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SWOT analysis of the application of artificial intelligence in radiologic technology and radiology

Mihovil Delija[1], **Frane Mihanović**[1]

[1]University of Split, University Department of Health Studies, Split, Croatia

Corresponding author: Mihovil Delija, e mail: mihovil.nfs@gmail.com

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Abstract

Artificial intelligence (AI) is bringing changes to radiology and radiologic technology, enabling the development of programs and algorithms that facilitate diagnosis and decisions. It is essential to understand how AI can improve patient outcomes, increase the efficiency of investigations and reduce costs. Machine and deep learning have proven to be extremely useful in the detection and characterization of lesions, improving routine imaging techniques and facilitating the work of radiologists by reducing workload and improving the quality of reporting. The practical application of artificial intelligence in radiology and radiologic technology has been slowed down by the lack of integrated solutions and well-structured data archives, as well as challenges such as non-transparency of decision-making systems and large amounts of quality data needed to train artificial intelligence models. There are concerns about the potential impact of AI on the work of radiologists and radiologic technologists, which may hinder the development and implementation of this technology. Textual data derived from image reports can provide valuable healthcare insights. Natural language processing (NLP), a subset of artificial intelligence, offers promising solutions for handling unstructured text in these reports, opening a new era in extracting information from medical images and related reports. Due to the challenges in training experts for the application of AI in healthcare, a multidisciplinary approach will have to be used and investments in collaboration and education will have to be made. There are outstanding issues of liability and regulation regarding data storage and privacy, particularly in the case of cloud storage. The concern of the workforce and their lack of education about artificial intelligence represents an obstacle to its adoption, but also offers an opportunity for the technological advancement of the profession.

Keywords: AI; radiologic technology; radiology; SWOT

Abbreviations and acronyms: AI (Artificial intelligence), CAD (Computer-Aided Diagnosis), CDS (Clinical Decision Support), CNN (Convolutional Neural Networks), CT (Computed Tomography), DL (Deep learning), GAN (Generative Adversarial Network), FDA (Food and Drug Administration), ML (Machine Learning), NLP (Natural Language Processing)

Introduction

History and evolution

The development of programmable digital computers in the 1940s sparked curiosity among mathematicians and philosophers about the capabilities of machines and their potential to mimic human functions. The concept of artificial intelligence (AI) was first introduced by John McCarthy of Dartmouth College in 1956 [1], defining it as any machine that exhibits intelligent behavior similar to humans. AI, in its broadest sense, involves advancements in computing hardware and software that leverage information to solve complex problems, generate solutions, and create new knowledge through algorithms inspired by human cognitive functions. The field of AI has experienced highs and lows but is currently undergoing a renaissance due to the increasing power and affordability of parallel computing systems, enabling the creation of more advanced AI systems with multiple layers of analysis, known as deep learning [2]. Radiology, born from the discovery of X-rays, has always been at the forefront of technological innovations. Radiologists eagerly adopted nuclear PET and SPECT, MRI, digital radiography, CT, ultrasound, and optical imaging as these advancements revolutionized medical imaging, thanks to breakthroughs in physics, engineering, and technical developments [3]. The automatic exposure device, introduced in the 1980s, was an early example of AI in radiography. It allowed radiographers to select the kV value and determined the optimal exposure by measuring the quantum quantity reaching the film. This technology improved efficiency and reduced radiation exposure, but human oversight was still crucial due to potential errors and technical variations. Despite its benefits, it highlighted the ongoing need for human expertise and supervision in radiology [4].

Thomas Kuhn, a renowned philosopher of science from Harvard University, introduced the concept of a “paradigm shift” in his influential book, “The Structure of Scientific Revolutions” [5]. He explained how scientific progress occurs within a set of accepted rules and assumptions (the paradigm) until a radical new idea or technology disrupts this paradigm, leading to a fundamental change in direction. The field of medical imaging has undergone significant paradigm shifts in the past, driven by innovations such as CT scanning, MRI, and digital imaging. These advancements have transformed radiology, enabling remote image viewing, digital storage, and the use of numerical values with clinical significance. The introduction of MRI in the 1980s brought another paradigm shift, offering new imaging protocols and a wealth of new information. The development of pulse sequences and imaging biomarkers expanded radiology’s role from diagnosis to patient management. Since then, all imaging modalities have continued to evolve, with improvements in resolution, speed, and safety. However, there are practical limits to these advancements, imposed by safety, cost, physics, and technology. As we look to the future, AI is poised to bring about the next paradigm shift in medical imaging. With its extensive collection of digital images and history of embracing technological advancements, radiology is an ideal field for AI integration. While AI’s impact will be felt across medicine, its use in radiology is likely to be particularly profound [3]. The vast amount of imaging data collected during routine medical procedures has led to the emergence and rapid growth of radiomics as a significant field of medical research. Radiomics involves extracting predefined engineered features from images, capturing radiographic characteristics such as shape, intensity, and texture, and combining them with clinical outcome data. More recently, deep learning techniques have been incorporated, enabling automatic feature representation learning from example images and highlighting the clinical relevance of many radiographic features [6].

