical practitioners may spend more time with certain patients than radiologists and so might choose to purchase particular AI technologies, and in doing so automatically compete with radiologists for resources [25]. By contrast, in a typical current practical scenario, the use of AI could be highly effective if integrated into the work of many professions and that of their respective colleagues. For example, even the simple analysis of electronic health records may improve the success rate of radiologists [26]. Thus, a strategic objective for radiologists could be to distinguish themselves by creating AI that does hybrid work through collective intelligence software [27].

Intelligence augmentation is a topical buzzword that often accompanies discourse in AI, such as found at a recent World Economic Forum (2017). Intelligence augmentation in radiology concerns higher levels of accuracy in diagnosis achieved through the amalgamation of human radiologists and AI, forming a hybrid intelligence [28]. It is effective because clusters of AI agents and humans working collectively make more effective predictions compared to AI techniques or humans used independently [26]. This process of evaluation may or may not hold for radiological diagnosis, however, which arguably requires greater scrutiny and validation of peer-reviewed articles. Patient safety standards must also be considered in these systems, while judicial transparency is created through observation of a human radiologist, providing legal accountability [28]. Also, the requirement for precision diagnostics requires additional research into AI approaches. Machine learning may become a leading tool in the future to extrapolate large data sets derived from imaging to evaluate cancer genes, behavior, and response to treatment, enabling radiologists to discover associations between pathogenesis and imaging features of tumors [27]. Also, precision diagnostics can plausibly be integrated for degenerative and chronic diseases, including coronary heart disorders and Alzheimer's disease, as well as for any disease with imaging and genetic biomarker associations [29].

While significant progress has been made, machine learning technology is currently quite a way from successful integration into radiology practice. While technologies have been publicly lauded and promoted in specialist disciplines, they have often failed to achieve potential in the implementation phase; indeed, the birth and death of technologies is often labelled the "hype cycle". One major issue, for instance, is that computing systems are not yet technically fast enough to render outcomes within a clinically appropriate time frame for urgent diagnoses and emergencies, especially if the required technologies are not widely available in medical institutions [29].

It is important to consider aspects such as picture archiving and communication system (PACS), electronic health records, IT environments, and radiology information systems in the implementation phase of AI [30]. Increasing technological sophistication is based on the acquisition and improvement of hardware, as well as communication between departments and hospitals. If the technology is indispensable, protecting data storage and cloud platforms will become increasingly important [31]. AI applications provide an essential approach in the extraction of latent information from images, and is not hindered by geographical distance with respect to the information source. Current advancements in deep learning and big data have laid the ground for the field of radiomics, involving the use of hundreds of abstract mathematical characteristics of images that can be characterized and interpreted using AI techniques, and also easily integrated with other data, such as that relating to therapeutic outcomes and genomics findings.

In recent years, there has been an increase in reported workload following the current reliance of hospitals on imaging. Thus, the use of an AI system may be beneficial in reducing daily workload in the radiology department and keeping up-to-date with hospital services [22]. Another crucial role of AI may be to screen for normal plain films and review abnormal films in cancer screening. Similarly, malignancy can be identified through using question-specific AI techniques. However, the use of AI technologies was found to be one of the most crucial challenges for the user in the initial phases of one study [1] [22]. Nevertheless, an AI tool gives independency to health professionals in the reporting of simple scans. AI tools may likely be developed as a way for doctors to incorporate a type of "autopilot" to their daily activities, which may perhaps be innovated upon to produce more complex integrated systems. In the context of neuroimaging, considerations about AI solutions have emerged in various MRI projects, such as the large-scale Human Connectome Project, which aims to access brain connectivity [7] [21].

4. Future Developments

One of the most central and complicated aspects of AI systems is dealing with the data source itself. Extensive medical data is required for moderate ease of retrieval and access [12]. Millions of medical images are produced each year, since one out of four patients receives a CT examination and one out of ten patients receives an MRI examination [10]. Progress in digital health system protocols worldwide have assured that medical images are electronically handled in a systematic way, permitting the use of appropriate practice for developing and emerging countries.

A patient cohort selection associated through AI identifies objects through segmentation techniques [34]. This ensures that a well-defined set of criteria is observed in the training data. Furthermore, it assists in mitigating unwanted variation in the data, which is a product of data acquisition principles and imaging protocols, including actual imaging and contrast agent administration across institutions [18].

