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An Artificial Intelligence Road Map to Unlocking Future Technologies and Transforming Radiology Practice

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Abstract: Today, artificial intelligence (AI) is one of the hottest buzzwords in technology. It is at the center of the global technological revolution, envisaged to replace or enhance human capabilities in the coming times. With AI projected to be one of the major disrupting forces in the future, this article engages with several scientific sources to highlight the step-by-step progress made since the inception of AI from the Turing test to the much-celebrated ChatGPT's (generative pre-trained transformer) launch, evolution in medical imaging (from early X-ray techniques to sophisticated AI-driven systems), and current research landscape, examining how AI gain can revolutionize radiology practice, while also pointing out pitfalls and future research directions. AI was found to be very useful across every aspect of the radiology work chain (diagnostic and therapeutic components all encompassing), such as scheduling and worklist management, image segmentation and classification, diagnosis, image measurement and assessment, image acquisition and reconstruction, and prediction. However, ongoing concerns were seen around cost, hardware limitations, data quality and quantity, bias, data privacy, training of users, transparency, and regulatory oversight. Several recommendations were then made to include extensive model training on large, diverse datasets/validation, creative research to address the black box phenomenon, AI integration with both virtual and augmented reality to improve models' robustness, regular user trainings and interdisciplinary collaborations, and developing regulatory frameworks (on data governance, transparency, cybersecurity, ethical issues, and post-market surveillance). It is foreseen that concerned authorities, now thoroughly furnished with knowledge on the historical antecedents upon review of this article, will take the necessary action to address these concerns, putting into consideration AI strategy, AI engineering, stakeholders' engagement, and regulatory/ethical concerns.

Keywords: artificial intelligence, road map, AI technologies, medical imaging, radiology, clinical practice

1. Introduction

Artificial intelligence (AI) is concerned with replicating human intelligence by building machines programmed to think, reason, and act like humans. These systems learn to be creative, perform knowledge-intensive tasks, solve problems, accomplish advanced functions, and make decisions [1]. This branch of computer science has a long history that stretches back to the 1940s, with significant milestones recorded nearly every decade. AI boosts a wide range of applications in education, business, automobiles, security, gaming, finance, marketing, social media, navigation, robotics, astronomy, and healthcare [2]. However, in the field of radiology, the application of AI has continued to thrive in leaps and bounds due to rapidly evolving imaging technology. This absorbing article is carefully structured into three interlinked sections. The first section looks to demystify AI by exploring its evolutionary journey, major events, and progress till date. The second section seeks to build on this historical account by delving into AI techniques.

2. History of Artificial Intelligence

2.1. First paradigm shift (symbolic/rule-based AI: 1940–1970)

The roots of AI can be traced back to the 1940s (see Figure 1) when the American science fiction writer, Isaac Asimov, in 1942 published his short story called "Runaround" – a story about a robot developed by engineers Gregory Powell and Mike Donavan. At about the same time, Alan Turing, an English mathematician, developed a code-breaking machine called "Bombe" for the British government, which was able to break the Nazi's Enigma code used by the German army during the Second World War, a task previously not possible. He is referred to as the father of modern computing and a key man for the British victory in World War II [3]. In the wake of his amazement at the intelligence of this machine, he published the article "Computing Machinery and Intelligence" in 1950, illustrating how to create an intelligent

