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The opportunities and challenges in deploying AI in medical imaging

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Abstract

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In recent years, artificial intelligence (AI) technology has made significant progress in the medical field, especially in the aspect of medical imaging, demonstrating great potential. By analysing medical images through AI algorithms, the AI system can assist doctors in identifying diseases more quickly and accurately. Although the prospects are promising, the application of artificial intelligence in medical imaging still faces many challenges. Issues related to data privacy and security need to be addressed urgently, and the transparency and explainability of algorithms also need to be improved.

This study aims to systematically explore the opportunity arising from the integration of AI in medical imaging and to identify the specific challenges healthcare organizations face in its deployment as well. The purpose of this study is to provide a synthesized understanding of how AI can be effectively and ethically utilized in medical imaging by integrating existing research data.

An umbrella review methodology was employed to collect and analyse evidence from 15 systematic review published between 2019 and 2024. Articles were collected from PubMed and ScienceDirect using defined inclusion and exclusion criteria. Data extraction and content analysis were conducted to identify recurring themes related to AI opportunities and challenges. The Critical Appraisal Skills Program (CASP) checklist was used to assess the quality of the included studies.

The thesis revealed three aspects of opportunities of implementation AI in medical imaging. AI can enhance diagnostic accuracy and efficiency through its advanced capabilities. It also optimizes workflow by automating image acquisition, triage, and reporting process. For the next generation, AI even advances radiological education through adaptive learning and interactive simulation tools. Nevertheless, the thesis also identified two primary aspects of challenges when AI was applied to medical imaging. Many AI tools are trained on limited data, which can lead to biased results. There are also big ethical dilemmas regarding accountability and bias, and inadequate legal and regulatory frameworks. Furthermore, the absence of external validation and transparency in AI model development limits trust and clinical adoption.

These results can be concluded that AI has presented transformative potential for improving the quality, accessibility, and efficiency of medical imaging. However, its successful and equitable integration requires robust governance frameworks, transparent algorithmic design, and multidisciplinary collaboration to ensure ethical deployment. By addressing data and regulatory shortcomings, AI can become a cornerstone of a more patient-centred and efficient healthcare system.

Keywords: Artificial Intelligence (AI), Medical imaging, Opportunities, Challenges

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1. Introduction

Back to the afternoon of November 8, 1895, the great German physicist Röntgen conducted an experimental study using a cathode ray tube in the laboratory. He accidentally discovered that when the cathode ray tube discharged, the fluorescent screen placed next to it emitted visible light. In the experiment, the cathode ray tube was shielded by opaque cardboard, indicating that the rays that stimulated the fluorescent screen to emit light had penetrating and fluorescent effects. Therefore, he implemented further experiments and found that the rays could make the photographic film wrapped in opaque black paper sensitive to light. To verify its photosensitive effect, Röntgen took a photo of his wife’s hand wearing a wedding band. This was the first X-ray photo of mankind. After repeated experiments many times, he was convinced that the cathode ray tube could emit a ray which was invisible to the naked eye. He named it X-ray using the most commonly code X for unknown numbers in mathematics. (Panchbhai 2015.)

The discovery of X-ray ushered in a new era of medicine, and Röntgen was awarded the first Nobel Prize in Physics for this. Initially, X-ray was used for diagnosis of skeletal system and chest diseases. Subsequently, people invented various imaging methods to introduce contrast agents into areas with poor natural contrast and artificially increase contrast, thereby being able to display structures such as the cardiovascular system, ventricles and cisterns, expanding the clinical application of X-rays, achieving good diagnostic results, and laying a solid foundation for modern medical imaging. (Panchbhai 2015.)

As time goes by, X-rays have mainly developed into the following five major branches, namely computed tomography, magnetic resonance imaging, ultrasound, interventional medical imaging and nuclear imaging and hybrid scanners (Bercovich & Javitt 2018).

After a century of development, medical radiology has formed an intact system and has become the major development area in modern clinical medicine, playing a great role in promoting many clinical disciplines. At present, medical imaging is the main symbol of the modernization of large hospitals, the most important clinical diagnostic method, a powerful means of medical research and important treatment method. (Bercovich & Javitt 2018.)

Nowadays, the healthcare system faces a critical shortage of medical specialist, particular radiologist worldwide (Frija, Blažić, Frush, Hierath, Kawooya, Donoso-Bach and Brkljačić 2021). According to the National Centre for Health Workforce Analysis, until 2037, there will be an 8% shortage in radiological physician in US (Health Resources & Services Administration 2024).

This shortage stems from a confluence of factors, including increasing aging population, escalating healthcare demands, and limited resources for medical education. The evolving disease landscape and rapid advancements in imaging technology have significantly increase the demand for radiology service. (Kerri 2022:27-28,30.) This shortage directly impacts patient care, leading to delays in imaging examinations and potentially delaying diagnoses and treatments. This can adversely affect patient outcomes and quality of life. In some regions, patients experience prolonged wait times for essential imaging, hindering access to timely medical care (Meng, Liu, Zhan and Zhang 2023: 1046-1048.)

To addressing this challenge, medical imaging, as the most advanced subject in the development and application of new technologies in the medical field, has taken the lead in participating in the research and development of artificial intelligence medicine due to its characteristics, such as store, data transmission and relative standardization. The use of artificial intelligence technology to make decisions and judgment on medical imaging data has significantly improved the efficiency and greatly reduced medical costs and has become the core of smart medicine. (Bercovich & Javitt 2018.)

Although AI has been constantly developing and evolving for decades and has been widely adopted in various areas, its application in radiology is still an emerging field. The aims of this study are to identify the opportunities raising from the integration of artificial intelligence (AI) in the field of medical imaging and to investigate the specific challenges that healthcare organizations face when deploying artificial intelligence in medical imaging field.

2. Theoretical Framework

2.1 Medical imaging modalities

Medical imaging is an invasive technology to acquire the images of parts of patients' bodies for diagnosis or treatment (Hussain et al 2022:1). In 1895, German physicist Röntgen discovered x-rays, which were soon used to detect human diseases, since then, diagnostic radiology started to play an important role in diagnosis (Panchbhai 2015). Medical imaging as a well-established diagnostic technology in the field of medical diagnosis, it is widely used in clinical departments and provides a great scientific and intuitive evidence for the disease's diagnosis. Medical imaging can be perfectly combined with other diagnostic methods such as clinical symptoms and test results, playing an irreplaceable role in the final accurate diagnosis. In this thesis, four of the most common medical imaging techniques will be discussed, which are Computed Tomography (CT), Magnetic Resonance Imaging (MRI), ultrasonography and Nuclear Medicine imaging (NMI). (Kasban et al. 2015:37-58.)

2.1.1 Computed Tomography

Computed Tomography (CT) is a technology that scans the layers of a part of body by using the X-ray beam. It receives the X-ray that pass through the human body via the detector, converts them into visible light, converts the visible light into electrical signals by photoelectric conversion, and then converts them into digital signals through analog-to-digital converter (ADC) and inputs them into computers for processing. CT images are composed of a certain number of pixels with different shades of grey from black to white arranged in a matrix. It reflects the degree of absorption of X-rays by organs and tissues. (Al-Naser & Tafti 2023.) Therefore, just like the black and white images shown in X-ray images, black shadows represent low absorption areas, that is low density areas, such as the lungs. White shadows represent high absorption areas, that is high density areas, such as bones. (Kasban et al. 2015:37-58.) Due to the high-density resolution of CT, CT can better display organs composed of tissues, such as brain, spinal cord, liver and gallbladder, etc., and show the lesions images on anatomical images (Patel & De Jesus 2023).

2.1.2 Ultrasonography

Ultrasonography, also known as ultrasound, uses the rules of ultrasound propagation in the human body, including sound reflection, projection, scattering, diffuse reflection, to understand the internal conditions of the human body. In modern medical imaging, it keeps pace with CT, X-ray and MRI and complements each other. It features no pain, no damage and no harm. It is especially unique in the detection of human soft tissues and the hemodynamic observation of cardiovascular organs. (National Institute of Biomedical Imaging and Bioengineering 2023.)

Through ultrasound imaging technology, healthcare providers can perform surgery and interventional treatment, such as puncture biopsy and vascular intervention. In addition, ultrasound imaging is also widely used to monitor fetal development with safety and non-invasive, and the field of oncology, gynaecology, neurology and so forth to help healthcare providers evaluate disease condition, make treatment plan and perform surgery. (National Institute of Biomedical Imaging and Bioengineering 2023.)

2.1.3 Magnetic Resonance Imaging

Magnetic Resonance Imaging (MRI) technology is the application of nuclear magnetic resonance in the medical field. The human body contains very rich water, different organizations, the water content is also different. The internal structure of human body can be drawn by detecting the distribution information of water. Magnetic Resonance Imaging technology is the technology that detects the internal structure of the human body by identifying the distribution of hydrogen atom signals in water molecules in the human body. (Berger 2002: 35.)

MRI is a non-invasive diagnostic technology. Compared with X-rays fluoroscopy and radiography, MRI has no radiation effect on human body. Compared with ultrasound detection, MRI is clearer and can show more details. In addition, MRI not only shows physical lesions, but also accurately determine the functional reactions of the brain, heart, liver, etc. MRI technology has played a significant role in the diagnosis of Parkinson’s diseases, Alzheimer’s disease, cancer and other diseases. (Moser et al. 2008: 30-41.)

The images obtained by MRI are very clear and detailed, which greatly improves the diagnostic efficiency and avoid the need for thoracotomy and laparotomy for exploratory diagnosis. MRI can scan various parts of the human body from multiple angles and planes. It has high resolution and can more objectively and specifically display the anatomical tissues and adjacent relationships. It can better locate and characterize lesions and has great value in the diagnosis of diseases of all systems in the body, especially the diagnosis of early tumours. (Moser et al. 2008: 30-41.)

2.1.4 Nuclear Medicine imaging

Nuclear Medicine imaging (NMI) is a type of medical imaging that uses small amounts of radioactive material to diagnoses or treat a variety of diseases. Before scanning, the patient is injected with radioactive agent labelled with certain positron, and the metabolic changes of the tissue are measured from the metabolic process in which the positron participates. As an imaging method that reflects molecular metabolism, when the disease is in the early stage of molecular changes, the morphological structure of the lesion has not yet appeared abnormalities, MRI and CT cannot make a clear diagnosis, nuclear imaging can find the location of the lesion, obtain three-dimensional images and perform quantitative analysis to achieve the goal of early diagnosis. (Papachristou et al. 2023:57-65.)

Single-photon emission computed tomography (SPECT) and positron emission tomography (PET) are two main kinds of nuclear medicine techniques. SPECT is an imaging method that utilize γ rays emitted from the patient’s body. As when a certain tracer is injected into a human body, the tracer will gather in a certain place and release γ rays at the same time. Then the radiological scanner is used outside the human body to detect where the γ rays is released. This will tell where the tracer is gathered and thus provide an image of the inside of the human body. The principle of PET to explore the human body is basically the same as SPET. The difference is that PET uses different tracers and only releases two ways in two opposite directions at a time. In this way, PET-CT and SPET-CT combine molecular imaging with CT, which uses X-rays for detailed anatomical images, to overlay functional data from a nuclear scan onto anatomical structures, while PET-MRI pairs PET with MRI, which uses magnetic fields and radio waves for superior soft tissue contrast and functional capabilities, offering a more comprehensive view with less radiation. In conclusion, PET is widely used due to its excellent imaging quality, and new PET tracer are still being developed. SPET, as an application of the previous generation, is also still undergoing new research to continue to play a better role. (Giraudo et al. 2020: 894.)

In terms of quantity, medical imaging data is the majority of medical data. Generally, medical imaging diagnosis mainly relies on manual subjectively analysis. This method heavily relies on the professionals’ experience to make decision, which is prone to misdiagnose. For radiologist, patients will produce hundreds or even thousands of medical images during the filming process. The heavy workload and fatigued working state can easily lead to misdiagnose as well. Hence, the big challenges the professionals face include a variety of large and complex medical data resources which involves huge manpower to deal with, this is where AI can step in. (Lundvall & Dahlström & Abrandt Dahlgren 2021.)

2.2 Artificial intelligence

AI is the abbreviation of Artificial intelligence. It is a technology that simulates human intelligence, enabling machines to learn, think and make decisions, like humans, so that they can perform various tasks autonomously. The field was formally established at the 1956 Dartmouth Conference, where John McCarthy, the originator of the term “artificial intelligence, defined AI as an interdisciplinary scientific domain. Initial advancements emphasized mathematical problem-solving. (Hamet & Tremblay 2017:36-40.) Nowadays, the ongoing evolution of AI has begun to be widely used in autonomous driving, supercomputing, and medical industry (Ongsulee 2017). It can not only improve the efficiency of medical resources but also provide high quality healthcare services to patients (Lee & Yoon 2021). Artificial intelligence is not just a single technology, as the technologies have been continuously advancing, AI has evolved derivative computational techniques such as machine learning (See Figure 1).