Applications of AI in radiology

Artificial intelligence and its subset, machine learning (ML), are rapidly evolving fields that have transformed computer science (Figure 2). AI in radiology is versatile, with applications in image-based analysis, computer-aided diagnosis (CAD) tools, and medical image classification. ML and its subset, deep learning (DL) are techniques that mimic the human brain, enabling systems to learn from data and adjust their actions. Radiomics, an ML subfield, extracts valuable quantitative properties from images. The integration of AI and ML algorithms in radiology aims to enhance existing algorithms and develop new ones to streamline diagnosis and reduce manual intervention in time-consuming conventional imaging tasks. This evolution is driven by two key factors: advancements in computer sciences and the growing availability of well-organized medical databases, which facilitate effective management and analysis of complex “big data” [7].

AI encompasses a diverse range of algorithmic learning techniques, including machine learning (ML), deep learning (DL) as a branch of ML, and natural language processing (NLP). ML empowers computers to learn from data through supervised, unsupervised, semi-supervised, or reinforcement learning approaches. Because of its exceptional performance, DL is the preferred learning technique in medical imaging for tasks like image segmentation, classification, and object detection. NLP, on the other hand, empowers computers to interpret un-

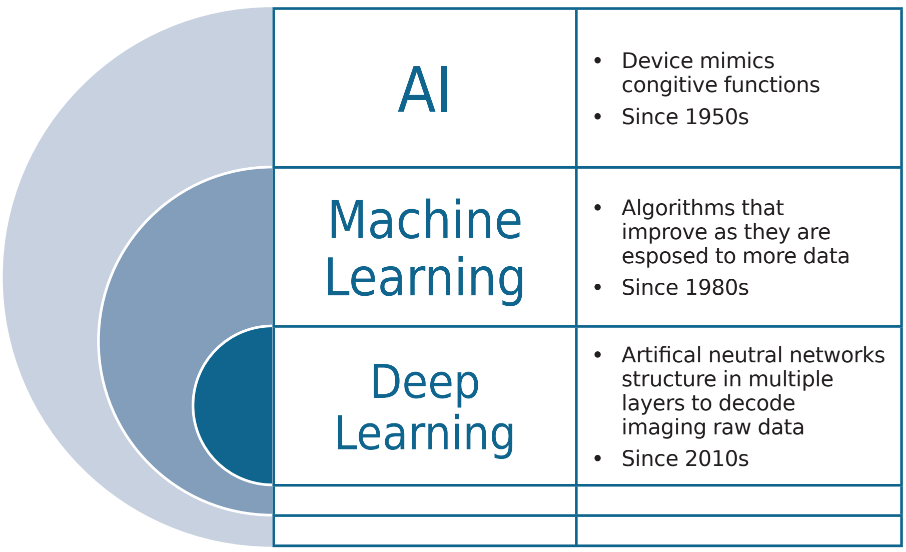

Figure 1. AI overview
Source: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6199205/figure/Fig1/

structured text, including sensor data, by converting it into a structured format suitable for subsequent ML or DL processes [8]. The healthcare industry is shifting towards value-based care, emphasizing standards and guidelines for diagnostics and therapeutics. Clinical Decision Support (CDS) tools have become crucial for high-quality, cost-effective care in radiology and imaging-focused specialties. The American College of Radiology (ACR) and extensive literature endorse CDS. As a result, there is interest in leveraging AI to enhance CDS in clinical imaging, potentially leading to more structured reporting and a positive feedback loop where AI refines its performance over time using generated data [9]. CAD systems were initially developed to assist radiologists in detecting lesions, which is a fundamental aspect of radiology practice. They are an example of practical applications of image-based ML in radiology. These systems can automatically extract and classify specific image features. Tools like these also enable the classification and grading of lesions as malignant or benign by analyzing their morphological and physiological characteristics. Today, advanced segmentation techniques go beyond simple detection, providing valuable data extraction from medical images [7]. The field of AI has seen significant advancements with the emergence of deep learning algorithms, which have revolutionized the way we approach medical imaging. These algorithms eliminate the need for explicit feature definition, instead learning from data spaces. Convolutional Neural Networks (CNNs) have become the go-to choice in medical imaging due to their ability to extract complex features and map image inputs to desired endpoints. CNNs are composed of layers that process input images through convolution and pooling operations, followed by fully connected layers and an output layer for predictions. They are typically trained end-to-end using labeled data. Other architectures, such as autoencoders and GANs, excel in unsupervised learning tasks. The popularity of deep learning stems from its ability to automatically learn feature representations from data, enhancing informativeness and generalizability. Deep learning has the potential to revolutionize diagnosis and clinical care by providing more abstract and complex feature definitions. The advancements in deep learning algorithms hold great promise for improving healthcare outcomes, particularly in medical imaging [6]. As AI becomes integral to radiology practices it is essential for radiologists to develop a strong understanding of the concepts and workflows related to ML. To assess the potential impact of AI and ML in radiology, we can employ the SWOT (strengths, weaknesses, opportunities, and threats) model, a commonly used business strategy tool [7].