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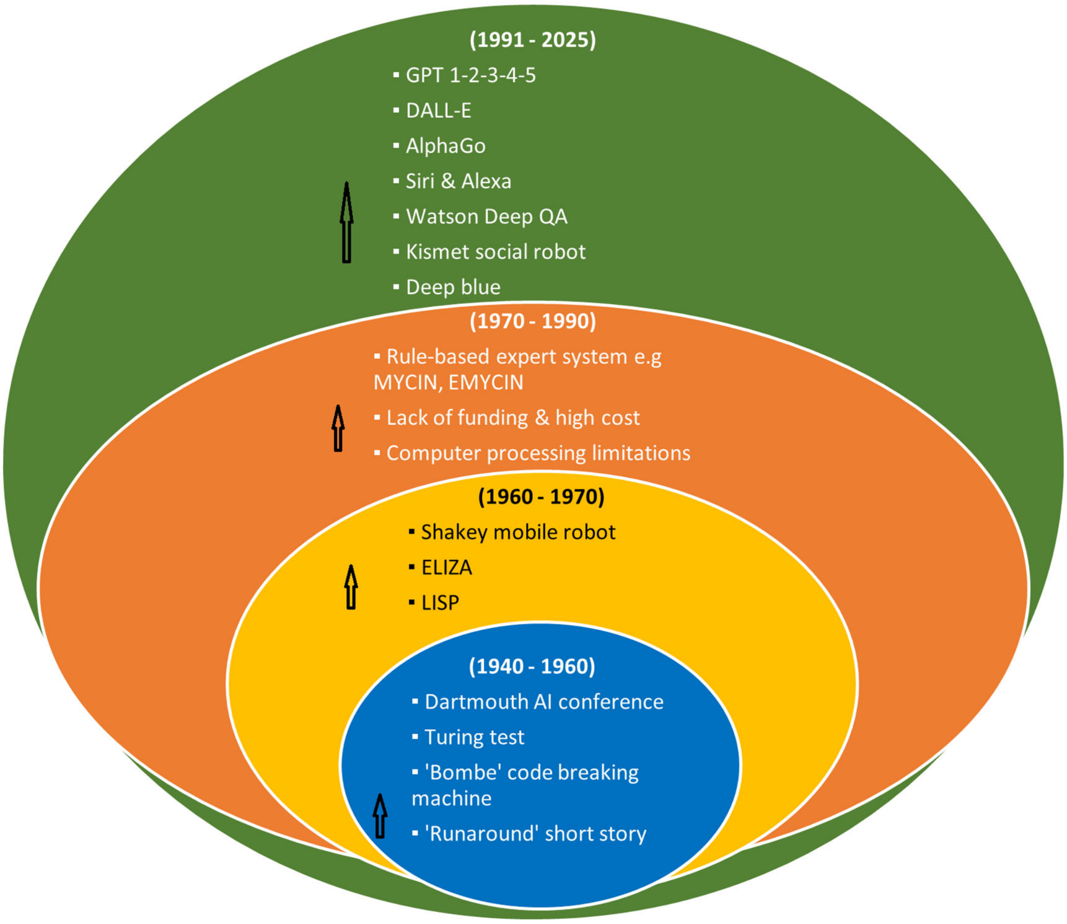

Figure 1. AI milestones historically since 1940 till date

machine and, most importantly, test their intelligence. This publication was the very first paper suggesting the possibility of AI, describing what is known today as the "Turing test" – a test to check the ability of a machine to exhibit intelligent behavior equivalent to human intelligence. Sadly, Turing could not prove this theory due to the lack of advancements in computing machines at that time. Nevertheless, he built the basis for comparative assessment on whether a machine thinks on par with a human [4].

This test sparked the coming together of scientists, resulting in the first AI program presented at the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI). Dartmouth College mathematics professor, John McCarthy, alongside another group of scholars, held conversations, investigating the possibility of thinking machines and believing that all aspects of learning, including every feature of intelligence, can in principle be delineated, and a machine made to simulate it [5].

The term "artificial intelligence" was first coined by John McCarthy in 1956, during the first AI conference held at Dartmouth College [6]. McCarthy already conceived this term during the summer conference, which would define the practice of humanlike machines two years after the death of Turing. Following the success in this conference, speculations on man-made intelligence equivalent to the human brain started growing, which began to attract major government and industry support. Newell and Simon published the general problem solver algorithm in the late 1950s, which, although it fell short of solving complex problems, laid the foundation upon which a more sophisticated cognitive discovery would emanate [7].

Innovations in the field of AI grew rapidly throughout the 1960s; several developments sprang up as McCarthy developed LISP (an AI programming language) and MIT computer scientist, Professor Joseph Weizenbaum, invented ELIZA in 1966 (an interactive natural language processing computer program that could functionally converse in English with a person) [8]. Professor Joseph Weizenbaum, in a research paper, further explained how many users found it hard to believe that ELIZA, widely referred to as the first chatbot, is not human; this underpins its massive impact [9].

Shortly afterward, early signs of progress started coming in, and the first general-purpose mobile robot called "Shakey" (programmed using LISP software) was built by Charles Rosen in 1969. With the aim to create concepts and techniques in AI that support functions independently in realistic environments, this mobile robot system was designed with sensors and a TV camera to navigate different settings. This robot has today assisted in advancing certain aspects of AI such as visual analysis, route finding, and object manipulation. The above historic period (1940–1970), known as the first paradigm shift, laid the foundation for the most well-known AI methods and algorithms [10].