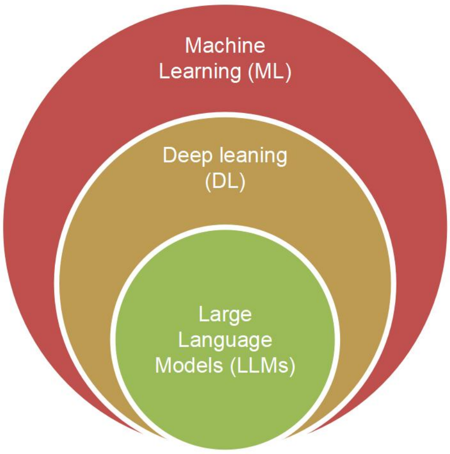

Figure 1. Hierarchical representation of AI technology

2.2.1 Machine Learning

In 1959, Arthur Samuel defined machine learning as enabling computer to learn without explicit programming (Ongsulee 2017). If data is the “food” of AI, then Machine Learning (ML) is the process of digesting the food for extracting valuable information (Papachristou et al. 2023: 57-65). It involves creating computational systems capable of autonomously analysing and utilizing data to improve performance. This learning paradigm initiates with either observational inputs or pattern recognition within datasets, enabling progressively refined decision-making through iterative exposure to representative examples. In essence, Machine learning emphasizes the learning process itself rather than explicit programming. It employs sophisticated algorithms to analyse vast datasets, identify underlying patterns, and generate predictions without requiring task-specific programming. As sample size increase, the systems self-correct and refines its learning objectives, autonomously improving its recognition capabilities through iterative error correction. (Yusoff 2024:89-99.) There are four main typical methods allow machine to learn, supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning (Ongsulee 2017):

- Supervised learning is a machine learning algorithm where a learning model is trained on a labelled dataset. The operator provides the algorithm with sample inputs and their correct outputs, such as photos labelled as “cat”, and it studies these examples to find patterns to develop predictive capabilities. As it practices, this algorithm makes prediction, receive corrective feedback on its errors, and gradually improves its accuracy. Over time, it learns to make correct predictions on new, similar data without being explicitly programmed for the new task. Classification and regression are the two main commonly used approaches of supervised learning. Classification categorizes input data into distinct classes, such as determining whether a tumour is malignant or benign. Regression is utilized to predict continuous clinical outcomes, such as tumour growth rates, blood pressure trajectories, and so forth.
- Unsupervised learning represents a branch of machine learning in which the algorithm is supplied with data that lacks predefined labels.in the absence of direct instruction, the system is compelled to independently investigate the dataset, deduce hidden structuring, and derive significant characteristics via a process of self-directed clustering. This process enables the algorithm to intrinsically characterize the data structure and ultimately assign categorical labels based on discovered similarities. In medical imaging, unsupervised

learning can be applied to identify latent tissue patterns in unannotated MRI scans, enabling automated tumour subtyping without prior pathological labels.

- Semi-supervised learning is a machine learning approach developed to address the common challenge of data scarcity. In many real-world applications, it is easy to find a massive number of unlabelled examples, yet obtaining labelled samples is often difficult due to the requirement of special equipment of expensive, time-consuming manual annotation processes. This results in a scenario with an abundance of unlabelled data and only a small amount of labelled data. Semi-supervised learning leverages this imbalance by combining a large quality of readily available unlabelled data with the limited labelled samples during training, aiming to significantly improve the learning performance and, in the process, avoid the waste of valuable data and resources.
- Reinforcement learning is another type of machine learning method where agent learns to take actions to maximize some cumulative reward by interacting with an environment. The core idea of reinforcement learning is to allow the agent to continuously adjust its strategy through trial and error, ultimately learning an optimal policy.

2.2.2 Deep Learning

Deep Learning (DL) also known as hierarchical or deep structured learning, is the subset of Machine Learning (Li & Dong 2014: 197-387). At its core lies the deep neural networks (DNNs) – a mathematical model inspired by the structure of neurons in the human brain. This model consists of multiple layers of nodes, like stacked neurons in the brain, with each layer performing specific transformations and abstraction on the input data, gradually extracting higher-level and more abstract features from raw data. (Parloof 2016.) This approach was well-known since 2006 and the definition has been iterative over time. However, two defining characters remain central to deep learning, which are “models consisting of multiple layers or stages of nonlinear information processing” and “methods for supervised or unsupervised learning of feature representation at successively higher, more abstract layers”. Deep learning excels at processing and learning from large volumes of both labelled and unlabelled data, making it highly capable of handling a broad range of complex tasks. (Li & Dong 2014: 197-387.)

Principal component analysis (PCA), support vector machine (SVM), convolutional neural networks (CNN) are the widely used deep learning algorithms to process and interpret complex patterns. Medical imaging has long been a critical application of deep learning in healthcare. Convolutional neural networks (CNN) - a deep learning architecture specifically design for image processing by automatically learning hierarchical features through convolutional layers, such as detecting edges, textures, shapes, and pooling layers, have demonstrated exceptional performance in analysing and diagnosing scans. (Tang 2019.) Deep learning enhances medical diagnostics processing X-rays, MRIs, and CT scan more quickly and accurately than radiologist. This technology makes tasks like medical imaging classification and recognition highly effective (Parloof 2016).

2.2.3 Large Language Models

The new development of DL is called Large Language Models (LLMs). Large language models possess a massive number of parameters, ranging from tens of billions to hundreds of billions, far exceeding the scale of traditional machine learning models. Through pre-training on massive amounts of text, these models acquire powerful capabilities such as cross-domain knowledge integration, complex reasoning, and content generation. Building upon this foundation, researchers can further fine-tune the models using specialized datasets, enabling them to perform specific tasks such as question answering and text generation. This technological paradigm has broken through the boundaries of traditional "narrow artificial intelligence," giving rise to many unprecedented application scenarios. (Kalyan 2024.)

Large Language Models demonstrate significant potential extracting electronic health records, personalizing treatment plans, and assisting clinical diagnosis through their advanced natural language processing capabilities to comprehend and generate human-like language. Although the application of LLMs also presents challenges including data bias and other limitations, we cannot deny that LLMs exhibit tremendous opportunities in improving patient communication, enhancing clinical decision-making efficiency, and supporting medical research. (Tessler et al 2024.)

3 Purpose and aims

The aims of this study are to identify the opportunities of applying artificial intelligence in the field of medical imaging and investigate the specific challenges healthcare organizations face when deploying artificial intelligence in medical imaging field.

The following questions are going to be discussed in this review:

- what are the opportunities arising from the integration of AI in medical imaging?
- what are the challenges faced in the deployment of AI for medical imaging?

4 Methodology

4.1 Umbrella review

The format of this thesis is umbrella review. Umbrella review is also called overviews of reviews, reviews of reviews, is a systematic review methodology designed to comprehensively evaluate and synthesize multiple systematic reviews or meta-analyses on the same topic. Rather than analysing primary studies, it builds upon existing high-quality reviews to provide a broader evidence overview, enabling decision-makers to rapidly grasp the collective research conclusions in a given field. (Aromataris, Fernandez, Godfrey, Holly, Khalil and Tunpunkom 2020.) This study will apply this methodology to identify the knowledge gap concerning artificial intelligence in medical imaging. It will integrate existing literature to synthesize a theoretical foundation in this area through the collection, evaluation, and analysis of up-to-date data.

Regarding to this study, there were several steps undergone below, and this comprehensive itinerary meticulously guided the entire research process. (Paré & Kitsiou 2017: 157.)

1) Formulating the study’s aims and questions,
2) Searching the extant literature with inclusion criteria,
3) Evaluating the quality of primary studies,
4) Categorizing data, and
5) Analyzing data

4.1.1 Formulating the study’s aims and questions

Research questions are crucial because they not only guide the literature search but also determine which research design will be used, as well as decisions about what data will be collected, from where the data will be collected, and which method will be used to analyse the data. Additionally, clear research questions will allow the readers to more understand your study. (Ratan, Anand and Ratan 2019: 15-20.)

The research questions for this study were initially formulated with a broad scope, using keywords “artificial intelligence”, medical imaging”, “opportunities”, and “challenges” to explore the current landscape of AI application in medical imaging. Although the rapid development of artificial intelligence in the medical imaging field has demonstrated its great potential in improving diagnostic accuracy, disease prediction, personalized treatment and medical resource management, as it is an emerging technology, its potential still needs to be explored further, and the challenges brought by AI also reveal successively. (Ye, Xue and Qiao 2024: 1030-1038.) The study’s questions were subsequently refined using PICo framework to ensure clarity and specificity (see Table 1) (Eriksen and Frandsen 2018:420-431). Ultimately, the refined research question guiding this study were:

- what are the opportunities (I) arising from the integration of AI (Co) in medical imaging (P)?
- what are the challenges (I) faced in the deployment of AI (Co) for medical imaging (P)?

P - Population	Medical imaging systems and their users, such as radiologist, clinicians, and patients.
I - Interest	The integration and deployment of artificial intelligence (AI) in medical imaging, specifically focusing on perceived opportunities and implementation challenges.
Co - Context	Medical imaging practice within healthcare settings.

Table 1 PICo framework for the research questions

4.2 Data collection

4.2.1 Data Sources and Search Strategies

The data for this study were combed via different databases. The author went through all the popular healthcare-related databases, such as Pubmed, ScienceDirect, MEDLINE, JBI, etc for navigating which one can provide more insights about the research questions, at the end, the databases of PubMed and ScienceDirect were chosen. Choosing PubMed and ScienceDirect because they are the experts in healthcare industry by providing sufficient and validated references for the research questions. Only were the research articles published from 2019 to 2024 were considered, because this period was regarded as the golden age of the advancement of AI applied in medical imaging (Cronin, Ryan and Coughlan 2008; Buaka & Moid 2024). The key words were used in search were Artificial intelligence, medical imaging, opportunities, challenges. The author used Boolean operator as main search model because Boolean operator is an excellent research strategy to narrow or expand the research publications by making the key search terms correlation formula with “and”, “or” and “not” (EBSCO 2022). The inclusion criteria were defined to limit the dataset to research directly applicable to human subject, excluding animal or in vitro models. The search strategy excluded non-English publications to mitigate translation-related discrepancies as well.

4.2.2 Inclusion/exclusion criteria

This thesis aims to provide an overview of the opportunities and challenges of deploying Artificial Intelligence in medical imaging. To achieve this, a targeted selection conducted across two databases, applying specific criterial beyond the criterias previously mentioned. First, only study with full free access was considered to enable in-depth exploration of the findings. Second, editorial articles and conference papers were excluded from the selection process. Third, studies that did not explicitly investigate the keywords “opportunities” or “challenges” were not included. Last, each selected article underwent a thorough review by the author, and the extracted data was systematically organized in a table (See Appendix 1). To ensure the focus remained on medical imaging, any research on AI applications in other medical fields such as patients care, pharmacometrics, or ophthalmology was excluded from this study (See Table 2).

Table 2. The criteria for screening research

Inclusion Criteria	Exclusion Criteria
Studies published between 2019 and 2024	Studies published before 2019
English	Studies not published in English
Human Medicine and Density Computer Science	Studies out these scopes
Meta-Analysis Review and systematic review	Studies designed in other methods, such as editorial
Articles available in full text	Studies only open access to abstract and summary
Relevant contents related to the highlight of research questions	Studies irrelated to the research questions and exclude research key words

4.2.3 Eligibility Criteria

The author used Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement for data collection and selection (See Figure 2). The PRISMA flow diagram is a standardized diagram used in systematic reviews or meta-analyses to visualize the study selection process. It is an evidence-based reporting guideline designed to enhance the transparency and methodological rigor of such studies. The flow diagram illustrates the journey from initial identification of potential studies to the final inclusion of those meeting eligibility criteria. It specifically outlines the stages which went through the entire data collection and selection process, such as database searching, screening of titles and abstracts, full-text access, and the reasons for excluding studies. This visual diagram allows researchers and readers to clearly understand the rigorous selection methodology employed, ensuring the reliability of the review's findings. (Page, McKenzie, Bossuyt, Boutron, Hoffmann, Mulrow, Shamseer, Tetzlaff, Akl, Brennan, Chou, Glanville, Grimshaw, Hróbjartsson, Lalu, Li, Loder, Mayo-

Wilson, McDonald, McGuinness, Stewart, Thomas, Tricco, Welch, Whiting and Moher 2021.)

The initial search, guide by the inclusion criteria, identified 2220 articles. Following the application of going through all the articles with the exclusion criteria (as illustrated in Figure 2), the number of eligible articles was refined to total of 15 for this systematic literature review.

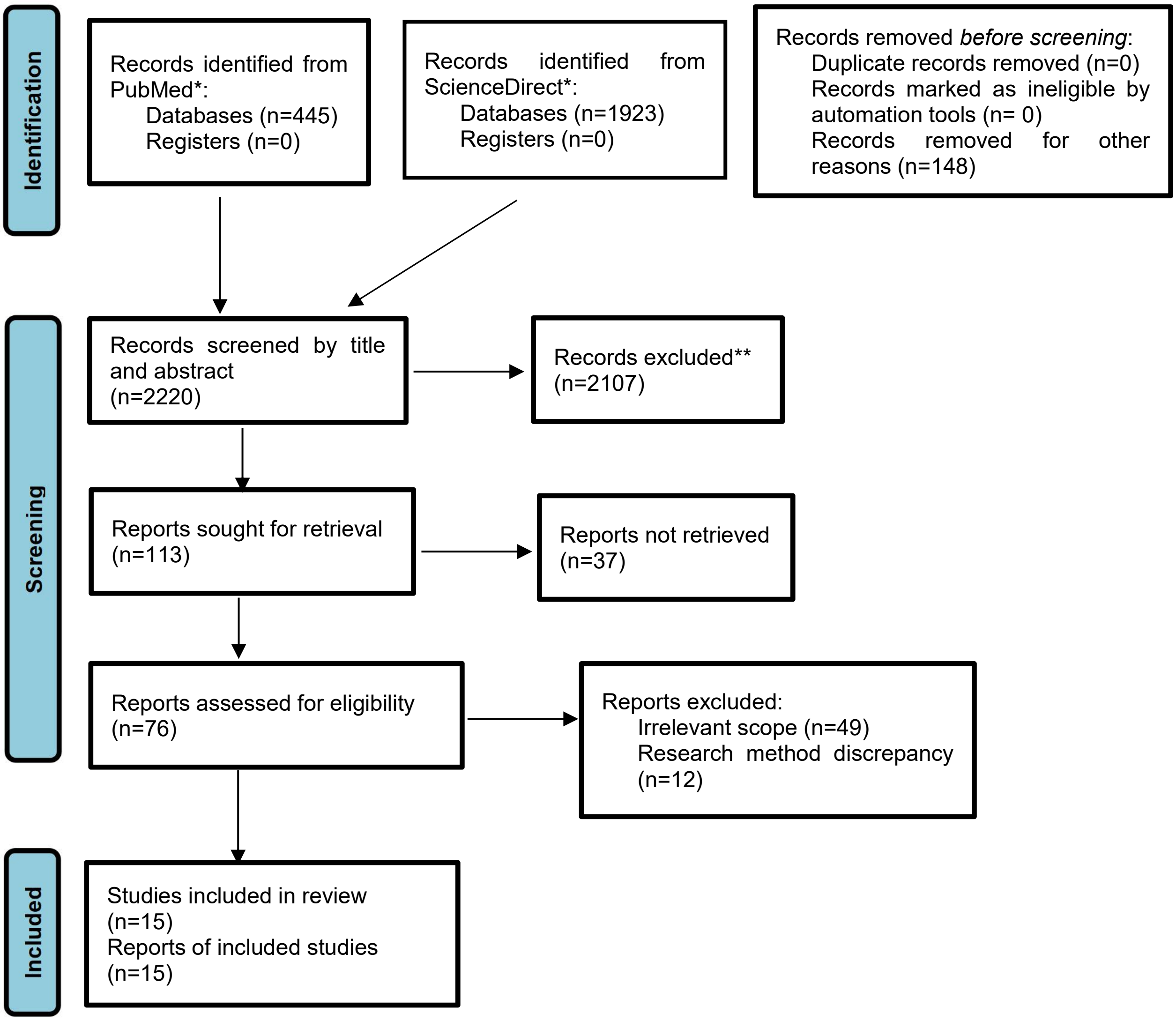

Figure 2. Reporting items for the systematic review (adapted the Preferred Reporting Items for Systematic Reviews (PRISMA) statement).