SWOT analysis is a strategic planning and strategic management technique used to identify Strengths, Weaknesses, Opportunities, and Threats related to business competition or project planning. It is intended to identify the internal and external factors that are favorable and unfavorable to achieving the objectives of the venture or project. By applying the SWOT model to the integration of AI in radiology and radiologic technology, we can gain valuable insights into the strengths, weaknesses, opportunities, and potential threats associated with this technological evolution [10].

Aim of the article

The aim of this article is to analyze the application of artificial intelligence in radiological technology and radiology using the SWOT model. Its development, current and future applications, as well as external and internal factors that can positively or negatively affect the application of this technology in the mentioned professions will be presented.

1.1. STRENGTH – Patient side

The main goal of early clinical AI research in imaging was to improve diagnostic accuracy, with recent studies demonstrating encouraging results and even human-level performance in AI-enabled computer-aided diagnosis. Beyond this core objective, AI can address practical issues in daily practice, such as optimizing worklists, pre-analyzing cases in high-volume settings to mitigate observer fatigue, extracting hidden information from images, and enhancing reconstructed image quality (Figure 2) [2].

AI excels in image-based diagnosis, detecting, segmenting, and classifying lesions. It can automatically identify anatomical landmarks and organs, improving scan times and reducing variability. Software for automatic organ segmentation and landmark detection is also showing promise, particularly in the spine, chest, and liver [7,11]. AI is being applied in various areas of oncology radiology and radiation treatment to improve accuracy, efficiency, and patient outcomes in cancer diagnosis and treatment. This includes early detection and characterization of cancers, assistance in radiation treatment planning, and continuous monitoring of treatment response, with appli-

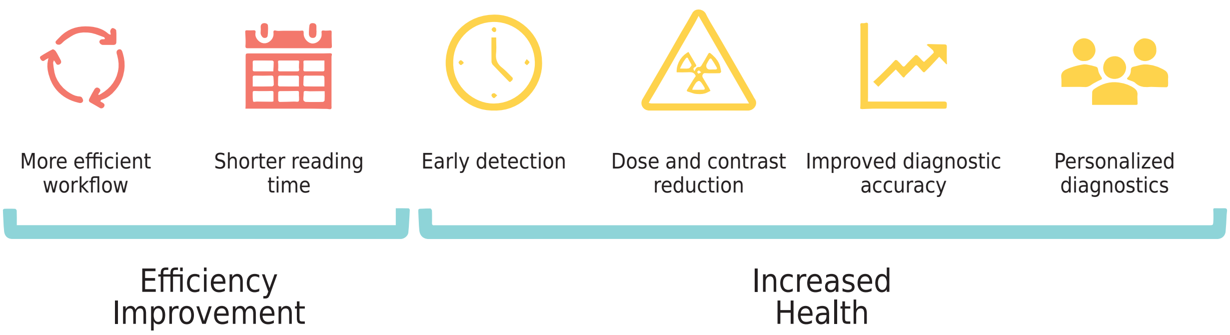

Figure 2. Possible improvements made possible by AI in healthcare
Source: https://link.springer.com/article/10.1007/s00247-021-05114-8/figures/1

cations in areas such as lung, colon, breast, and brain cancers, as well as incidental findings like liver lesions [6,12]. CNNs are well-suited for supervised diagnostic classification tasks, and studies have reported significant performance improvements in breast lesion and lung nodule classification using deep learning-based methods. Staging systems in oncology, such as the tumor-node-metastasis (TNM) system, rely on information from segmentation and diagnosis to classify patients into predefined categories, guiding treatment choices and predicting survival likelihood and prognosis. Deep learning is particularly suited for this multifaceted classification problem as it can learn joint data representations simultaneously [6]. In pediatrics, the automated bone age prediction is a well adopted AI solution aiding the quantification and reading efficiency of hand radiographs. The device could be used autonomously, potentially reducing the reading time to zero [13]. There is also a growing range of AI-driven methods for reducing radiation doses in mammography, CT scans, and PET/CT, as well as techniques for reducing MR scan times. These advancements offer the possibility of faster image acquisition and improved patient flow.