2.2. Second paradigm shift (AI winter: 1970–1990)

During the 1970s and 1980s, advancements in AI were hampered by limitations in computer processing and memory, as well as the complexity of the problem. Thus, governments and other organizations backed away from their support for AI research. Most notably in 1974, the applied mathematician, Sir James Lighthill, asserted in his published report on "academic AI research" that researchers had over-promised and under-delivered with reference to the potential intelligence of machines. This condemnation further led to stark funding cuts [11].

In the 1980s, the adoption of Edward Feigenbaum's expert system and research on deep learning (DL) techniques fueled hope and gave a new wave of AI enthusiasm, only to suffer setbacks due to a lack of funding and support from the government and industries, driven by excessive cost in developing and maintaining expert digital information databases [5, 7].

The development of MYCIN – a 500 rule-based expert system utilizing backward-chaining reasoning (systematic approach through exploring rules otherwise called potential causes to find evidence that supports a hypothesis) in dealing with bacterial infections – and EMYCIN, a domain independent version of MYCIN, further elicited the creation of many expert systems (from 50 to 2200 and later 12,500 in 1985, 1988, and 1992, respectively) [12]. In 1986, a German scientist, Ernst Dickmanns, invented the first self-driving car (Mercedes van) made of sensors and computer system features to read the environment, but this car could only drive on roads without other cars and passengers [13]. Hence, from the 1970s through much of the next two decades, signified gaps between AI expectations and the technology's shortcomings emerged despite a brief resurgence in the early 1980s; this timeframe is commonly referred to as "AI winter." This interval, model-driven, connotes the second paradigm shift and is related to "symbolic algorithms and expert systems," otherwise known as knowledge-based systems.

2.3. Third paradigm shift (Modern Renaissance: 1991–2020s)

Increase in computational power and explosion of data sparked by AI renaissance persisted in the 1990s until in 1997, when the supercomputer "deep blue" designed by IBM (which has the capacity to process information at a rate far quicker than the human brain, reviewing 200 million potential chess moves in one second) went to defeat world champion chess player, Garry Kasparov, in a match. This incredible scene captivated the public and signified the great milestone achieved by IBM, although this system didn't have the functionality of today's generative AI [14].

A research project on Kismet, a social robot created for identifying and simulating human emotions, was conducted in MIT's Artificial Intelligence Laboratory under Dr Cynthia Breazeal in 1997. Kismet came to fruition in 2000, containing sensors, a microphone, and programming that specified the human emotion processes. This was instrumental in enabling the robot to read and mimic a range of feelings, thriving on social interactions. Kismet was perceived by many people as a technology that makes humans less, as opposed to a celebration of humanity [15].

Later in 2002, the first commercially successful robotic vacuum cleaner was created, and since 2005, rapid advancement in AI has gradually emerged in the form of speech recognition, robotic process automation, dancing robots, smart homes, and other innovations [16].

Following the success of IBM's Deep Blue program in defeating the world chess champion, IBM created a similar computer system in 2011 called "Watson Deep QA," built to receive natural language questions and respond by getting data from an encyclopedia and the internet. Watson went on to play the hit US quiz show Jeopardy, defeating two of the show's all-time champions, Ken Jennings and Brad Rutter [17].

In 2011, the newly launched virtual assistants from Apple and Amazon, "Siri" and "Alexa," respectively, possessing natural language processing abilities, were programmed to understand a long list of spoken questions and respond with an answer. A limitation of both systems was the inability to provide answers to questions outside their purview [18].

Computer scientist, Geoffrey Hinton, while working on his PhD research in the 1970s, preconceived and already started exploring the idea of neural networks – an AI system built to process data similar to the human brain. But it wasn't until 2012 that Geoffrey and two of his graduate students displayed their research at the ImageNet competition, showing the progress levels of the neural network. His work on DL, an AI system that processes a vast amount of data to make accurate predictions, laid the foundation for several AI processes, namely, natural language processing and speech recognition [19].

AI research lab, Google DeepMind, created "AlphaGo," an AI program combining neural networks and advanced search algorithms via reinforcement learning. AlphaGo defeated Lee Sedol, one of the best global players in 2016, in an ancient game ("Go"), more complex than chess, proving that AI could tackle insuperable tasks [20].