4.3 Critical appraisal

All the included studies are evaluated by using CASP (Critical Appraisal Skills Programme) checklist. CASP Checklist is a set of standardized tools designed to evaluate the quality, validity, and relevance of research studies. It is widely used in evidence-based medicine and research to critically appraise different types of studies, including systematic review, randomized controlled trials (RCTs), cohort studies, and qualitative research. Specifically, the CASP checklist for Systematic Review was applied to ensure a rigorous appraisal process, guiding the evaluation of study focus, appropriate of included quality assessment, and applicability of results. The CASP checklist questions used were: (How to use the CASP checklist 2025.)

1) Did the review address a clearly focused question?
2) Did the authors look for the right type of papers?
3) Do you think all the important, relevant studies were included?
4) Did the review's authors do enough to assess quality of the included studies?
5) If the results of the review have been combined, was it reasonable to do so?
6) What are the overall results of the review?
7) How precise are the results?
8) Can the results be applied to the local population?
9) Were all important outcomes considered?
10) Are the benefits worth the harms and costs?

Across the 15 included articles, CASP appraisal demonstrated generally strong methodological quality, with most questions receiving a 'Yes' response. However, for CASP Question 4, the majority were scored as 'Can't tell', reflecting limited reporting of critical appraisal methods. This represents a potential limitation in the overall evidence base. Table 3 presents a summary of the critical appraisal conducted in this thesis and its findings.

Despite these limitations, all studies made strong contributions by contextualizing their results within current healthcare literature and highlighting transferability considerations. Importantly, the consistent findings provide a clear AI's potential in medical imaging while also addressing deployment challenges, such as ethical and legal barriers, thereby offering strong support for answering the research questions.

Table 3 Summary of the CASP checklists evaluation results

	Questions in CASP checklist for Systematic Review									
References	1	2	3	4	5	6	7	8	9	10
1P	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
2P	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
3P	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
4P	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
5P	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
6P	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
7P	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
8P	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
9P	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
10P	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
11P	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
1S	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
2S	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3S	Yes	Yes	Yes	Can’t tell	Yes	Yes	Yes	Yes	Yes	Yes
4S	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

P=PubMed S=ScienceDirect

4.4 Data analysis

In this thesis, qualitative content analysis method was conducted. Qualitative content analysis is a systematic research approach that enables researchers to examine keywords, themes, and trends in the literature to identify key issues and concepts within field of the study. Through coding and analyzing literature on a specific topic, researchers can uncover relationships, patterns, and distinctions among various studies, thereby developing a more thorough understanding of the current state of research. This method facilitates a structured and in-depth exploration of textual data, enhancing the interpretative rigor of the findings. (Elo & Kyngäs 2007:107-115.)

To thematize the findings, there were steps involved in this process. First, all of the data was analyzed in an inductive way by identifying the content units which generated from original studies. Second, for make the data analysis more manageable, then the content units were condensed concisely without losing the core information. Third, the condensed meaning units were further synthesized into high-level main categories that capture the core themes of the data. These categories were defined and named to reflect the underlying patterns in the data. Last, the relationship between categories were clustered together to identify overarching themes (See Table 4). (Graneheim & Lundman 2003.)

Table 4 Thematic Summary of Findings

Step 1	Step 2	Step 3	Step 4
Meaning units	Condensed meaning units	Categories	Themes
AI models offer radiologists valuable prognostic insight, leading to more definitive diagnoses and precise clinical management recommentation	AI models enhance radiologists' prognostic insight, improving diagnostic accuracy and clinical management precision	AI improves diagnostic accuracy and clinical management precision	The opportunity of deploying AI in diagnostic accuracy and clinical decision-making (or the application of AI in diagnosis and clinical decision-making)
AI reduces radiologists' workload by 40%-72% through triage system that exclude low-suspicious DBT images while maintaining non-inferior cancer detection sensitivity, and by cutting interpretation time up	AI cuts radiologists' workload by 40%-72% through triaging low suspicious DBT images and reduces interpretation time by up to 53% via real-time analysis, while maintaining cancer detection sensitivity.	AI streamline radiologists' workload and interpretation time through triaging and real-time analysis.	The opportunity of deploying AI in enhancing radiological workflow efficiency

to 53% via real time AI analysis of suspicious findings during image view.			
Large AI models are transforming medical education by serving as interactive learning tools, such as answering clincial queries, assiting in differential diagnosis, simplifying complex concepts, generating teaching materials, and even achieving exam performance comparable to students, thoguh with varying accuracy across specialities.	Large AI models are reshaping medical education by providing interactive learning support, aiding diagnosis, simplifying concepts, creating teaching materials, and perform at student-level on exam with variable accuracy across specialties.	Large AI models enhance medical education through interactive learning, diagnostic support, content generation, and student-level exam performance.	The opportunity of deploying AI in empowering radiological education
AI in cancer diagnosis requires large, high-quality datasets to learn diverse disease presentations, but data must also be unbiased and representative to avoid perpetuating health disparities while improving patient outcomes.	AI in cancer diagnosis needs large, unbiased datasets to capture disease diversity and prevent health disparities.	AI in cancer diagnosis depends on diverse, unbiased data to ensure equity.	The challenge of data limitation in the deployment of AI for medical imaging
The intergration of AI in clinical decision-making raises complex ethical and legal dilemmas regarding accountability for	AI integration in clinical decision creates ethical and legal challenges over who is accountable for errors or adverse outcomes.	AI in clinical decisions raise ethical and legal questions about accountability for errors.	The challenge of ethics and legal and regulatory in the deployment of AI for medical imaging

errors or adverse outcomes, as responsibility may ambiguously fall on developers, data providers, physicians, or healthcare institutions.			

5 Results

The systematic search initially identified 2220 articles across PubMed and ScienceDirect databases (Figure 2). After removing duplicates and ineligible records, 15 articles met the final inclusion criteria and were incorporated into this umbrella review. All 15 reviews included in the analysis were sourced from reputable publications and were published between 2019 and 2014, which is a period characterized by rapid advancements in artificial intelligence. The results revealed five dominant themes that collectively provide a comprehensive framework for understanding the opportunities and challenges associated with deploying AI in medical imaging.

5.1 The opportunity of deploying AI in medical imaging

5.1.1 Theme 1: AI increases diagnostic accuracy and efficiency

Artificial intelligence technology has been deeply integrated into modern clinical radiological diagnosis, with the application of deep learning technology being particularly significant. This trend is evidenced by regulatory approval data: the U.S. Food and Drug Administration has approved approximately 500 artificial intelligence/machine learning medical devices, nearly 80% of which are applied in the field of radiology, and most are designed as clinical decision support tools to assist in diagnosis. (Kim, Kang, Kim, Nagar, Sabuncu, Margolis and Kim 2023.) These systems enhance clinical workflow through three core capabilities: classification, segmentation, and detection. Collectively, these functionalities improve diagnostic accuracy, operational efficiency, and transforming radiological practice. (Mall, Singh, Srivastav, Narayan, Paprzyci, Jaworska and Ganzha 2023.)

1. Classification

Classification is to determine the category of objects contained within an image via a trained Convolutional Neural Networks (CNNs) model (Goldberg, Reig, Lewin, Gao, Heller and Moy 2022). CNNs leverage a combination of convolutional layers, pooling layers, and fully connected layers to automatically extract image features and perform image classification (Mall, Singh, Srivastav, Narayan, Paprzyci, Jaworska and Ganzha 2023).

As Figure 3 indicates, the convolutional layers slide the convolution filters over the input image to extract local features. Each convolution filters generates a feature map, and multiple convolution kernels can extract different features. Next, the pooling layer reduces the size of the feature map through down sampling operations, therapy reducing computational complexity and preventing overfitting. The commonly used pooling operation is max pooling. Then CNNs introduce nonlinearity to learn complex patterns. Finally, the full connected layer integrates extracted features for final classification, mapping learned representation to output classes. (Mall, Singh, Srivastav, Narayan, Paprzyci, Jaworska and Ganzha 2023; Zaidi & Naqa 2021:249-276.).

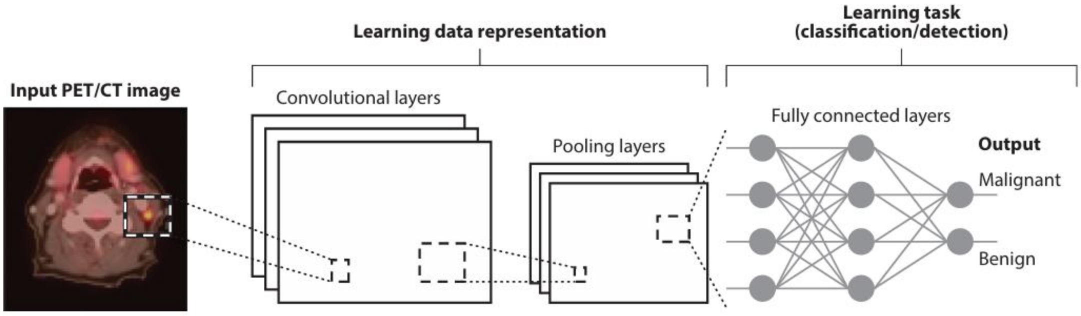

Figure 3 The CNNs architecture for classification (Applied according to Zaidi & Naqa 2021)

The common application of classification in medical imaging is to recognize abnormal anatomical findings automatedly, thereby increasing diagnosis accuracy and screening efficiency. Such as in breast cancer, by analysing mammography, image classification algorithms can assist doctors in identifying abnormal areas in breast tissue and distinguishing between benign and malignant lesions, thereby improving the early diagnosis rate of breast cancer. By extracting and analysing features such as microcalcification, the shape and margin of masses in mammography, AI can also help determine whether there are signs of cancer. (Goldberg, Reig, Lewin, Gao, Heller and

Moy 2022.) In addition, in lung CT images, algorithms can detect pulmonary nodules and classify them based on features such as size, shape and density to determine whether they are malignant. This plays a critical role in early lung cancer screening and diagnosis, enabling physicians to promptly identify potential cancerous lesions and develop appropriate treatment plans. (Zaidi & Naqa 2021:249-276.)

2. Detection

The second application of AI in medical image is detection. While both image classification and object detection can identify entities, they serve distinct purpose. As mentioned above, image classification assigns a single label to entire image without spatial information, whereas object detection advanced this by localizing multiple objects with bounding boxes when classifying each instance. Abnormality detection in medical images, including tumors and other suspicious growths, is a routine part of radiologists' work. However, lesion areas are often very small relative to the entire image, making manual annotation time-consuming and subjective. AI-based automated detection methods can improve both efficiency and reliability in lesion identification, currently being widely applied in detecting pulmonary nodules cancers and cardiovascular diseases. (Chavva, Crawford, Mazurek, Yuen, Prabhat, Payabvash, Sze, Falcone, Matouk, Havenon, Kim, Sharma, Schiff, Rosen, Cramer, Gonzalez, Kimberly and Sheth 2022:574-587.)

For cancer diagnosis, Alshuhri et al have stated that early cancer detection is crucial because it significantly improves survival rates, reduces treatment invasiveness, and lower healthcare costs (Alshuri, Al-Musawi, Al-Alwany, Uinarni, Rasulova, Rodrigues, Alkhafaji, Alshanberi, Alawadi and Abbs 2024). Conventional imaging detection approaches have been constrained to subjective visual tumor assessment and oversimplified morphometric analyses for tracking therapeutic efficacy. Although computer-assisted diagnosis (CAD) has been applied to cancer detection since 1990, but early CAD systems failed to significantly improve diagnostic accuracy, primarily due to a trade-off between marginally increased sensitivity and substantially reduced specificity. Introducing AI in imaging detection provides new opportunities for cancer detection (Cheung and Rubin 2021:728-736). With its powerful computational and analytical capabilities, AI can identify cancerous cellular structure, classify and subtype cancers, while providing radiologists with evidence-based guidance for personalized treatment planning (Alshuri, Al-Musawi, Al-Alwany, Uinarni, Rasulova, Rodrigues, Alkhafaji, Alshanberi, Alawadi and Abbs 2024). Studies show that AI-assisted interpretation increases diagnostic sensitivity for malignancies while preserving specificity, with achievement of 100% sensitivity for calcifications and 91% overall malignancy detection. When integrated as a decision support tool, AI elevates radiologists’ sensitivity by 8% percentage point (to 85%) and specificity by 7% (to 70%). In addition, AI also outperform in lung disease with an accuracy of about 95% in Covid-19 diagnosis. (Goldberg, Reig, Lewin, Gao, Heacock, Heller and Moy 2022; Mall, Singh, Srivastav, Narayan, Paprzyci, Jaworska and Ganzha 2023.) These results collectively establish AI as a transformative adjunct in radiological practice, enhancing both detection reliability and diagnostic confidence.