One of the most exciting aspects of AI-augmented image acquisition is its potential application in ultrasound examinations. Ultrasound image quality has traditionally been seen as highly dependent on the operator's skill and experience. However, with automated AI positioning and measurement tools, sonographers will be able to produce higher-quality ultrasound assessment reports with reduced error rates [14]. AI algorithms can enhance patient safety by suggesting appropriate imaging workups for each item on a problem list and identifying contraindications. This problem list-based approach could offer a "one-click" response with ranked, recommended examinations. AI tools will improve by extracting information from electronic health records (EHRs) more accurately, creating interconnected models of patient clinical problems, and assisting in decision-making by prioritizing acute issues. AI can also enable cohort-wide EHR monitoring, identifying high-value imaging opportunities and specific patient cohorts requiring further investigations, leading to earlier diagnoses and reduced low-value acquisitions, unnecessary procedures, and costly delays [9, 11].

Deep learning networks have also advanced radiomics, a field focused on extracting quantitative features from radiological images. Radiomics has the potential to provide valuable insights for predicting treatment responses, differentiating between benign and malignant tumors, and understanding cancer genetics across various cancer types by analyzing features such as intensity, shape, texture, and wavelength extracted from medical images [12, 15].

1.2. STRENGTH – Worker side

The application of ML techniques in radiology primarily focuses on image-based approaches. As the amount of detail and the number of images in radiological studies increase, radiologists may struggle to keep up with the workload. ML algorithms come into play by extracting information from images, aiding in lesion detection, and image segmentation, ultimately enhancing imaging reports with new data [7, 12]. The diagnostic process can be optimized with AI, improving the overall workflow. An example of this is already being used widely; AI software is now used to detect tuberculosis on chest radiographs. AI-supported tuberculosis detection has proven especially useful in developing countries, where staffing, expertise, and financial resources are often limited. This technology acts as an autonomous pre-screening tool, reducing the need for more time-consuming and costly microbiological tests [13]. AI can improve timeliness in urgent cases by automatically detecting life-threatening conditions and prioritizing them for immediate attention. It can also assist in addressing observer fatigue, especially in screening exams, by identifying cases with a high likelihood of true positives for early review [2]. The combination of AI and CDS improves the work of referrers and radiologists by increasing the appropriateness of ordered studies and enhancing the value of reports. AI technologies have the potential to revolutionize CDS by evolving today's scoring systems into advanced algorithms that consider the patient's comprehensive profile and the population receiving care. This combination has the potential to provide more structured guidance and automated data collection, improving workflow efficiency and patient care through data-driven decisions [9].

The field of radiology is shifting from a subjective skill to an objective science due to the increasing volume of imaging data. This change is necessary, as radiologists' work is currently limited by subjectivity, variability, and fatigue. AI can revolutionize radiology by automating routine tasks such as detection, characterization, and quantification, currently done manually by radiologists [15, 16].

AI applications may enhance the reproducibility of technical protocols, improving image quality and decreasing radiation dose, decreasing MRI scanner time and optimising staffing and CT/MRI scanner utilisation, thereby reducing costs [12]. With healthcare costs rising globally, it is crucial that we make efficient use of our limited resources. AI software could assist in scheduling imaging appointments and predicting no-shows even before the patient arrives at the radiology department. This predictive capability can be used for more efficient scheduling. Most of these solutions are not designed for patient detection or diagnosis, but rather for optimizing peripheral conditions like patient management. Consequently, they carry less risk and are subject to fewer regulations, making it easier to implement them in clinical practice [13]. AI can help streamline medical imaging guidelines by analyzing radiology referrals for CT and MRI scans, ensuring that the benefits outweigh the risks. AI can also aid in justification audits and real-time analysis, reducing radiation exposure and waitlist burdens. Additionally, DL techniques have been developed to synthesize contrast-enhanced CT images from non-contrast CT scans, potentially reducing the need for contrast media and minimizing risks associated with its use [17].

2.1. WEAKNESS – Standards and black boxes

The practical application of ML in radiology is hindered by several factors, including the lack of integrated solutions from industry vendors and well-structured archives of clinical data. Retrospective data usage is limited due to the predominance of free-text imaging reports, which are not easily usable for AI algorithm training. External limitations include the need for advanced storage systems to handle the large volumes of data required by DL algorithms. Additionally, there is a lack of clear multidisciplinary road maps and standardization for ML implementation in imaging societies, requiring a clear definition of the radiologist's and radiologic technologist's role in this evolving landscape [7].

In a review from 2021, reseachers wanted to map the current landscape of commercially available artificial intelligence (AI) software for radiology and review the availability of their scientific evidence. The overview included 100 CE-marked AI products from 54 different vendors. For 64/100 products, there was no peer-reviewed evidence of its efficacy. There was a large heterogeneity in deployment methods, pricing models, and regulatory classes. The evidence of the remaining 36/100 products comprised 237 papers that predominantly (65%) focused on diagnostic accuracy. From the 100 products, only 18/100 AI products have demonstrated (potential) clinical impact [8]. Establishing standards and infrastructure, as well as creating a categorical model to understand the value of AI in clinical and research settings, are key to advancing AI in imaging. Developing image-sharing networks, reference datasets, standardized protocols, and a common language for AI applications would greatly benefit AI imaging research. Quality control, data integrity, curation standards, and informatics systems are important considerations [2, 18]. While ML techniques have the potential to revolutionize radiology, their wider implementation is hindered by several internal challenges. A major concern is the opacity of ML systems, often termed "black box" systems. This opacity makes it difficult for radiologists to trust and comprehend the decision-making process of the algorithms. It raises ethical and legal concerns and is a significant factor in radiologists' reluctance to adopt ML systems [7].