Advances in AI led to developments in generative AI (GenAI), as AI could generate images, texts, videos, and 3D designs in response to prompts, unlike past systems that were coded to respond to a set of inquiries. GenAI continues to learn and evolve, using neural networks to identify patterns and undergoing training on large unlabeled datasets to predict outcomes same ways humans act. A GenAI architectural foundation known as GPT was built into different language models such as GPT-1 and GPT-2 by an AI research company called "OpenAI." However, the ability to produce separate responses was limited. Much later, it was GPT-3, a large language model released in 2020 and trained on 175 billion parameters (as against the 1.5 million parameters GPT-2) that addressed this limitation, signaling a major development in AI. Afterward, the same AI research company (OpenAI) released DALL-E in 2021, a text-to-image model utilizing natural language text to generate realistic and editable images. Although DALL-E presents with several drawbacks such as difficulty generating texts within its images and ethical concerns (e.g., bias, deepfakes), it supports a wide variety of functions such as brainstorming and custom art, marketing and branding materials, and creating educational visual aids. In 2022, OpenAI again released ChatGPT, trained on billions of inputs to improve natural language processing abilities. Users can prompt ChatGPT for various responses, including making inquiries, getting help with writing, and conducting research. Unlike previous chatbots, ChatGPT can request follow-up questions and detect incorrect prompts, owing to its GPT-3 foundation. 2023 marked a milestone year for GenAI in two areas. First, OpenAI launched GPT-4, built on the power of GPT-3 and capable of generating creative responses and engaging in a wide array of tasks. Second, Microsoft unified ChatGPT into its search engine Bing, and Google officially announced its GPT chatbot Bard. There is an expectation that multiple models will be unified into one to create GPT-5, building on the huge knowledge base of GPT-4 but with improved reasoning and multimodal capabilities [21]. Thus, this period of increased availability of digital data/computing power (data-driven) resulted in the third and final paradigm shift, commonly referred to as machine learning (ML) and DL.

3. AI Techniques, Technologies, and Imaging

The rapid transformation process witnessed in AI has resulted in several AI techniques, otherwise known as domains. AI techniques refer to a set of methods and algorithms utilized in the development of intelligent systems so they can successfully carry out tasks requiring humanlike intelligence. Below is a look at the five major AI techniques (ML, DL, natural language processing, expert system, fuzzy logic) and robotics, examining the differences in their performance and when to use each algorithm in imaging.

3.1. Machine learning (ML)

ML, a subset of AI (Figure 2), is concerned with creating machines that have the ability to learn from data and experience through "algorithms." Algorithms are the engines that power ML, informing the computer how to learn to operate on its own. They are simply the step-by-step instructions that help a computer complete a task. Therefore, infusing such daily descriptive functions needed by the computer to perform a given task, many of these processes that could have possibly taken years to be completed by humans are automated [22]. Algorithms are of three major types: supervised, unsupervised, and reinforcement learning, with the difference among them being how each learns from data to make predictions.

In supervised ML, the data scientist acts as a guide, teaching the algorithms what conclusion to make; the model is trained with a labeled dataset and has a predefined output. The most common supervised tasks are "classification," which separates the data to predict distinct class labels, and "regression," which fits the data to predict a continuous quantity [23]. Classification tasks can be further summarized as binary classification (involves 2 class labels such as yes or no, true or false), multiclass classification (having labels within a range of specified classes more than 2), and multi-label classification (having an example connected with several classes or labels, which can concurrently belong to more than one class in a structured ranking level) [24]. Regression tasks include simple and multiple linear regression (linear relationship between a continuous dependent variable and either a continuous or discrete independent variable), polynomial regression (nonlinear relationship between independent variable and dependent variable, expressed as nth degree polynomial), etc. Popular ML algorithms that can carry out both classification and regression tasks are linear discriminant analysis, k-nearest neighbors (KNN), support vector machine (SVM), random forest (RF), logistic regression, and decision tree (DT) [25]. In radiology, the most common supervised learning is for classification problems, where the algorithm is tasked with assigning a category to a new image based on features. For example, in a case of benign or malignant, Hoang demonstrated an automated supervised ML classifier performance of 98.25% sensitivity and 96.14% specificity in classifying computed tomography (CT), magnetic resonance imaging (MRI), and positron-emission tomography (PET) cancer images from a large pool to support cancer registries [26].