3. Segmentation

The third powerful capability of AI is segmentation. Image segmentation is highly valuable in medical imaging, as it plays a critical role in analysing and diagnosing specific diseases. Accurately identifying regions of interest (ROIs) in samples is a key step for performing effective features segmentation. (Xie, Pan, Zhang and An 2022.) The objective of medical image segmentation is to classify pixels as belonging to specific anatomical structures or pathological regions, with accurate segmentation being prerequisite for volumetric and shape-based quantitative measurements in clinical practice (Litjens, Kooi, Bejnordi, Setio, Ghafoorian, Laark, Ginneken and Sánchez 2017:60-88). The process of image segmentation is to partition a digital image into multiple distinct regions, where pixels within each region share similar characteristics such as grayscale intensity, colour, texture, or shape (Mall, Singh, Srivastav, Narayan, Paprzyci, Jaworska and Ganzha 2023). By introducing DNNs-based segmentation method, particularly CNNs, image segmentation can be performed by automating the extraction of complex, discriminative features directly from input images, and classifying each image unit into anatomical/pathological regions without requiring manual ROI delineation. (Xie, Pan, Zhang and An 2022; Mall, Singh, Srivastav, Narayan, Paprzyci, Jaworska and Ganzha 2023.)

In medical segmentation, the most renowned architecture is U-Net (Chavva et al 2022). Here, the author took U-Net as an example to exemplify the mechanism behind DL-based segmentation. The U-Net architecture consists of two primary components: an encoder, also known as contracting path, and a decoder path. In this network, the input image first undergoes down sampling through the encoder to capture contextual features, the decoder then restores spatial resolution through up sampling. Last, the final output is a segmentation map with identical dimension to the input image (See Figure 4). (Siddique, Paheding, Elkin and Devabhaktuni 2021.)

Multiple U-Net variants have been successfully utilized in image segmentation such as Inception-ResNet-V2, GAN, and so forth (Constant, Aubin, Kremers, Garcia, Wyles, Rouzrokh and Larson 2023). These methods have demonstrated robust performance in segmenting different anatomical structures, such as abdominal organs, cardiovascular anatomy, and neuroanatomical regions (Singh, Srivastav, Narayan, Paprzyci, Jaworska and Ganzha 2023).

According to Kim et al, in prostate gland segmentation, U-Net architecture has achieved Dice similarity coefficients of approximately 0.9, indicating excellent agreement between algorithm-generated segmentations and manual ground-truth annotations. Another example of DL based segmentation architecture is the 3D V-Net, proposed by Ronneberger, Fischer, & Brox. This well performance architecture was tested across diverse medical tasks, for instance lung segmentation in CT scans with Dice score of 98.7%, brain tumor segmentation in MRI with Dice score of 98.67%. (Mall et al 2023.)

Segmentation and quantitative analysis of neuroimages is essential for diagnosing, monitoring, and treating stroke. Neuroimaging enables precise hematoma localization, volumetric quantification, and spatial characterization. Human-performed segmentation demands substantial time investment while remaining vulnerable to inter-rater variability and measurement inaccuracies while deep neural networks (DNNs) have revolutionized neuroimages by offering automated, precise, and efficient solutions for analyzing complex anatomical and pathological structures. As Chavva et al stated in their studies, Architectures like U-Net, with its encoder-decoder design and “overlap-tile” strategy enables accurate segmentation while handling spatial context and large image sizes effectively. The integration of specialized modules, such as attention mechanisms and dense connectivity further enhances model performance by focusing on relevant regions and reusing features. Three-dimensional CNNs, like DeepMedic, have successfully segmented stoke lesions by using multi-modal MRI data (Chavva et al 2022:574-587.) The applications of DNNs based segmentation have significantly reduce manual annotation workload in medical image analysis while improving segmentation accuracy.

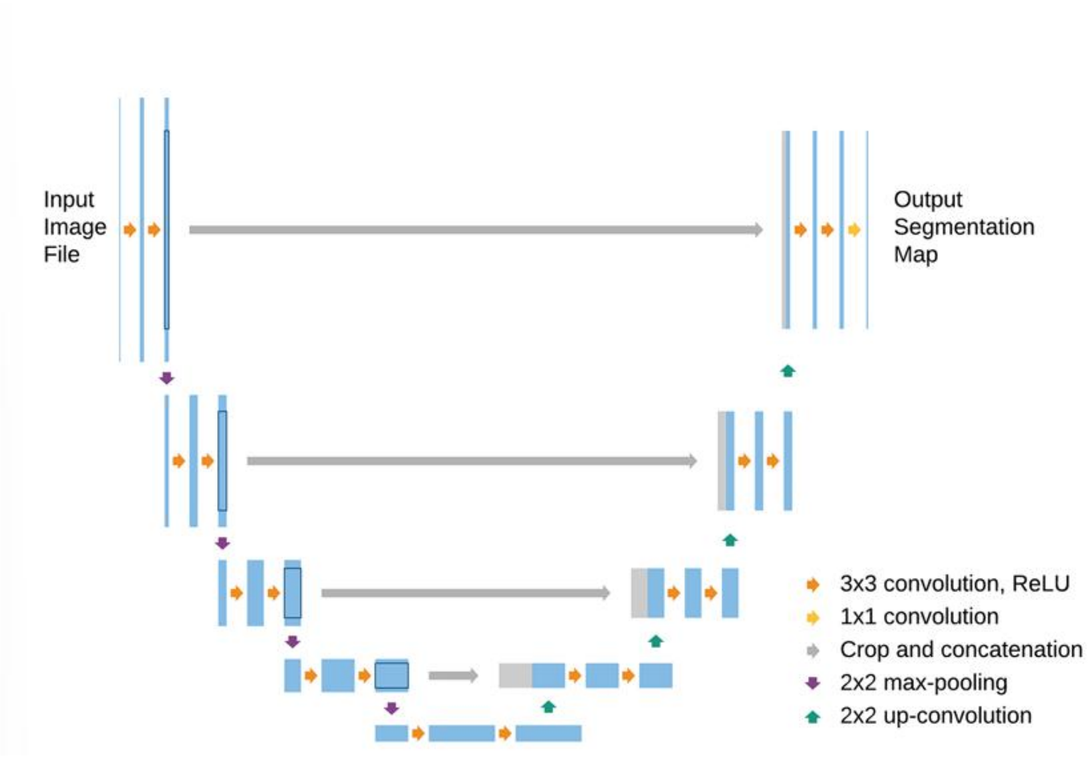

Figure 4 The basic U-Net architecture (Applied according to Siddique, Paheding, Elkin and Devabhaktuni 2021)

5.1.2 Theme 2: AI enhances radiological workflow efficiency

With the advancement of scientific technology and the widespread adoption of medical imaging applications, the escalating demands on radiologists, which are driven by growing imaging volume, complex multi-modal studies, and diagnostic time pressure, have made workload reduction a pivotal focus of AI development (Vrudhula, Kwan, Ouyang and Cheng 2024; Flory, Napel and Tsai 2024:152-160).

The clinical utility of medical imaging hinges on two critical phases: image acquisition and image interpretation. Both of which directly impact diagnostic accuracy and patient management. AI is now revolutionizing these processes (See Figure 5). (Vrudhula, Kwan, Ouyang and Cheng 2024).

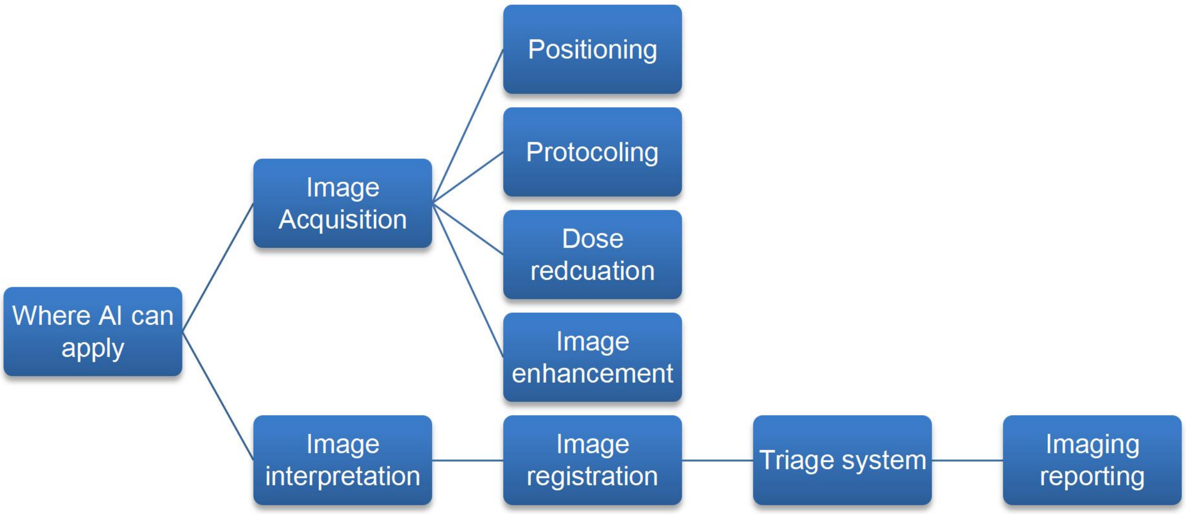

Figure 5 Major processes in medical imaging with the potential of AI application

1. Image acquisition

Recent development in AI-powered MRI workflow has significantly enhanced automation and standardization, effectively reducing manual labor and minimizing inter-operator variability. One of the key focuses has been the AI-driven auto positioning, which is used deep learning algorithms to automatically detect anatomical structures for precise scan plane positioning, reducing manual adjustment. (Potočnik, Foley and Thomas 2023:376-385.) AI, and Natural Language Processing more specifically also enables intelligence protocol selection by recommending radiologists the optimal scan parameters based on exam type and patient history, which will significantly reduce variability in protocols across institutions or operators, improving result comparability. (Flory, Napel and Tsai 2024:152-160).

The use of ionizing radiation in medical imaging carries potential risks that be balanced against diagnostic benefits. Elevated exposure to medical radiation has led researcher to project thousands of future radiations induced cancers in the U.S due to the per capital radiation dose increase dramatically. (Hendee and O'Connor 2012:312-321). Fortunately, AI has demonstrated significant potential in enhancing low-dose medical imaging across multiple modalities. For PET and CT scans, AI can augment low-dose images to match standard-dose quality, even reducing radiation exposure by nearly half for children. In MRI, AI can also augment low-resolution MRI image to high-resolution outputs while suppressing noise. This approach also outperforms in digital breast tomosynthesis (DBT). (Singh et al 2024; Goldberg et al 2022.)

With the rapid advancement of computer vision technology, AI is now being applied to image enhancement to improve both image quality and information extraction. This is a computational approach utilizing algorithmic processing to improve image fidelity through detail enhancement and tissue contrast resolution. (Vrudhula, Kwan, Ouyang and Cheng 2024.) Some studies have shown that advanced algorithms can effectively address artifacts, such as metal-induced distortion, and motion blur, denoise noise, enable high-quality reconstructions from low-dose, and accelerated MRI with super resolution CNNs. These techniques are widely used in lung, cardiac, and brain scan. (Mazurowski, Buda, Saha, Bashir 2020; Flory, Napel, Tsai 2024; Zaidi, Naqa 2021.)

2. Image interpretation

The rapid advancement and widespread clinical adoption of medical imaging technologies have led to an exponential growth in the volume of medical images requiring interpretation, posing increasingly formidable challenges for physicians in diagnostic imaging practice.

Despite the three core capabilities mentioned before, AI can also be applied to image registration. The purpose of image registration is to compare or fuse images of the same object acquired under different conditions, such as from different imaging devices, at different time points, or from vary acquisition angles. Taking human anatomical structures as an example, CT and MRI images can be registered to observe variations of the same anatomy across modalities, thereby facilitating disease diagnosis. Image registration has long been a classic technical challenge in the field of image interpretation. The introduction of AI has brought novel solution to this persistent challenge. (Chen, Tustison, Jena and Gee 2023: 435-458.) In prostate MRI, for instance, traditional multimodal image registration techniques often depend on manual parameter adjustment and metrics such as mutual information and often yield inconsistent performance. The application of deep learning in image registration now offers transformative solutions through learned similarity metrics, cross-modality synthesis, and adversarial training, which not only automate the alignment process but also improve its accuracy. Although further validation of the technology’s robustness across varied patient anatomies and imaging protocols is necessary, the potential of AI in multimodal image registration position it as the promising approach to overcome this long-standing hurdle in medical image analysis. (Goldberg, Reig, Lewin, Gao, Heacock, Heller and Moy 2022; Mazurowski, Buda, Saha and Bashir 2019.)

AI-based triage systems revolutionize medical imaging workflow by automatically prioritizing studies-based urgency and pathology likelihood, leveraging AI models to flag critical findings such as nonmalignant and malignant for immediate review while filtering normal cases. One study has shown that this AI-driven approach can reduce radiologists' workload by 40-72% while maintaining non-inferior sensitivity in cancer detection, Additional studies also evaluate the efficiency of the AI-based triage system and get positive result with reported reductions in reading time ranging from 12% to 53%. These figures demonstrate its dual benefit of enhancing efficiency without compromising diagnostic accuracy. (Goldberg, Reig, Lewin, Gao, Heacock, Heller and Moy 2022.)

Additionally, the powerful language generation capabilities of large AI models have made significant contribution to medical imaging reporting. AI and NLP technologies are reshaping radiology reporting by enhancing accuracy, efficiency, and clinical relevance through automated error detection, personalized report generation that adapts to individual radiologist's style, and seamless integration of quantitative measurements and standardized scoring systems. (Flory, Napel and Tsai 2024:152-160.) Systems such as R2GenGPT optimize report generation quality through visual-language alignment technology while the emergence of general medical artificial intelligence (GMAI) paradigms and multimodal models such as CXR-LLaVA demonstrates the potential to simulate expert-level image interpretation capabilities. These systems can not only automatically generate diagnostic reports and propose evidence-based follow-up recommendations to optimize workflows, but also effectively reduce the cognitive load on physicians. (Pan, Zhao, Lu, Tang, Fu, Liang and Peng 2024.)