The transition from rule-based programs to data-driven learning paradigms has sparked discussions about interpretability and transparency. Despite the successes of deep learning, there remains a lack of comprehensive theoretical understanding, hence the term "hidden layers" for the layers between inputs and outputs. Identifying the specific image features that contribute to a prediction is largely speculative, making the decision-making process obscure. This lack of transparency makes it challenging to anticipate failures, address generalization issues, or explain the logic behind specific conclusions [6, 11, 17].

2.2. WEAKNESS – Quality of datasets

AI is only as good as the data used to train it and AI programs require vast amounts of data for effective training, but limited access due to institutional barriers and proprietary interests can result in insufficient training sets, leading to potential overfitting and reduced accuracy or generalizability. The ability of AI to handle diverse patient populations and variations in image acquisition protocols is also uncertain, which may introduce errors and affect the accuracy of results [2, 17]. ML algorithms depend on quality training data, but generating labeled data is costly and time-consuming. Unsupervised and semi-supervised ML algorithms are being developed to reduce this burden but are not as powerful yet.

Another challenge is the large volume of training data required by ML and DL algorithms, and the potential for overfitting if the model is not properly validated during training. This can lead to a model that performs poorly on new, unseen data. The development of advanced ML techniques and the need to process massive amounts of digital data have also led to increased hardware requirements, which can drive up costs [7].

Further research is required to validate the accuracy of deep learning-based reconstruction algorithms and their capacity to accurately replicate rare, unseen structures, as initial errors introduced during this stage can have detrimental consequences on patient outcomes [6]. A key limitation of current AI tools is their specialization in performing only one task. We have yet to create a comprehensive AI system capable of detecting multiple abnormalities across the entire human body. Data remains the most crucial element for training AI systems effectively. With a significant portion of population undergoing CT and MRI examinations annually, the volume of medical images generated is substantial. The implementation of advanced digital health systems, such as PACS, has facilitated the systematic organization and storage of these images. While large amounts of medical data are available, they are often uncurated, creating a significant challenge for AI model training. Curation, which involves selecting relevant patient cohorts and segmenting objects within images, ensures data quality and consistency. It is a time-consuming and expensive process that requires domain knowledge and expertise to ensure credibility. The volume of data needing curation, which deep learning methods are particularly susceptible to, further exacerbates this challenge [11, 12].

2.3. WEAKNESS – Job changes

Obermeyer and Emanuel [19], in an article for the New England Journal of Medicine, predict that machine learning will take over most of the work of radiologists and anatomic pathologists, and that machines will soon be more accurate than humans. Similarly, Chockley and Emanuel [20] argue in the JACR that machine learning will become a dominant force in the next decade and could potentially cause the decline of radiology as a specialty. Radiologic technologists and radiologists were at the forefront of the digital revolution in medicine. They were the first medical workers to embrace computer science and are now among the most digitally savvy healthcare professionals.

History has shown that radiologic technologists and radiologists have successfully incorporated seemingly disruptive technologies, such as non-X-ray-based modalities like ultrasound and MRI, into their practice. As a result, the definition of "radiology" has expanded to include radiation-free imaging modalities, encompassing almost all diagnostic medical imaging. Furthermore, electronic systems for reporting and archiving images were designed with radiologists in mind, reflecting their central role in healthcare [15]. While it is theoretically possible that the increased efficiency brought about by AI could reduce the number of radiologists needed, it is also possible that the opposite could occur, and the field may require more professionals. Historically, automation has not resulted in job loss but rather a reshaping of roles. The efficiency gains provided by AI will enable radiologists to undertake more value-added tasks, such as integrating patient clinical and imaging information, having more professional interactions, becoming more visible to patients, and playing a vital role in integrated clinical teams. Thus, AI will not replace radiologists, but those who embrace AI will replace those who do not [12, 15, 16]. AI has the potential to revolutionize and greatly enhance the radiologic technologist's role in cross-sectional imaging. However, this level of automation also raises concerns about a potential reduction in radiologic technologists' responsibilities and roles. As healthcare organizations explore the benefits of AI technologies in improving radiology department efficiency, it is crucial to simultaneously address the associated risks and liabilities. Increased automation will lead to greater patient throughput and impact staffing requirements. With the continuous increase in demand for imaging, radiologic technologists will need to develop a range of competencies across different modalities and technologies. Given the expected importance of AI in future imaging approaches, radiologic technology graduates should possess the foundational skills to operate and oversee image acquisition across various imaging modalities [4,14].