A more independent approach is required for unsupervised ML in which the computer learns to identify complex processes and patterns without constant guidance from humans, including identifying trends and groupings. This system is based on a dataset that does not have labels or a defined output, mainly for "cluster analysis" and "feature learning tasks." Cluster analysis involves grouping similar data points or objects into groups, called clusters, often used to discover trends and patterns. Common clustering algorithms are k-means clustering, GMM clustering (Gaussian mixture models), DBSCAN (density-based spatial clustering of applications with noise), and mean-shift clustering [27]. Feature learning technique comprises two major tasks, namely, "feature extraction" and "feature selection," aimed at improving human interpretations, preventing overfitting/ redundancy, and reducing computational cost. Feature extraction requires generating new features from existing ones and discarding the original features to improve accuracy. Principal component analysis is a typical example of this system. On the other hand, feature selection entails keeping a subset of original features and eliminating irrelevant features; analysis of variance test, Pearson's correlation, and chi-squared test are among popular approaches [28]. Unsupervised learning is seen to identify radiological progression markers that predict outcome, such as idiopathic pulmonary fibrosis in chest CT images, revealing pathways of progression from healthy lung tissue to a sequence of diseased tissue [29]. It was also found to predict survival and freedom from nodal failure in non-small cell lung cancer patients receiving stereotactic body radiation therapy via a clustering technique with better performance [30].

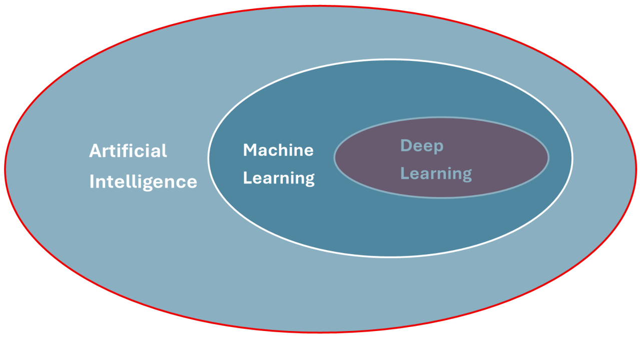

Figure 2. Relationship between AI, ML, and DL

Reinforcement learning (RL) is a concept where machines can teach themselves depending upon the results of their own actions. Absence of both human intervention and training dataset is a remarkable characteristic in reinforcement learning as the system learns from its experience through repeated trial and error interactions with a dynamic environment, compiling decisions in a sequential manner. RL can be divided into "model-based" and "model-free techniques," a key difference lying in the policy network required for model-based RL. Common model-based algorithms are AlphaGo and AlphaZero, while model-free algorithms include Deep Q Network, Q-learning, and Monte Carlo Control [31].

3.2. Deep learning (DL)

The availability of large datasets and the increasing computing capabilities have been the pillars for the development of artificial neural networks (ANN), designed to mimic the way the human brain processes information by intelligently combining several processing layers (Figure 3) to learn from data. This is known as "deep learning" [23]. Commonly used DL algorithms are multi-layer perceptron (MLP), convolutional neural network (CNN), Long Short-Term Memory Networks (LSTMs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), and Autoencoders. Less common ones are Radial Basis Function Networks, Self-Organizing Maps, and Deep Belief Networks [32].

1) MLP consists of a fully connected network of an input layer, one or more hidden layers, and an output layer. It adopts the backpropagation method, the foundational building block in a neural network [23]. It is used for image analysis tasks, particularly in conjunction with radiomics, classifying diseases

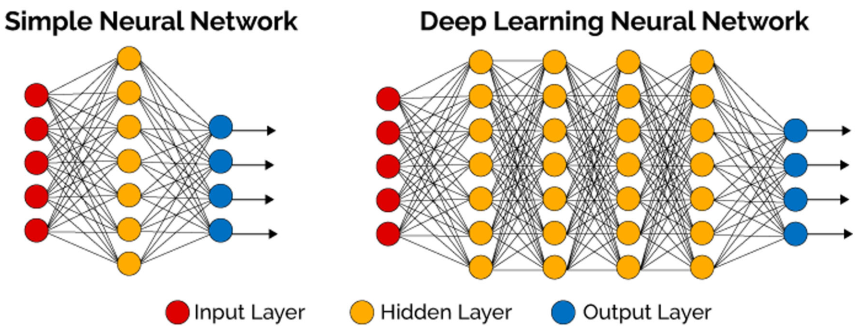

Figure 3. DL neural networks

or predicting outcomes based on extracted features from CT, MRI, and X-ray images. It predicted X-ray spectra for a tube with voltages 20–150 kV and two separate filters of aluminum and beryllium with thicknesses 0–2 mm [33]. MRI radiomic-based MLP model showed better performance than clinical models in predicting treatment response and optimizing therapeutic strategies for patients with locally advanced rectal cancer, with mean area under the curve (AUC) values of 0.718 and 0.810 [34].