5.1.3 Theme 3: AI empower radiological education

The field of medical imaging education is undergoing profound transformation through the integration of artificial intelligence technologies. AI not only improve teaching efficiency but also meaningfully ameliorate the training quality for medical students and radiologist through intelligent analysis, simulation training, and personalized learning. (Pan, Zhao, Lu, Tang, Fu, Liang and Peng 2024.) AI enables rapid processing of historical imaging data such as CT, MRI and X-rays to build structure case libraries, facilitating trainees' education on both typical and rare pathologies. These systems also incorporate adaptive learning method that personalizes content based on skills level, for example, novice focus more on anatomical recognition, while advanced learners engaged more in complex lesion analysis. By creating a tiered and personalized education framework, AI is optimizing the progressive competency development. (Flory, Napel and Tsai 2024:152-160.)

In addition, the shift from paper-based to digital learning is accelerating. AI has demonstrating cross disciplinary potential. Many AI models have been experimented on medical imaging education. For example, CPT-4 has achieved 76.4% accuracy on Korean General Surgery Board Examination, which outperformed lower-level students. AI also provides real-time diagnostic support and differential diagnosis guidance for students, these tools can, for instance, simplified complex image concepts and generates customized teaching materials and Q&A session. This inevitable AI-driven educational transformation is unfolding globally. (Pan, Zhao, Lu, Tang, Fu, Liang and Peng 2024.)

5.2 The challenges in the deployment of AI for medical imaging

5.2.1 Theme 1: Data limitations

Datasets are fundamental to training machine algorithms. By learning patterns and relationship from large volume of data, these algorithms can make predictions and classifications on unseen data. A high-quality dataset provides diverse, well-annotated samples that enable algorithms to better understand the underlying nature of the problem, thereby improving recognition accuracy. (Gong, Liu, Xue, Li and Meng 2023.) Data serves as both fuel for AI advancement and a source of its greatest challenge. Developing robust medical imaging AI faces three key data-related challenges: scarcity, diversity, and high-quality (Hasani, Farhadi, Morris, Nikpanah, Rhamin, Xu, Pariser, Collins, Summers, Jones, Siegel and Saboury 2022:13-29; Singh, Sarrami, Gatidis, Varniab, Chaudhari, Daldrup-Link 2024; Constant, Aubin, Kremers, Garcia, Wyles, Rouzrokh and Larson 2023).

1. Data scarcity and diversity

While AI models training relies on massive datasets, insufficient data, particularly for rare disease and underrepresented populations, severely hinders their development and clinical application in these critical areas and public imaging repositories show severe paediatric data deficit. For example, in the Cancer Imaging Achieve (TCIA), only 8 of 208 published datasets focus on paediatric cases. Although Medical Imaging and Data Resource Centre (MIDRC) is expanding, it currently lacks dedicated paediatric oncology collection. (Singh, Sarrami, Gatidis, Varniab, Chaudhari and Daldrup-Link 2024.) Rare diseases were defined as when its prevalence affects fewer than 200000 individuals in the United States. Although AI technology can be used to improve diagnostic rate, this small sample size still hindered the AI training and the development of AI tools. (Hasani, Farhadi, Morris, Nikpanah, Rhamim, Xu, Pariser, Collins, Summers, Jones, Siegel and Saboury 2022.) Even though the additional data cannot be obtained in short term, alternative strategies such as data augmentation or transfer learning can be employed to mitigate data scarcity (Zaidi and Naqa 2021).

Ensuring diversity and inclusivity in dataset is also critical for both technical performance and ethical AI development. A diverse dataset enhances model capabilities by exposing the system to broader linguistic patterns, knowledge, and cultural contexts. (Gong, Zhong and Hu 2019:64323-64350.) According to Buolamwini and Gebru's research that social biases such as gender, race, and region can be amplified during the model training, leading to systematic biases in generating text or decision-making outcomes. Taking facial recognition technology as an example, its algorithms exhibit significant difference in accuracy across different groups. Studies have demonstrated that the errors rate for recognizing darker-skinned women can be up to 34.7% higher than that for lighter-skinned men. This difference primarily stems from the insufficient representativeness of specific groups in training data. (Buolamwini & Gebru 2018:1-15.)

Furthermore, existing datasets are often overly concentrated on certain disease types, languages, or social groups, failing to fully reflect global diversity. For example, in AI-assisted cancer diagnosis, models trained on data from specific populations often show a significant decrease in diagnostic efficacy when applied to other groups due to data bias. (Alshuri, Al-Musawi, Abdulhasan, Al-Alwany, Uinarni, Rasulova, Rodrigues, Alkhafaji, Alshanberi, Alawadi and Abbas 2024.) These challenges urgently call for across institution collaboration to build diverse, representative datasets (Flory, Napel and Tsai 2024).

2. Data quality

“Garbage in, garbage out” (GIGO) is a fundamental concept in AI models training that stress the critical importance of input data quality. It means that if the data fed into AI models or algorithm is poor, inaccurate, or irrelevant, the system’s output will likewise be flawed, unreliable, or meaningless. (Gong, Liu, Xue, Li and Meng 2023.) Within data quality, data annotation and labelling serves as the cornerstone for building high-quality AI models. Like GIGO principle, if the training data suffers from poor quality, such as high error rates in labelling, inconsistent annotations, or insufficient sample diversity, the critical technical challenge in medical imaging, even the most advanced models and algorithms will inevitably produce subpar AI systems. (Flory, Napel and Tsai 2024; Pan, Zhao, Lu, Tang, Fu, Liang and Peng 2024.)

Researchers Pan et al. and Flory et al. also point out that reginal and cultural variations in language, alone with terminology that evolves due to technological advancements and shifting medical knowledge, present persistent challenges to established algorithms. Compounding these difficulties, the continuous research and innovation in the medical field mean that outdated content can substantially degrade accuracy in algorithms result. In addition, the lack of radiology language consensus also hinders AI development. (Flory, Napel and Tsai 2024; Pan, Zhao, Lu, Tang, Fu, Liang and Peng 2024.)

Therefore, establishing clear and unified data annotation and labelling standards has proven to effectively reduce ambiguity and subjective bias (Alshuhri et al 2024). It is important emphasize that these standards should not remain static but rather be dynamically optimized and iteratively improved through continuous collection of annotate feedback, systematic analysis quality issues, and timely summarization of best practices (Pan, Zhao, Lu, Tang, Fu, Liang and Peng 2024).

5.2.2 Theme 2: Ethics and legal and regulatory

Although the rapid development of artificial intelligence has brought transformative changes to the field of medical imaging, it has also introduced complex governance challenges. Ethic guidelines, legal compliance, and regulatory oversight serve as three core dimensions that are both interconnected and occasionally conflicting. Achieving a balance between technological innovation and social responsibility has become a critical issue in global AI governance. (Pesapane, Volonté, Codari and Sardanelli 2018:745-753.)

1. Ethical challenge

The question “If an AI system makes a misdiagnosis, where bears liability, the developer, the hospital, or the algorithm itself?” has provoked intense debate. (Goldberg, Lewin, Gao, Heacock, Heller and Moy 2022; Mazurowski, Buda, Saha and Bashir 2019). This dilemma intensifies with diagnostic disagreements between physicians and AI systems. Clinician then face the complex challenge of determining the appropriate weight to give an algorithmic diagnosis, particular when DNNs were trained differently from physicians, lacking their equivalent medical education, clinical experience, and adherence to established medical standards. (Chavva et al 2022.)

To resolve diagnostic disagreements, a prior challenge must be addressed: the “black box” (Chavva et al 2022). In artificial intelligence, a “black box” refers to systems or models whose internal mechanisms are invisible or incomprehensible to users or even developers. For such models, while we can observe their inputs and outputs, the exact process of how they transform those inputs into outputs remains complex and opaque. (Bathaee 2018.) To provide epistemic justification for AI-assisted diagnosis, researchers propose visualizing the decision rationale of deep learning models using techniques like Gradient-weighted Class Activation Mapping (Grad-CAM). This method generates coarse location map highlighting which features, such as specific image region most influenced the AI’s output, offering clinicians transparency. (Selvaraju, Cogswell, Das, Vedantam, Parikh and Batra 2017:618-626.)

2. Legal and regulatory challenge

In 2021, Ireland’s Health Service Executive (HSE) suffered a major cyberattack when criminals infiltrated its IT systems, including PCs and servers, using Conti ransomware. The attack catastrophically exposed vulnerabilities in the national healthcare infrastructure, forcibly shutting down critical IT systems and compromising sensitive data from 520 patients. This incident raises urgent questions about privacy protections in automated health ID systems. (Conti cyber-attack on the HSE 2021.)

Specifically, while current legal framework, such as EU General Data Protection Regulation (GDPR), mandate strict informed consent, the collection of historical medical data, such as decade old medical imaging archives, often occurred without anticipating secondary used in the AI era, making retrospective consent technically and operationally challenging to implement. (Chavva et al 2022; Cheung and Rubin 2012:728-736.) Additionally, the de-anonymization risks in medical imaging data also pose a critical concern for AI development. For instance, the conventional privacy protection for DICOM-standard files primarily involves removing metadata like patient names and IDs from files headers, recent studies indicate that these images can still be reidentifies using imaging reconstruction. (Cheung and Rubin 2021:728-736; Moore, Maffitt, Smith, Kirby, Clark, Freymann, Vendt, Tarbox and Prior 2015:727-735.)

The lack of external validation is also a problem that directly impacts reliability and safety of AI models in real world clinical settings. Studies show that only 8% of research independently validates pre-trained models, and only 15% of newly developed models use external data independent of the training set for testing. This lack of validation leads to significant performance bias, limiting the models' generalization ability across diverse population and medical scenarios. (Constant et al 2023.) The WHO warns that large AI models in radiology may induce systemic diagnostic errors without rigorous validation, such as labelling benign lesion as malignancy. Current legal regulations and oversight systems lack provisions to address this issue. (Pan et al 2024; Goldberg et al 2022.)

6 Discussion

6.1 Key findings

The study conducted an umbrella review approach, analysing 15 selected articles from PubMed and ScienceDirect with systematic analysis methods. This thesis investigated that the developmental potential of artificial intelligence (AI) in the field of medical imaging, with particular emphasis on its opportunities to enhance diagnostic accuracy, optimize workflow efficiency, and advance radiology education, alongside with its strong capability in the medical image classification, detection, segmentation and registration. Meanwhile this thesis also provided an in-depth analysis of key challenges including data limitations, ethical concerns, and regulatory barriers. The review listed the key findings of this thesis as below.

Image classification is a fundamental application of artificial intelligence in medical imaging. The introduction of Convolutional Neural Networks (CNNs) is particular crucial, as it effectively promotes the development of the automatic classification ability if visual content. One of the most influential implementations of this technology is the automatic identification of abnormal anatomical findings. For example, in breast cancer screening, image classification algorithms can assist in identifying abnormal areas by analysing mammograms and distinguishing between benign and malignant lesions based on microcalcifications and mass characteristics. (Goldberg, Reig, Lewin, Gao, Heller & Moy 2022.)

Unlike classification, object detection utilizes bounding boxes to precisely locate and identify multiple anomalies within an image. This capability proves particularly valuable in radiology, where small lesions such as tumors are often missed during manual annotation, and the labeling process itself tends to be time-consuming and susceptible to subjective interpretation. AI-driven detection methods have substantially enhanced both the efficiency and reliability of lesion identification, with current applications including pulmonary nodules screening, diagnosis of various cancers, and detection of cardiovascular disease. (Chavva, Crawford, Mazurek, Yuen, Prabhat, Payabvash, Sze, Falcone, Matouk, Havenon, Kim, Sharma, Schiff, Rosen, Cramer, Gonzalez, Kimberly and Sheth 2022:574-587.)

Moreover, AI significantly optimizes the medical imaging workflow by enhancing the efficacy of automation and standardization. Specifically, the automatic positioning technology based on deep learning can achieve precise alignment of anatomical structures, while the intelligent protocol selection combined with natural language processing can optimize the configuration of scan parameters, thereby reducing manual labor and inter-operator differences while improving the comparability of result. (Potočnik, Foley and Thomas 2023:376-385; Flory, Napel and Tsai 2024:152-160).

Besides workflow optimization, this technology can also effectively mitigate radiation risk by augmenting low-dose PET/CT images to standard-dose quality and transforming low-resolution medical imaging into high-fidelity outputs with noise suppression (Singh et al 2024; Goldberg et al 2022). In terms of image quality improvement, advanced computer vision techniques significantly improve the tissue contrast and diagnostic efficacy in the diagnosis of neurological, cardiovascular, and pulmonary disease by correcting artifacts, denoising, and performing super-resolution CNN reconstruction on images obtained from accelerated acquisition or low-dose scanning (Mazurowski, Buda, Saha, Bashir 2020; Flory, Napel, Tsai 2024; Zaidi, Naqa 2021). Examples like U-Net and its variants, these architectures overcome challenges of noisy, low-contrast imaging modalities via encoder-decoder frameworks augmented by attention mechanisms for ROI focus (Chavva et al 2022:574-587).

Image registration is another important area where AI has had a great impact. For a long time, aligning scan images collected at different times or from different devices has always been a technical challenge. AI-driven image registration provides a key solution for observing anatomical structure changes and assisting in disease diagnosis by enabling the comparison and fusion of multimodal. (Chen, Tustison, Jena and Gee 2023: 435-458.) Deep learning has brought fundamental changes to this process. Instead of relying on manual adjustments, which often yield inconsistent outcomes, deep learning automates image alignment by using learned similarity measures and then can even synthesize information across image types, substantially improving both precision and reproducibility. (Mazurowski, Buda, Saha and Bashir 2019.)