The substandard performance of a number of automated and semi-automated segmentation AI programs has perhaps restricted their use in the curatation of data [20] Complications with machine learning have emerged with respect to rare diseases, where automated labeling algorithms are not effective. This issue is exacerbated when a number of human readers lack prior exposure and so are not able to verify unidentified diseases. However, unsupervised learning is an approach that allows automated data curation [32]. Recent developments in unsupervised learning include various auto-encoders and generative adversarial networks; these are highly effective, where discriminated aspects are learned despite a lack of comprehensive labeling [33].

Unsupervised domain adaptation has been explored recently through the use of adversarial networks for segmenting brain MRI, which permit accuracy and generalizability closer to supervised learning methods [23]. Sparse auto-encoders using an unsupervised approach are also employed for segmenting mammographic textures and breast density. Spatial context information is employed in self-supervised learning to identify body parts in MRI and CT volumes by means of paired CNNs [24]. Unparalleled open-access to labeled medical imaging data is offered by the Cancer Imaging Archive, which allows rapid AI model prototyping and hence reduces the need for comprehensive data curation procedures.

The use of patient data brings forth ethical concerns with respect to the training of AI systems. Data are not securely connected to state-of-the-art AI systems in medical institutions [28]. However, recently, a stricter privacy policy has been made possible in the US through the Health Insurance Portability and Accountability Act of 1996, which has enforced compliant storage systems. These systems share only the trained model and allow multiple actors to work collaboratively with AI models irrespective of their input data sets [29].

A decentralized federated learning approach has been used in other contributions to the field. In this system, data remains local during training, but the combination of local updates permits the interpretation of a shared model. The live copies of the shared model result in the desired inference, but reduce privacy concerns and data sharing [33]. Encrypted data train deep learning networks for predicting decryption keys to assure comprehensive confidentiality in the overall process. All these solutions create sustainable data for an AI ecosystem, without undermining privacy and compliance, even though this system is only in an early phase of development [33].

The advancements made in radiological imaging and diagnosis through AI calibration is an important development of medical practice. However, the full benefit may be in the collaboration of AI with humans. Using AI systems, radiologists can help promote and improve the diagnostic capability of radiological modalities, and in return this can help the advancement of the field. Future studies need to focus on the application of AI in clinical diagnosis using radiological images. Radiologist suggestions and requirements should be considered in the process of AI advancement in radiology, to enable smoother implementation and strengthen clinical practice.

This study may limit in that it included a language bias, since only data in English was considered. It also had to include grey literature owing to a limitation in the actual quantity of relevant studies; for example, none of the studies used was a randomized control trial. However, as grey literature was also searched in this study, there was no publication bias. Finally, all included studies had high heterogeneity because a meta-analysis was not carried out; the results were synthesized in a narrative manner. Therefore, the limitations associated with narrative review. However, by preventing reviewer selection bias and extensive referencing, the bias related to narrative review was minimized.

5. Conclusion

The integration of automated systems through information systems and AI is an important prospect for the future of medical imaging. Decision support systems may substantially improve medical practice if integrated into routine clinical functions. A number of different aspects of learned knowledge can be shared through the selection, analysis, and diagnostic interpretation of radiological imaging. This study also found that it was necessary to combine clinical care functions, research, and education to inform radiologists about current technology in the medical imaging community. The computer-based patient record is now an important objective for healthcare administrators that could provide a platform for the integration of clinical information, medical literature, decision support technology, and imaging, and thus markedly improve clinical practice. A valuable contribution can be made in clinical information systems through using decision support systems. These may improve medical care quality through the use of computer-based patient records.

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Conflicts of Interest

The study has no competing interests.

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Abbreviations

(AI) Artificial Intelligence;
(PRISMA) Preferred Reporting Items for Systematic Reviews and Meta-Analyses;
(MRI) Magnetic Resonance Imaging;
(US) Ultrasound;
(CT) Computerized Tomography;
(STROBE) Strengthening the Reporting of OBservational Studies in Epidemiology;
(ANNs) Artificial Neural Networks;
(CAD) Computer-Aided Design;
(PACS) Picture Archiving and Communication System.