3.1. OPPORTUNITY – New front

AI is expected to revolutionize image-based tasks in clinical radiology, including preprocessing, reporting, and diagnostics. One area where AI can make a significant impact is image reconstruction, as there is a growing gap between advancements in hardware and software. The first step in this process is reconstruction, which is an area where we see a growing disparity between advancements in image acquisition hardware and image reconstruction software. AI, particularly deep learning, can develop innovative methods to enhance image quality and reduce artifacts. For example, CT reconstruction algorithms have remained static for decades, and deep learning can provide alternative approaches [6]. Text-based data derived from imaging reports can be a valuable source of healthcare big data. Natural language processing (NLP), a subset of AI, has emerged as a promising solution to handle the unstructured text within these reports and extract valuable information. Advanced CT and MRI studies generate a lot of data, but the challenge is in generating labeled data. Transfer learning and data augmentation techniques are being used to reduce the need for extensive labeled data. GANs are also showing promise in generating large labeled datasets and enhancing image quality in low-dose CT scans. These NLP and ML approaches have the potential to revolutionize the handling and analysis of imaging data in radiology [7]. AI applications in healthcare open up new possibilities for extracting valuable information from images, advancing precision medicine. AI will play a pivotal role in discovering new imaging features to enhance the imaging phenotype, making it an indispensable tool in the pursuit of precision medicine [2, 12]. AI has a wide range of potential applications in radiology that could have an immediate positive impact. It can help prioritize reporting by automatically selecting urgent findings, compare current and previous examinations to save time, and quickly identify negative studies, especially in high-volume screening. AI can also aid in aggregating electronic medical records, automating recall and rescheduling of imaging follow-ups, and providing clinical decision support for ordering, interpreting, and managing patient care. Additionally, AI can assist in quality control, peer review, and resident training, as well as extract valuable insights from data, including radiation dose management [15].

Some potential application in radiologic technology that could have a positive impact include: AI-enabled devices are improving the quality of chest radiographs, such as GE's Critical Care Suite 2.0, which can detect issues like pneumothorax and prioritize critical studies. Philips' Radiology Smart Assistant provides real-time feedback to radiographers on image quality, improving departmental productivity and reducing radiation exposure [17]. Siemens Healthineers' YSIO X.pree system uses a 3D camera to speed up image acquisition and automatically detects the thorax, optimizing collimation and reducing radiation exposure. Modern CT scanners also use 3D cameras with deep learning to accurately position patients, reducing human error and improving image quality [17].

Deep learning algorithms can improve image quality and reduce radiation exposure in CT scans, and AI-based image reconstruction methods have reduced MRI scan times by up to 50% while maintaining image quality. Additionally, AI-enabled fluoroscopy systems can reduce radiation exposure by over 60% while maintaining high-quality images [17].

3.2. OPPORTUNITY- Multidisciplinary collaboration

Close collaboration between radiologists, AI developers, and industry partners is essential to drive innovation, create advanced AI tools that meet clinical needs, and ensure their safe and effective deployment [11, 16]. The upfront costs for AI, including investigator salaries, hardware, and software, are considerable. Nonetheless, forward-thinking departments and institutions will recognize the value of investing in these resources to support researchers and establish AI core laboratories accessible to all, similar to other core laboratory operations [2]. One challenge is the limited pool of investigators trained in radiology AI methods. However, this can be addressed by attracting AI specialists to the field of radiology and through educational initiatives already being pursued by radiology professional societies. Historically, important areas quickly attract capable individuals, so this is unlikely to remain a long-term problem. Practicing radiologists will need to familiarize themselves with AI but not necessarily become experts in AI research or program design to utilize AI-based outcomes effectively [2]. AI in radiology relies on human intelligence for tasks like creating training datasets and interpreting results. Radiologists' expertise is key to labeling data and identifying clinical applications where AI can make a meaningful impact. They can also interpret complex AI-generated data and link it to clinical utility [15].

Radiologists should recognize the value they bring to the table with these datasets and clinical knowledge and negotiate their role in guiding the clinical application of AI programs. This will involve increasing partnership with bioengineers and computer scientists and embedding these professionals within radiological departments to foster everyday collaboration. Creating a "multidisciplinary AI team" will help ensure patient safety standards are met and judicial transparency is maintained, allowing legal liability to be assigned appropriately [12, 15].

4.1. THREAT – Legality, data, security concerns

Internationally, policy issues regarding the storage and custody of medical and imaging data, especially in cloud-based solutions, remain unresolved. Clear external regulatory policies are needed to define the responsibilities and duties of radiologists and ML systems, including data privacy and preservation. Inconsistent labeling of radiological data due to a lack of standardized agreements can also lead to reproducibility issues [7, 11].