AI also plays a crucial role in triage system. It can automatically prioritize studies based on urgency, flagging critical findings for immediate review, and filtering normal cases (Goldberg, Reig, Lewin, Gao, Heacock, Heller and Moy 2022). In addition, the combined use of AI and Natural Language Processing (NLP) can elevate the quality of medical report by helping to identify potential errors, generate tailored report drafts for each individual patient, and incorporate quantitative imaging data directly into the narrative. (Flory, Napel and Tsai 2024:152-160.)

The discipline of medical imaging education is undergoing a profound transformation, with the integration of AI technology significantly enhancing both teaching efficiency and training quality for medical students and radiologists (Pan, Zhao, Lu, Tang, Fu, Liang and Peng 2024). By rapidly analyzing historical imaging data, AI enables the construction of systematic case libraries, allowing trainees to learn from a wide range of typical and rare pathological examples. These intelligent teaching systems incorporate adaptive learning methods that tailor educational content to individual competency levels, allowing novices to focus on anatomical recognition while advanced learners engage in complex lesion analysis. (Flory, Napel and Tsai 2024:152-160.) Furthermore, AI provides real-time diagnostic support and differential diagnosis guidance, simplified complex image concepts, and generates customized teaching materials and Q&A sessions (Pan, Zhao, Lu, Tang, Fu, Liang and Peng 2024).

The author also identified primary data-related challenges for deployment AI in medical imaging which are widely prevent AI from further development and application. The first challenge is data scarcity and diversity, particularly for rare diseases and underrepresented populations. For instance, public imaging repositories exhibit a significant deficit in paediatric data. (Singh, Sarrami, Gatidis, Varniab, Chaudhari and Daldrup-Link 2024.) Only overcome data scarcity alone is insufficient. Actively prioritizing diversity and inclusivity in datasets is vital to enhance technical performance and uphold ethical standards in AI development. Nevertheless, current datasets suffer from widespread biases pertaining to gender, ethnicity, and geographical location, which can be exacerbated throughout model training process. As a result, models trained on data from particular population limit generalizability and perform ineffectively for other groups. (Alshuri, Al-Musawi, Abdulhasan, Al-Alwany, Uinarni, Rasulova, Rodrigues, Alkhafaji, Alshanberi, Alawadi and Abbas 2024.)

The “garbage in, garbage out” (GIGO) principle highlights a fundamental truth in AI development. The quality of input data directly determines the reliability of model outputs. (Gong, Liu, Xue, Li and Meng 2023.) When training datasets include mislabeled examples, inconsistent annotations, or limited diversity, the models will yield questionable results (Flory, Napel and Tsai 2024; Pan, Zhao, Lu, Tang, Fu, Liang and Peng 2024). According to recent studies by Pan et al. (2024) and Flory et al. (2024), medical AI algorithms continue to face significant hurdles due to geographical and cultural languages difference, evolving terminologies from ongoing technological and medical progress, and the lack of standardized radiology language. all of these risk factors collectively threaten to render models less accurate and eventually obsolete in rapidly changing in clinical settings.

The deployment of AI in medical imaging also faces significant ethical and interpretability challenges. Latent biases in training datasets risk perpetuating algorithmic discrimination, disproportionately impacting marginalized populations, such as elevated misdiagnosis rates among African American patients (Vrudhula, Kwan, Ouyang and Cheng 2024; Flory, Napel and Tsai 2024). Furthermore, when diagnostic assessments by AI systems and human clinicians diverge, the ongoing ambiguity regarding liability intensified existing ethical (Goldberg, Lewin, Gao, Heacock, Heller and Moy 2022). The inherent “black box” nature of deep learning coupled with persistent interpretability limitations continues to amplify these tensions (Chavva et al. 2022).

The absence of data privacy and security regulation has exposed critical vulnerabilities within the medical digital system. The incident where the Irish Health Service Executive (HSE) was attacked by Conti ransomware in 2021 was a clear example. This event not only led to the leakage of many patients’ sensitive information, but also severely disrupted healthcare operations, revealing the systemic risks faced by digital health infrastructures. Although existing regulatory frameworks such as the EU's General Data Protection Regulation (GDPR) are robust in principle, they still fall short in handling the retrospective authorization issues related to historical medical imaging data (Cheung & Rubin 2021:728-736). What is even more concerning is that with the advancement of imaging reconstruction technology, even if DICOM files are anonymized, there is still a risk of re-identifying patients' identities (Moore et al. 2015).

The current widespread issue of the absence of external validation has also drawn attention. Study by Constant et al. indicates that only a limited number of models have undergone independent or external testing (Constant et al. 2023). This deficiency often leads to inflated performance outcomes and undermines its generalizability. The WHO has issued a warning that if radiology AI is not subjected to strict validation, it may pose a risk of systematic misdiagnosis. These findings stress the importance of regulation, including requirements for external validation, safety testing, and adherence to ethical guidelines before clinical deployment. (Pan et al. 2024.)

6.2 Reliability and validity

Reliability in research refers to the stability and consistency of the research results in the thesis. When conducting research, ensuring the reliability of the data is of great significance for obtaining reliable results. The central question is: if the study were repeated, would it yield the same or very similar results? A reliable study is like a precise scale, every time it weights the same object, it shows almost identical results. (Olmsted 2024: 53-57.) Unlike reliability in quantitative research, which concerns the consistency and stability of measurements, reliability in qualitative is more concerned with the rigor of the research process and the precision of data collection, encompassing the soundness, transparency, and persuasiveness of the reasoning (Golafshani 2003). In this thesis, reliability was ensured through several methodological and procedural strategies throughout the umbrella review process.

This review adopted a systematic and transparent research design following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The PRISMA flowchart not only enhanced the transparency of this thesis, but also helped reader clearly understand the entire process of study screening, thereby improving the reproducibility and reliability of this thesis. The search strategy, databases information, and time range used in this thesis were fully documented in detail, providing a necessary foundation for subsequent researcher to replicate the experiment under the same conditions.

During the data extraction and analysis stage, the thesis employed an inductive qualitative content analysis method by using a unified coding procedures to identify and categorized themes. This systematic and iterative process effectively enhanced internal reliability by reducing interpretive bias and ensuring consistency in themes development. Through cross validation between identified themes and original materials, the coherence of the argument logic and the accuracy of the conclusion explanation were further strengthened.

The incorporation of a data extraction table (Appendix 1) provides a traceable audit trail of how each conclusion was derived from each study, which reinforced credibility and replicability. Although publication bias and language restrictions may limit the generalizability of the results, the structured and repeatable methodology employed provides solid support for the reliability of the presented outcomes.

The concept of validity in research is to measures the degree to which your research methods and results genuinely support the statements you have put forward. Take the example of scale again, the core questions about the validity are: is your scale accurate? Did you accurately measure what you intended to measure? (Golafshani 2003.) In this thesis, validity was guaranteed through methodological transparency with clearly defined research questions, construct validity, and triangulation of data across multiple high-quality reviews from PubMed and ScienceDirect.

In this thesis, the validity was first established by defining aims and questions derived from the PICo framework. The research questions, which focused on identifying both the opportunities and challenges in deploying artificial intelligence in medical imaging, were directly aligned with study’s theoretical foundation and analytical approach. This ensured that the methods and interpretations accurately reflected the study’s objectives.

This study conducted a comprehensive umbrella review of fifteen high quality reviews, employing a rigorous methodological approach to achieve a systematically integration of existing evidence, thereby providing support for validity. Clear inclusion and exclusion criteria effectively ensured the relevance and logical consistency of the research questions. The use of the Critical Appraisal Skills Program (CASP) checklist further strengthened the credibility by systematically assessing the methodological soundness of the selected studies. By following a transparent data collection and analysis process, the author maximized the control of bias during study screening and integration stages. At the same time, validity was also guaranteed through the inclusion of studies from diverse healthcare contexts and imaging modalities published between 2019 and 2024.

However, several limitations may impact the overall validity. Focusing only on English-language publications may lead to language bias, resulting in the omission of research perspectives from specific regions and the latest technological advancements. Not including the studies outside the specified timeframe might limit the comprehensiveness of the review. Only relying on reviews rather than primary research may also reduce the direct evidentiary value for practical application scenarios. Some included studies did not provide detailed descriptions of their systematic search strategies or inclusion/exclusion criteria, which may introduce selection bias. Transparency about data analysis methods was inconsistent across studies, which could affect the robustness of findings. Despite these limitations, the systematic evaluation, critical appraisal, and transparent reporting collectively uphold the methodological validity of this thesis, proving a trustworthy synthesis of the opportunities and challenges associated with deploying AI in medical imaging.

6.3 Ethical considerations

McGregor (2023: 4-23) pointed out that research ethics refer to the principles and standards that should be followed when designing, implementing and reporting scientific research activities. These norms aim to safeguard the rights and well-being of research subjects, maintain academic integrity, and enhance public trust in scientific work. Based on this concept, this study strictly adhered to the requirements of scientific research ethics throughout its entire implementation process, always placing transparency, integrity and a sense of responsibility at the core (Arene 2020).

Since this thesis was written solely on previously published literature and did not involve human or animal subjects, therefore, no ethical approval was required. All reviewed studies were properly cited and referenced to ensure academic honesty and to acknowledge the original authors’ contributions. The originality of this thesis was verified using Turnitin software, ensuring compliance with academic integrity standards. Additionally, the thesis presented findings objectively and avoided overgeneralization or biased conclusions. This thesis not only affirms the applications value of artificial intelligence in medical imaging, but also critically discusses its limitation. It neither exaggerates the potential of the technology nor avoids the potential challenges.

During the writing process, ChatGPT version 3.5 of OpenAI were used. It is used only for language polishing, grammar checking, and proofreading purpose. No AI system was used for content generation, data collection and interpretation. The conceptualization, analysis, and all interpretations of findings were entirely the author's own work. The use of AI was to assist language editing for improving readability, clarity, and academic tone, without altering the science meaning or integrity of the text. As the author of this thesis, I am responsible for all its content.

7 Conclusion

In this thesis, the author has demonstrated the opportunities and challenges of deploying artificial intelligence (AI) in medical imaging with synthesizing insights from previous systematic reviews and research articles. Based on qualitative analysis, it can be concluded that AI has transformative potential in enhancing diagnostic accuracy to improve patient outcomes, optimizing radiological workflows by alleviating the growing pressure on radiologist, and enhancing medical education to faster clinical decisions through its capabilities of classification, detection, segmentation, registration, and workflow automation.

Meanwhile, the challenges of application of AI in medical imaging cannot be overlooked. Data limitation including data scarcity, lack of diversity, and quality concerns remain persistent obstacles to building robust and generalizable AI models. Ethical dilemmas including algorithmic bias, liability in misdiagnosis, and the "black box" nature of deep learning also raise fundamental concerns about trust and accountability. Moreover, regulatory frameworks are still struggling to keep pace with technological innovation, leaving unresolved issues around privacy, consent, and external validation.

In conclusion, the thesis demonstrated that the successful integration of AI into medical imaging depends not only depends on technological advancement but also require cross-disciplinary collaboration among clinicians, researchers, policymakers, and industry stakeholders. To fully unleash the benefits of AI and effectively manage risks, the future focus of work should be on developing diverse and high-quality datasets, enhancing algorithmic transparency, and establishing a strict governance system and framework.

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Data Extraction Table

Reference	Title/author/year	Type	Opportunity	Challenge
1P	Deep learning application for acute stroke management (Chavva et al 2022)	Review	• DNN have been applied in acute ischemic stroke (AIS) detection to prioritize urgent cases, identify arterial occulusions using 4D CTA, distinguish between stroke and other pathologies and rapidly quantify ischemic lesion on MRI, aiding clinicians in triage and decision-making. • DNNs have been successfully applied in intracranial hemorrhage (ICH) detection, demonstrating performance comparable to radiologists in identifying ICH and its subtypes (intraparenchymal, intraventicular, subdural, extradural, and subarachnoid), optimizing radiology workflows, and even detecting cases missed by experts, though challenges remain in recognizing rare subtypes like subarachnoid extradural hemorrhages. • DNNs, particularly U-Net-based architectures and thier enhanced variants, have advanced qutomated lesion segmentation in stroke imaging by leveraging 2D and 3D convolutional approaches, attention mechanisms, and dense connectivity to achieve precise volumetric and semantic segmentation across maodalitie like MRI, CT, and CTP. • DNNs have been applied in ischemic stroke outcome prognostication by integrating perfusion imaging (TTP,CBF, CBV,Tmax) with clinical data (mRS, NIHSS, TICI scores) to predict tissue fate and functional recovery, demonstrating improved accuracy over traditional scoring systems while aiding in clincal decision-making for thrombolysis and patient selection.	• A key issue in AI-assisted diagnosis is determining the appropriate weight clincians should give to DNN's output when it conflicts with their judgement, compunded by the "black box" nature of deep learning models-lack of interpretability, corporate secrecy, and techical complexity which undermines trust and raises epistemic concerns about whether algorithmic decisons consitute reliable medical knowledge. • When artificial intelligence is integrated into the clinical decision-making process, the responsibility for any errors or adverse consequences may be ambiguously attributed to the developers, data providers, doctors, or medical institutions. This has led to a series of comples ethical and legal dilemmas. • When applying DNNs to stroke management, a key limitation is the data hereogeneity. This includes the diversity of pathological manifestations, differences in scanner models, and variaiton in imaging parameters. • In the process of implementation AI diagnostic tools, a crucial but often overlooked obstacle lies in how to gain the acceptance and trust of doctors. This requires clearly demonstrating how DL models can enhance the efficiency of diagnosis and treatment, improve patient outcomes, and alleviate the professional burnout of medical staff, rather than attempting to replace the professional role.
2P	Artificial intelligence in cancer diagnosis: opportunities and challenges (Alshuhri et al 2024)	Review	• Transform cancer diagnosis by automated image analysis. • Enhanced accuracy and improved efficiency in the cancer diagnostic process. • Image analysis algorithms also enble the monitoring of a patient's condition over time to assess treatment effectiveness.	• AI in cancer diagnosis requires large, high-quality datasets to learn diverse disease presentations and make accurate predictions, but data must also be unbiased and representative to avoid perpetuating health disparities while improving patient outcomes. • Despite AI's potential in cancer detection and therapy, key technical challenges include limited

				interpretability ('black box' algorithms), scalability constraints, generalizability issues across diverse populations, data quality concerns, and insufficient regulatory frameworks. • AI in cancer detection raises critical ethical and privacy challenges which include patient data protection, algorithmic bias risks, informed consent requirements, impacts on doctor-patient trust, and liability concerns, all demand robust governance frameworks and multi-stakeholder collaboration to ensure ethical deployment that prioritizes patient rights and equitable care.
3P	Artificial intelligence in medical imaging and its impact on the rare disease community: threats, challenge and opportunities (Hasani et al 2022)	Review	• Enrich medical imaging data diversity. • Implementing TB-PET dynamic imaging with AI-based kinetic modeling can yield valuable pharmacokinetic data for investigational using a limited subject pool.	• The limited population leads to insufficient data and less reliable pharmacokinetic estimations due to small sample sizes and sparse data.
4P	Artificial intelligence in radiology opportunities and challenges (Flory, MN., Napel, S., Tsai, EB. 2024)	Review	• AI models offer radiologists valuable prognostic insight, leading to more definitive diagnoses and precise clinical management recommentation. • AI/ML techniques enhance image quality, leading to lower rescan. and recall rates. • To help radiologist manage increasing workloads through protocoling and worklist prioritization. • Streamline report generation and appropriate follow-up, facilitated by algorithms lead to improvements in patient care. • AI offers potential for personalized radiology education. • Radiology-pathology case correlation, feedback, and AI-driven task delegation can prioritize trainee time and mental energy for higher-level learning. • AI processes large data for personalized mangement, better disease characterization, early detection, and automation/efficiency in key tasks.	• Uncertain diagnostic thresholds and limited generalizability pose challenges to the clinical integration of AI algorithms. • Over-reliance on AI can lead to automation complacency, include annotator reporting bias, and foster anchoring bias in decision-making. • Bias in sampling, systemic factors, and availability, decontextualization, non-generalizability, and a lack of inclusive data. • AI data handling faces issues with aleatoric uncertainty, the potential for bias through simplification, and the influence of human factors like proxies and latent variables.
5P	Challenges and opportunities for artificial intelligence in oncological imaging (Rubin,	Review	• While predominantly manual detection is current practice, the adoption of automated or semi-automatic techniques, with the potential for AI integration, could significantly improve accuracy and efficiency.	• Access to large, good-quality, multi-institutional datasets remains a key obstacle for AI research in the field of oncology. • Inconsistent or poor-quality imaging data acts as a substantial

	D. & Cheung, H.M.C. 2021)		• The accuracy of diagnosis and risk stratification, currently guided by predominantly clinical ”rules” (TI-RADS, Lung-RADS,PI-RADS, etc.), has the potential for imprvement through AI. • While tumor segmentation is not typically performed due to its labor-intensive nature, AI technology has the potential to significantly improve both its efficiency and reliability, thereby enabling feature extraction for other AI applications in oncological imaging. • AI technology presents an opportunity to enhance precision oncology by subtyping tumors into established or newly identified histopathological and genomic categories, thus guiding targeted therapeutic ineterventions. • To improve upon the limitations of anatomical staging for prognosis and size-based criteria (e.g., RECIST) in assessing treatment response (which can be confounded by pseudoprogression/pseudoresponse), AI technology can subtype tumor by their biology and grade to guide therapy, and leverage additional features like tumor morphology, beyond just size, to better detemine response and differentiate it from treatment effects.	impediment to progress in AI research within oncology. • The labour-intensive nature of tumor segmentation and annotation poses a significant barrier to the efficient development and application of AI in oncology research. • Integrating the perspectives and workflows of multiple disciplines, a necessity for impactful AI resaerch in oncology, can present a considerable barrier. • Leveraging AI research for oncology is the difficulty in developing and implementing streamlined processes that seamlessly integrate with established. clinical workflows. • Legal and ethical hurdles satnd as important barriers that must be addressed to facilitate the progress of AI research in oncology.
6P	Deep learning in radiology: an overview of the concepts and a survey of the state of the art within focus on MRI (Mazurowski, MA., Buda, M., Saha, A., and Bashir, M. 2020)	Review	• In radiology, classification tasks include detecting abnormalities, distinguishing benign from malignant lesion, categorizing tumors by histopathological/genomic features, predicting prognoses, and organizing imaging data. • Fully Convolutional Neural Network (fCNN) can be applied to address the shortcoming of voxel-based segamentation methods • Deep learning approach can be used for high sensitivity and sub-images extraction in detection. • Deep learning can be used in spatial alignment in medical images. • Deep learning leverages technologies such as convolutional neural networks (CNN) and genrative adversarial networks (GANs) to enable applications in medical processing including cross-parameter image synthesis, low-dose CT reconstruction, and real-time compressed sensing MRI reconstruction. • Deep learning enhances medical image quality through super-resolution	• The implementation of deep learning in radiology raises legal and ethical challenges, primarily concerning liability for AI errors, a question that has historical paralles with the introduction of other technologies and will likely be addresses as AI becomes more widespread. • Patient acceptance of AI interpreting their images without direct human involvement, alongside evolving regulatory requirements. • Effectively integrating deep learning algorithms into the radiology workflow, with the primary goal of improving rather than disrupting current practices, is a key practical concern.

			and denosing techniques, significantly reducing scan time and radiation/contrast agent dosage while outperforming traniditional methods. • Deep learning enables effcicient similarity search in medical imgage databases by leveraging pre-trained CNNs to extract organ-specific features, utilizing comparison of fully connected layer features for retrieval. • Deep learning automatically assesses medical image quality (e.g., fetal ultrasound, liver MRI) via CNNs, classifies diagnostic usability, reduces data acquisition variability, and enhances the reliability of subsequent clinical decisions.	
7P	New horizons: Artificial Intelligence for Digital Breast Tomosynthesis (Goldberg et al 2022)	Review	• AI algorithms achieve non-inferior or improved sensitivity in cancer detection compared to traditional interpretation of screening DBT studies in clinical settings. • AI reduces radiologists' workload by 40%-72% through triage system that exclude low-suspicious DBT imges while maintaining non-inferior cancer detection sensitivity, and by cutting interpretation time up to 53% via real-time AI analysis of suspicious findings during image view. • AI reduces unnecessary recall rates in breast cancer screening by 17%-25% through triage systems that excluded low-suspicious DBT studies from radiologist review, while maintaining non-inferior cancer detection sensitivity, though effectiveness varies by AI system, dataset coposition, and clinical workflow. • AI localize and classifies abnormal imaging findings via CNN-generated bounding boxes with malignancy confidence scores and cross-modal integration, achieving up to 97% sensitivity in malignancy detection while highlighting suspicious regions through comparative analysis of normal tissue patterns. • AI enhances the conspicuity of suspicious lesions in DBT by reconstructing synthetic two-dimensional mammograms (SDM) with highlighted abnormalities, denoising images while preserving critical features, and reducing anatomic noise, improving diagnostic accuracy despite variability in vendor-specific reconstruction algorithms. • AI reduces radiation dose in DBT by	• AI systems are often tailored to specific vendor acquisition/reconstruction techniques, limiting generalizability across platforms. • Many AI tools focus on specific findings (e.g., masses or calcifications), missing the ability to identify overlapping or coexisting abnormalities. • Legal responsibility for AI false negatives (e.g., missed cancer) is unclear-liability may fall on radiologists, developers, or AI itself. • Use of "big data" raises risk of re-identification and breaches unless robust anonymization protocols are enforced. • AI trained on non-diverse datasets may perpetuate racial/ethic disparities (e.g., underdiagnosis in black patients). • AI outputs often ignore electronic health records, leading to false positives. • Many studies are retrospective or proof-of-concept, lacking real-world validation (e.g., impact of AI triage on clinical outcomes). • Historical failures of CAD tools hinder trust in newer AI systems, slowing adoption. • Cross-institutional collaboration and transparent algorithms are required to be benchmark performance consistently. • Patient resistance to AI-driven care due to transparency gaps or fear of algorithmic errors. • Prospective syudies are needed to evaluate long-term improvement in patient care (e.g., cancer detection

			generating SDM to replace higher-dose DM acquisitions and enhancing low-dose tomosynthesis images via neural networks trained to reconstruct diagnostic-quality visuals from reduced exposures (e.g., halving dose while preserving microcalcification visibility), with parallel applications in PET and CT for dose optimization. • AI assesses breast cance risk by objectively quantifying breast density (reducing radiologist variability) and analyzing parenchymal complexity via radiomics, leveraging volumetric DBT data for stronger risk association than 2D mammography, though current models remain limited to 2D modalities and require further development for 3D integration and diverse population validation.	rates, mortality reduction).
8P	Machine learning and bias in medical imaging: opportunities and challenges (Vrudhula, A., Kwan, A. C., Ouyang, D., and Cheng, S. 2024)	Review	• Machine learning reduces bias in imaging by analyzing geographic inequities (e.g., travel distance disparities), optimizing resource allocation, automating workflows to address personnel shortages, and guiding evidence-based imaging decision via clinical decison support systems, thereby mitigating systemic disparities and improving equitable resource distribution. • Machine learning reduces bias in imaging acquisition by adapting to technical variability (via diverse dataset training), compensating for patient-specific factors (e.g., body habitus, positioning) through AI-guided protocol adjustments, and optimizing study protocol to minimize repeat exams-particularly in underserved populations-using semi-automated tools that standardize quality across equipment and operators. • Machine learning reduces bias in imaging intepretation by automating and standardizing traditional feature measurements (e.g., tumor quantification) and identifying novel biomarkers through computer vision-driven pattern recognition, thereby minimizing subjective interpreter variability and enhancing diagnostic consistency across diverse patient population.	• Machine learning entrenches bias when trained on imbalance datasets (e.g., sex, age, race), leading to underperformance in underrepresented racial, gender, and age groups and perpetuating healthcare diaparities in diagnosis and treatment. • Inadequate or misaligned labeling of clinical variables in AI models entrenches biases, leading to misclassification of patient health status, unless mitigated by explainability methods ensuring predictions rely on biologically plausible features. • Machine learning risks amplying biases by inferring demographics (e.g., race) from imaging through confounding factors like medical device prevalence or comorbidities, reinforcing systemic healthcare disparities despite lacking direct biological revevance.
9P	Quantitative molecular positron emission tomography imaging using	Review	• Deep learning enhances PET instrumentation design by improving spatial resolution, optimizing time-of-flight (TOF) resolution via CNNs analyzing detector waveforms, and	• Determing an adequate sample size is a key challenge in the the application of ML/DL algorithms in the field of molecular imaging, which stems from the absence of

	advanced deep learning techniques (Zaidi, H., and Naqa, I. E. 2021)		enabling cost-effective partial-ring geometries through missing dat restoration-collectively advancing performance while reducing system costs. • Deep learning provides multi-dimensional optimization opportunities in PET imaging. Including end-to-end image reconstruction (such as direct mapping from sine plots), joint attenuation and scattering correction (especially solving the attenuation problem guided by MRI in PET/MRI), high-precision lesion segmentation (such as achieving a Dice coefficient of 0.87 through U-Net), and fast unsupervised image registration (with computational efficiency improved by several orders of magnitude) Significantly improve the accuracy of quantitative analysis and support personalized diagnosis and treatment. • Deep learning offers significant opportunities in PET image enhancement, enabling denoising, low-dose to standard-dose image conversion (with and without anatomical MRI integration), and superresolution through implementation in both image and projection spaces-where projection-based methods demonstrate superior quality-while reducing acquisition times in oncological and cardiac imaging and outperforming classical techniques like penalized deconvolution. • Deep learning presents significant opportunities in radiation dosimetry calculations (therapy planning) by enabling efficient and accurate absorbed-dose estimations for external radiotherapy, brachytherapy, and internal dosimetry—outperforming traditional methods (e.g., voxel S-value convolution) and matching Monte Carlo precision through U-Net-based models, hybrid techniques, and patient-specific whole-body approaches that account for heterogeneous tracer dynamics and attenuation, thereby addressing limitations of conventional methods. • Deep learning revitalizes computer-aided detection and diagnosis (CADe/x) in molecular imaging by enabling high-accuracy disease prediction and improved lesion localization/classification in cancers through multimodal integration and interpretable CNN architectures,	traditional statistical power analysis tools. This situation requires researchers to conduct empirical learning curve evaluations and, when data is limited, to rely on data augmentation or transfer learning instead. • In modular imaging ML/DL application, another critical challenge is to ensure model generalizability beyond training data. This requires rigorous validation (e.g., cross-validation, external cohort) and adherence to reporting guidelines like TRIPOD to achieve reliable, clinical translatable performance. • The third challenge in clinical ML/DL implementation is to ensure the interpretability, particularly for complex applications like outcome prediction. This requies the use otechniques such as attention maps, disentangled representations, or integration of known operators to build trust and understanding in model decision.