Regulatory bodies like the FDA have overseen CAD systems using machine learning and pattern recognition for decades. However, the shift to deep learning presents new challenges and requires updated guidance in the approval process. Deep learning methods continue to evolve after market release as they process and learn from increasing data, making it crucial to address the implications of lifelong learning. One possible solution is to conduct periodic testing to ensure performance aligns with projections. There are ongoing discussions about whether regulatory entities have the right to question AI frameworks about their mathematical reasoning. This is challenging with deep learning, which has opaque inner workings. Despite this, the FDA has approved high-performance software solutions with unknown mechanisms of action, similar to some approved drugs [6]. Another issue that needs to be faced are the legal implications of AI systems in healthcare. As soon as AI systems start making autonomous decisions about diagnoses and prognosis, and stop being only a support tool, a problem arises as to whether, when something 'goes wrong' following a clinical decision made by an AI application, the reader (namely, the radiologist) or the device itself or its designer/builder is to be considered at fault. It is probable that a multidisciplinary AI team will take responsibility in difficult cases, considering relevant, but not always conclusive, what AI provided [12, 15]. The use of patient data to train AI systems raises important ethical concerns, and ensuring secure and privacy-preserving handling of this data is crucial. Typically, patient data is stored within networks of medical institutions, and when it comes to connecting this data to external, cutting-edge AI systems for analysis, security and privacy become a challenge [6]. The electronic databases storing identity photos must be secured within a robust, cyber-attack-proof system to safeguard individuals' identities and personal data from potential theft.

Concerns about data privacy and safety are not unfounded, as demonstrated by the Conti ransomware attack on Ireland's healthcare IT system on May 14, 2021, which compromised sensitive data of 520 patients [23]. This incident highlights the critical need for robust security measures to protect personal information in the context of automated personal identification systems in healthcare [17].

4.2. THREAT – Workforce opposition

Perceptions from both the general population and the medical community also play a role as an external obstacle, as there exists a belief that machines cannot provide more accurate diagnoses than radiologists, especially when it comes to interventional tasks [7]. This kind of opposition by the community may represent the biggest obstacle to potential implementation of AI in radiology and is explored in the context of an external factor. A study [21] published in 2021 which interviewed UK radiologists and radiographers found that radiographers expressed concerns about the potential impact of AI on their skills and job security, suggesting that their roles might be more vulnerable to capture by AI technology. Radiologists, on the other hand, felt less concerned that AI technology might constrain their professional role and autonomy and believed that AI could potentially enhance their skills [21]. In a survey from 2019: One hundred ninety-eight radiologists (198/270; 73.3%) estimated they had received insufficient previous information on AI, and 37/270 (13.7%) declared having received no previous specific information at all. Thirty-seven (37/270; 13.7%) attended a dedicated teaching on AI, and respectively 73/270 (27.0%) and 33/270 (12.2%) had taken part in one or more demonstrations of AI-based solutions. Two hundred thirty-one respondents (231/270, 85.6%) admitted they had read no (89/270; 33.0%) or less than five (142/270; 52.6%) scientific publications about AI over the last 12 months. Based on the aforementioned criteria, the authors estimated that 62/270 respondents (23.0%) had basic knowledge on AI in radiology [22]. The perspective of radiographers on AI adoption and automation has been largely absent from professional and industry literature, contrasting with the lively debates among radiologists about diagnostic AI. Since 2015, radiologists have published numerous papers discussing and evaluating AI, addressing concerns about role erosion and highlighting AI's potential as a supportive tool. This surge in interest may have been motivated by a desire to safeguard their profession, but it also emphasizes the value of human workers in the imaging process factor that is often overlooked in the pursuit of efficiency gains and cost reductions [4]. In a survey [25], conducted in 2020 on radiography professionals worldwide: A proportion of the respondents agree (n = 76, 26.2%) or somewhat agree (n = 70, 24.1%) that they feel well prepared to implement new AI technologies and innovations in daily practice. Of the respondents, 31.4% (n = 91) are somewhat confident in using AI technologies or innovations in their daily practice while 44.1% (n = 128) feel somewhat confident with AI terminologies. Some respondents disagree (82, 28.3%) or strongly disagree (55, 19.0%) that there is enough AI training opportunities currently available for radiographers. Thus, most respondents agree (n = 120, 41.4%) or strongly agree (n = 81, 27.9%) that the teaching of AI technologies should be included in the radiography teaching curriculum. Most respondents supported [strongly agree (n = 80, 27.6%) and agree (n = 116, 40.0%)] that AI will change daily clinical radiography practice. Only 2.8% (n = 8) of respondents disagreed to this view. Majority of respondents somewhat agree (n = 95, 32.8%) that AI will reduce the workload of the radiography workforce while only few (n = 6, 2.1%) strongly disagreed [25]. A survey [26] found most radiologists have basic or advanced AI knowledge, and this is associated with a more positive attitude towards AI, increasing the likelihood of clinical adoption. It seems that AI receptivity can vary from acceptance of the perceived inevitability to a positive enthusiasm for such change. The more educated the workforce is regarding AI, the more levels of positive, active acceptance and engagement are seen [25]. Radiologists tend to view AI technology as affording an opportunity for professional development, whereas radiographers were more reticent, highlighting the possible threat which AI posed to their roles. It is likely that with wider availability of formal education in AI for radiographers, enhanced AI transparency and explainability radiographers' views towards AI will become more favourable. Of note, Yang and colleagues [27] concluded in a scoping review that the replacement of radiologists by AI is considered unlikely in the near future and the stakeholders identified the need for training and education since they anticipate a significant impact on radiology. The fear that the machines will "take over", reducing the professional value, job demand and roles is shared by a considerable part of the radiography workforce [25]. Respondents indicated that AI should be included in the radiography training curriculum at universities and reported that, currently, there aren't enough AI training opportunities available for the radiography workforce. There was consensus about this across all continents surveyed in this study. The need for more training and education is vital to successfully implement AI into clinical practice, with these views being shared globally by all key AI ecosystem stakeholders. Lack of understanding may lead to uncertainty in how to make sense of AI as it relates to radiography practice/careers, and thus education is needed in order to build the proficiency necessary to appreciate future directions [25].