			overcoming historical limitations of complexity and limited data in quantitative PET analysis. • Deep lerning advances radiomics and outcome prediction models by transtioning from human-enginering features to automated data representation, enabling hybrid frameworks that synergize traditional radiomics with Dl to overcome sample size constrints while integrating expert knowledge, particular enhancing predictive accuracy in oncology.	
10P	Application of artificial intelligence for pediatric cancer imaging (Singh, S. B., Sarrami, A. H., Gatidis, S., Varniab, Z. S., Chaudhari, A., and Daldrup-link, H. E. 2024)	Review	• AI offers transformative opportunities in medical image acquisition and processing by enabling radiation dose reduction (e.g., augmenting low-dose PET/CT to standard-dose), accelerating MRI scan via resolution enhancement, improving pediatric-specific diagnostics through tailored models (overcoming adult-to-child anatomical mismatches). • AI presents significant opportunities in medical image segmentation by leveraging encoder-decoder architectures for adult and emerging pediatirc application-enabling automated tumor detection, pediatric-specific organ segmentation. • AI offers opportunities to enahnce pediatric tumor diagnosis and treatment response by integrating radiomics (handcraft features) and deep learning for comprehensive analysis of tumor characteristics.	• The challenge mentioned is balancing noise reduction with image fidelity, where AI might remove important details. • Challenge in whole-body imaging for pediatrics: variability in protocols, complex anatomy, and size diversity. [Deep learning algorithms for adults can be adapted via tranfer learning. The example is U-Net pretained on adult data and cross-trained for pediatric CT and PET] • Limited pediatric data hinders clinical application. • Rapidly evolving anatomieis of pediatric patients and the lack of standardized imaging protocols across institutions and modalities.
11P	The role of AI in prostate MRI quality and interpretation: opportunities and challenges (Kim et al 2023)	Review	Image interpretation • AI present transformative opportunities in tumor detection and diagnosis by leveraging ML with hand-engineered radiomics features and DL (CNN/U-Net architectures) to automate feature learning, enhance diagnostic precision (e.g., prostate cancer detection with AUC > 0.82), reduce radiologist workload, and enable clincial translation through large-scale challenges (PI-CAI, PROSTATEx) and FDA approved tools for real-world integration. • AI offers opportunities in segmentation by using U-Net and GAN to achieve high accuracy (Dice~0.9), aiding biopsy and treatment planning, and overcoming challenges like small lesions through multi-scale designs and augmentation. • In image registration, AI presents	Image interpretation • A key challenge in applying AI to prostate cancer management is the scarcity of well-curated, diverse MRI datasets (due to costly expert annotations and protocol variability), leading to overfitting risks in DL models, limited generalizability across patient cohorts and imaging setups, and insufficient external validation for clinical translation. • Another key challenge in utilizing public prostate MRI datasets for AI is their heterogeneity in annotations, small sizes, and overlapping cases, leading to inflated aggregate data perceptions and unreliable model conclusions when merged. Image quality • Deep learning faces many challenges in MRI post-processing,

			significant opportunities. By leveraging deep learning techniques, such as adversarial learning, contrastive learning, and image synthesis, AI can address cross-modality challenges (e.g., MRI-US/CT fusion), thereby enhancing robustness and clinical precision for biopsy guidance and radiation therapy planning. • AI offers new opportunity for improving prognosis and active surveillance in prostate cancer by integrating multimodal data, the AI system can overcome the limitation of traditional ML approaches that relies on hand-engineered features and improve predictive accuracy. Image quality • Deep learning has opened up a new path for improving the qulity of prostate MRI acquisition by enabling accelerated imaging via compressed sensing/parallel imaging, reducing contrast agent use in mpMRI through synthetic DCE-MRI generation, and maintaining diagnostic quality while lowering computational complexity and scan costs. • Deep learning offers new possibilities for enhancing image quality evaluation in prostate MRI by automating artifact detection and quality scoring through CNN-based framworks, reducing the differences among obsevers and building on proven success in other modalities for standardized efficient assessment. • Deep learning has brought significant opportunities to the field of MRI post-processing by transferring its proven experience in correcting artifacts such as motion,Gibbs-ringing, noise, and susceptibility distortion in brain, cardiac, and live imaging to enhance prostate MRI quality and salvage previous unusable scan data.	including limited generalizability across modalities and planes, potential clincial workflow distruption from incorrect model decisions, incomplete artifact correction and unresolved technical issues like local signal variations. • The current assessment of the quality of prostate MRI images shows inconsistency. Although it achieves relatively high accuracy (0.92-1.0) in classifying T2-WI and DCE images, when it comes to individual DWI and ADC slices, the assessment results differs significantly from manual interpretation (23%-25%), which indicates that this methods still has limitations in slice-level reliability and generalization across modalities. • The clincal application of deep learning in the quality assessment of prostate MRI faces the challenge of insufficient generalizability. Since most methods are trained and validated only on data collected from single centers, scanners, or protocols, leadning to inconsistent performance across diverse clinical distributions and raising concerns about real-world reliability. • Deep learning in the field of prostate MRI faces chellenges brought about by subjectivity of annotation and evaluation.Sepcifically, there are significant differences in judgment among different readers. and it relies on evolving, inherently subjectively criteria, which introduce biases and inconsistences in training data, undermining model reliability and clincal applicability.
1S	A comprehensive review of deep neural networks for medical image processing: recent developments and future opportunities (Mall, P. K.et al 2023)	Review	• CNNs apply deep learning to classification tasks through layered architectures-convolution, pooling, fully connected, and softmax layers-that extract hierarchical features and enable automated pattern recognition for accurate categorization. • The deep learning techniques such as U-Net and its variants (e.g., 3DV-Net, AFTerUNet) are driving the transformation in the field of medical image segementation. Through innovative designs like hierarchical	• The primary challenge is to develop robust, DNN-driven virtual healthcare systems that ensure diagnostic accuracy across geographic locations, particularly need to bridgethe gap in medical analysis and remote patient care between urban and rural areas.

			feature extraction, end-to-end training, and transformer-convolution hybrid models, this technology can achieve precise two dimension/three dimensional segmentation (with dice scores up to 98.67%) for organs and lesions such as lungs, blood vessels, brian tumors. At the same time, it effectively addresses traditional challenges such as complex anotomical structures and multi-scale data integration. • Deep learning has achieved technological breakthroughs through architectures like Faster R-CNN and Enhance-NetDLM. This technology integrates image enhancement, transfer learning, and context analysis methods, not only demonstrating high accuracy in task such as musculoskeletal X-ray assessment and prostate biopsy segmentation, but also meeting the clinial requirements for real-time computing. • DNNs play a vital role in the diagnosis of lung disease. By utilizing architectures like U-Net, V-Net, ResNet, and Bayes-SqueezeNet, this technology has accomplished tasks such as segmentation, clissificaiton, registration, and detection of COVID-19 and pneumonia in CT scans and chest X-rays. Throughadavanced regualtion methods, multi-view fusion, and preprocessing techniques, its diagnostic accuracy can reach up to 99.84%. • DNNs have achieved multi-task applications in ophthalmic image analysis. Based on architectures such as VGG-16, NFN+, InceptionV3 and U-Net, this technology can complete tasks such as diabetic retinopathy grading, retinal vessel segmentation, age and gender prediction, and glaucoma detection through fundus images. Tests on public datasets such as DRIVE, STARE, CHASE and EyePACS show that its performance is excellent. DNNs are applied for automated bone age assessment and pediatric skeletal maturity prediciton using architectures like CNNs, ResNet-50. Inception-ResNet-V2, and VGG on pediatric X-ray datasets, achieving mean absulute errors as low as 0.8 years and accuracy up to 94.45%, with transfer learning enhancing classification accuracy for metabolic	

			disorders and endorine evaluations. • DNNs have achieved automated osteosarcoma detection and classification in histopathology. This technology is based on H&E stained biopsy images and utilizes convolutional neural networks, Faster R-CNN, and an interpretable artificial intelligence (XAI) framework to effectively address challenges such as tissue complexity, staining variations, and small sample data. It achieves an accuracy rate of up to 97% in distinguishing malignant tumor cells (such as nuclear atypia, necrotic areas) from normal tissues.	
2S	Current and potential applications of artificial intelligence in medical imaging practice: a narrative review	Narrative review	• AI is reshaping the practice mode of conventional radiological imaging. This technology optimizes image quality assessment enables automatic detection of key signs like pneumothorax and pipeline positions, prioritizes handling of emergency cases, and provides real-time feedback to technicians. It significantly enhances work efficiency, reduces operational errors, and optimizes the overall workflow on mainstream equipment platforms such as General Electric, Philips, and Siemens. • The application of artificial intelligence technology has significantly enhanced the comprehensive performance of CT scans. By optimizing the positioning accuracy of patients, intelligently determining the scanning range, achieving low-dose high-quality reconstruction based on deep learning, and predicting equipment failures for preventive maintenance, this technology has effectively improved dose efficiency, image consistency, and system operational reliability in the equipment of major manufacturers such as Siemens, Philips, and General Electric, and has comprehensively optimized the workflow. • AI is reshaping the technological landscape of magnetic resonance imaging. By using image reconstruction techniques based on deep learning, the scanning speed can be increased by up to 80%. Combined with the automated patient positioning and protocol selection functions, this technology has achieved workflow standardization on the platforms of major manufacturers such as General Electric, Philips, and Siemens. While	• The current challenge lies in how to develop an accurate and unbiased artificial intelligence system for identifying patients' identities. This system needs to achieve reliable facial recognition among diverse populations and establish a robust cybersecurity protection framework to safeguard sensitive personal information from being leaked. • The current technical challenge lies in developing an artificial intelligence system that can accurately interpret unstructured radiological examination requests. This system must be able to accommodate variations in physician expressions and the diversity of institutional practices while automatically determining compliance with guidelines, thereby facilitating real-time rationality verification and reducing unnecessary imaging examinations.. • In the DL-based metal artifact reduction (MAR) technology, the core challenge lies in how to balance the effect of artifact elimination with the image fidelity. The ideal solution should effectively eliminate artifacts while fully preserving the anatomical details, and surpass the traditional MAR methods in terms of processing speed and accuracy.. • In the DL-based metal artifact reduction (MAR) technology, the core challenge lies in how to balance the effect of artifact elimination with the image fidelity. The ideal solution should effectively eliminate artifacts while fully

			ensuring the quality of diagnosis, it significantly shortens the examination time. • Introducing artificial intelligence technology in CT scans can significantly reduce radiation doses by enabling real-time automatic alignment and optimization of imaging parameters. This improvement maintains the efficiency of diagnosis and treatment while effectively protecting both patients and healthcare workers from excessive radiation risks. • AI is transforming the workflow of radiotherapy: by generating synthetic CT images to achieve pure MRI positioning planning, it eliminates the need for additional CT scans; at the same time, through the use of automated and standardized organ and target area delineation techniques, it not only enhances efficiency and treatment accuracy but also effectively reduces the risk of radiation exposure. It is worth noting that the issue of operational skill degradation that may arise during the application of this technology still requires attention..	preserving the anatomical details, and surpass the traditional MAR methods in terms of processing speed and accuracy.
3S	Opportunities and challenges in the application of large artificial intelligence models in radiology (Pan, L. 2024)	Review	• Large-scale AI models are becoming interactive learning tools for clinical education, capable of answering clinical questions, assisting in differential diagnosis, interpreting complex medical concepts, and automatically generating teaching materials. Although there are differences in accuracy rates across different specialties, their performance in exams has reached a level comparable to that of medical students. • Large-scale AI models are reshaping the practice paradigm of radiology: by conducting multi-disease analysis to enhance diagnostic accuracy, generating structured reports (such as R2GenGPT, MAIRA-1), providing expert-level insights to areas with scarce medical resources, and assisting in optimizing clinical workflows. Although there are still challenges in improving diagnostic depth and controlling error rates, models like Med-PaLM2 and ChatRadio-Valuer are gradually bridging these technological gaps while maintaining consistency with the standards of radiologists. • AI is driving transformative changes in	• Large AI models have several key limitations: their performance depends on insufficient or poorly labeled training data; there is a risk of "AI hallucinations" that seem reasonable but are actually incorrect; and there are integration barriers with clinical workflows. Solving these problems requires the development of interpretable model architectures, achieving real-time compatibility with PACS systems, ensuring diagnostic accuracy through rigorous validation, and avoiding increasing the workload of clinicians. • The current promotion and application of medical AI models are being constrained by unresolved legal and ethical issues. These challenges are specifically manifested as: the ban on LLM-generated content in the academic field, the warning from the World Health Organization regarding unverified diagnostic tools, the risk of data privacy leakage, and the potential infringement on patients' autonomy. To effectively address these problems, a strict governance system must be established,

			the field of medical imaging through advanced image segmentation techniques (such as ProstAttention-Net, SynthSeg+), classification models (A3Net, MBTFCNy), and detection tasks. These technologies not only achieve precise lesion analysis, multi-disease diagnosis (with the highest AUC reaching 0.9842), and surgical planning support, but also continuously push the boundaries of real-time clinical processing and automated analysis through emerging multi-task models (Cerberus, ResGANet) and basic models (SAM, Label-Studio SAMed). • Multimodal large models are reshaping the analysis paradigm of medical imaging. By integrating multi-source data such as CT, MRI, PET, and ultrasound, and applying cross-modal learning, attention mechanisms, and basic models (RadFM, LlaVA-Med), this model system not only achieves comprehensive tumor assessment and personalized treatment plan formulation, but also reduces the annotation cost by 90% through semi-supervised cross-modal learning. Meanwhile, clinical-ready systems like OpenMEDLab, which have the ability to process multiple images in three dimensions, are continuously expanding the application boundaries of this technology.	medical ethics norms followed, and clear and traceable responsibility division ensured, thereby preventing the abuse of technology and maintaining public trust.
4S	The use of deep learning in medical imaging to improve spine care: a scoping review of current literature and clinical applications (Constant, C. et al 2023)	Scoping review	• DL in spin imaging primarily focuses on diagnostic tools (74% of studies), with three key applications: 1) disease detection via screening/anomaly identification, 2) predictive diagnosis using historical patient data, and 3) differentiation of clinically similar spinal conditions based on imaging features. • DL in spine imaging also enables clincial decision support and outcome prediciton, focusing on two key areas: 1) personalized treatment palnning through preoperative risk factor analysis (e.g., predicting surgical outcomes), and 2) procedural guideance for intervention like image-guided injections or intraoperative navigation.	• The challenge is in developing DL models for medical imaging is ensuring sufficient high-quality data, as models often face imbalanced or sparsely annotated datasets with sample sizes typically far smaller, and raising concerns about overfitting and generalizability despite reported performance metrics. • The challenge is in evaluating DL models for medical imaging is the prevalent use of potentially misleading performance metrics (e.g., accuracy, AUC) on imbalanced datasets, where class disparities can artificially inflate results and obscure true model reliability—with most studies (91%) failing to explicitly address label imbalance or pre-test probability biases in their analyses. • A critical barrier to clinical adoption is the lack of rigorous external

				validation - with only 15% of spine imaging DL studies testing models on independent datasets, and minimal real-world testing, raising concerns about generalizability across diverse patient populations and clinical settings.