CONCLUSION

The development and evolution of artificial intelligence has fueled a revolution in computer science, with far-reaching implications for a variety of industries, including radiologic technology and radiology. Its integration with these sciences, which have always accepted technological progress, has great potential. Artificial intelligence in radiology is characterized by its versatility, impact on diagnostics and treatment. On the patient side, AI improves diagnostic accuracy, early disease detection and treatment planning. In oncology, for example, artificial intelligence helps in the detection and characterization of lesions, early detection of neoplasms, and treatment planning for brain tumors. AI also improves efficiency by optimizing work lists, pre-analyzing cases and reducing radiologist fatigue. However, there are challenges and limitations. The lack of integrated solutions, well-structured clinical data and clear standardization hinders the implementation of artificial intelligence. External factors, such as the need for advanced and secure systems to store large amounts of data, the negative attitude of the profession towards this technology and regulatory restrictions, represent obstacles. In conclusion, AI has the opportunity to lead to a paradigm shift in radiologic technology and radiology, advancing these fields and improving patient care and outcomes. Although challenges exist, the benefits of integrating artificial intelligence are significant and far-reaching.

All data in this paper are part of the results of the undergraduate thesis "SWOT analysis of the application of artificial intelligence in radiologic technology and radiology – review paper" written at the University Department of Health Studies, University of Split [28].

SWOT analiza primjene umjetne inteligencije u radiološkoj tehnologiji i radiologiji

Sažetak

Umjetna inteligencija (AI) unosi promjene u radiologiju i radiološku tehnologiju, omogućavajući razvoj programa i algoritama koji olakšavaju dijagnozu i odluke. Bitno je razumjeti na koji način AI može poboljšati ishode pacijenata, povećati učinkovitost pretraga i smanjiti troškove. Strojno i duboko učenje pokazali su se kao iznimno korisni u otkrivanju i karakterizaciji lezija, poboljšavajući rutinske tehnike snimanja i olakšavajući rad radiologa smanjenjem opterećenja i poboljšanjem kvalitete izvještavanja. Praktična primjena umjetne inteligencije u radiologiji i radiološkoj tehnologiji usporena je nedostatkom integriranih rješenja i dobro strukturiranih arhiva podataka, a također i izazovima kao što su netransparentnost sustava kod donošenja odluka i velika količine kvalitetnih podataka potrebnih za obuku modela umjetne inteligencije. Postoji zabrinutost zbog potencijalnog utjecaja AI na posao radiologa i radioloških tehnologa što može kočiti razvoj i primjenu ove tehnologije. Tekstualni podaci izvedeni iz slikovnih izvješća mogu pružiti vrijedne uvide u zdravstvu. Obrada prirodnog jezika (NLP), podskup umjetne inteligencije, nudi obećavajuća rješenja za rukovanje nestrukturiranim tekstom u ovim izvješćima, što otvara novu eru u izdvajanju informacija iz medicinskih slika i pripadajućih izvješća. Zbog izazova u obuci stručnjaka za primjenu AI-a u zdravstvu morat će se koristiti multidisciplinarni pristup i ulagati u suradnju i obrazovanje. Postoje neriješena pitanja o odgovornosti i regulaciji u vezi s pohranjivanjem podataka i privatnosti, osobito u slučaju pohrane podataka na sistemu „oblaka“. Zabrinutost i neinformiranost radne snage o umjetnoj inteligenciji predstavlja prepreku za njeno usvajanje, ali i nudi priliku za tehnološko napredovanje struke.

Ključne riječi: AI; radiologija; radiološka tehnologija; SWOT

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