2) CNN enhances the standard ANN design by consisting of convolutional layers (detects and extracts features), pooling layers (feature aggregation by selecting and reducing the number of features), and connected layers (integrates all features extracted by the previous layer). It comprises a series of programmed algorithms from a large visual database (such as ImageNet) through which data are fed to teach the computer to simulate human decisions, broadly used for image/video/document recognition, image processing, image classification, and natural language processing. Examples of CNN models include Visual Geometry Group (VGG), LeNet, AlexNet, GoogLeNet, and ResNet [35]. These models were useful in image classification for brain MRI, a pre-trained VGG-19 model with data augmentation and transfer learning techniques exhibiting the best performance [36]. Elsewhere, the DenseNet121 model outperformed ResNet50 and EfficientNetB1 in detecting thoracic pathology diseases from chest radiography images [37].
3) GAN is a two-player minimax generative algorithm consisting of a generator that creates the content and a discriminator that checks it for accuracy; it is utilized in video game production, photography, and 3D imaging. Most importantly in medical imaging, it has reportedly played key roles in image generation such as MRI image reconstruction for musculoskeletal imaging [38] (incorporating a discriminator that generates results closer to full reconstruction), CT image enhancement (denoising and resolution by generating images resembling normal-dose CT from low-dose CT), and classification of pulmonary adenocarcinoma/lung nodule detection in CT scan adopting a CNN combination approach [39].
4) RNN contains input, hidden layers (for remembering information), and output; it is utilized in image captioning, machine translations, handwriting identifications, natural language processing, and time analysis since it has LSTM [37, 40]. It is effective jointly with CNN for sequential data (compared to static data) and disease annotation tasks such as segmentation in cardiac MRI scan analysis, diagnosis of COVID-19 from X-rays (accuracy and AUC value of 99.9%), identification and classifion of intracranial hemorrhage on non-contrast head CT (99.41% accuracy, 99.70% sensitivity, 98.91% specificity), and automatic disease annotation (high precision, recall, accuracy, and F1 scores of 0.967, 0.967, 0.982, and 0.967, respectively) [41–43].
5) LSTMs are a form of RNN, consisting of four interacting layers in a chain-like manner, with a default behavior of recalling past information over a long period of time. It is best utilized for time-series predictions including voice recognition, music creation, and pharmaceutical research. It is applied in natural language processing, speech recognition, time-series analysis, etc. [43]. LSTM outperformed the traditional ML textual annotation-based system in the classification of chest CT reports based on a schema proposed by a radiologist [44]. It also recorded a high success rate for three-class classification (COVID-19, pneumonia, and normal) on X-ray images. A hybrid CNN-LSTM produced a better result in MRI brain tumor classification (validation accuracy of 97.94%) [45] and breast cancer histopathology imaging (99% for binary classification of benign and malignant, 92.5% for multiclass subtypes) [46].
6) Autoencoder is a form of feedforward neural network trained to repeat data from the input to the output layer, resulting in the same input and output. It is made of the encoder, the code, and the decoder and is beneficial in reducing the dimension of data, image processing, and novel discovery [46]. Autoencoders demonstrated 99.09% accuracy in retrieving MRI images for medical education [47], as well as substantial improvement in denoising MRI images (validation loss of 0.0001) [48]. Figure 4 gives a flowchart of ML and DL algorithms and workflow.

3.3. Natural language processing (NLP)

NLP is a branch of AI concerned with the ability of computers to understand and process human language in the form of texts and spoken words (voice data) just the same way as humans (Figure 5). NLP can be divided into two parts: natural language understanding (NLU) and natural language generation (NLG):

1) NLU involves phonology (systematic arrangement of sounds), morphology (nature of words), lexical (meaning of individual words), synthetic (forming grammatically correct sentences), semantic (proper meaning of a sentence), and pragmatic (context that influences the meaning of sentences).
2) NLG is the production process of meaningful sentences, paragraphs, or phrases; made up of three components, namely, speaker/generator (generates the text), process of language generation (comprises content selection, textual organization, linguistic resources, and realization), and application or speaker (maintains the model of the situation) [49].

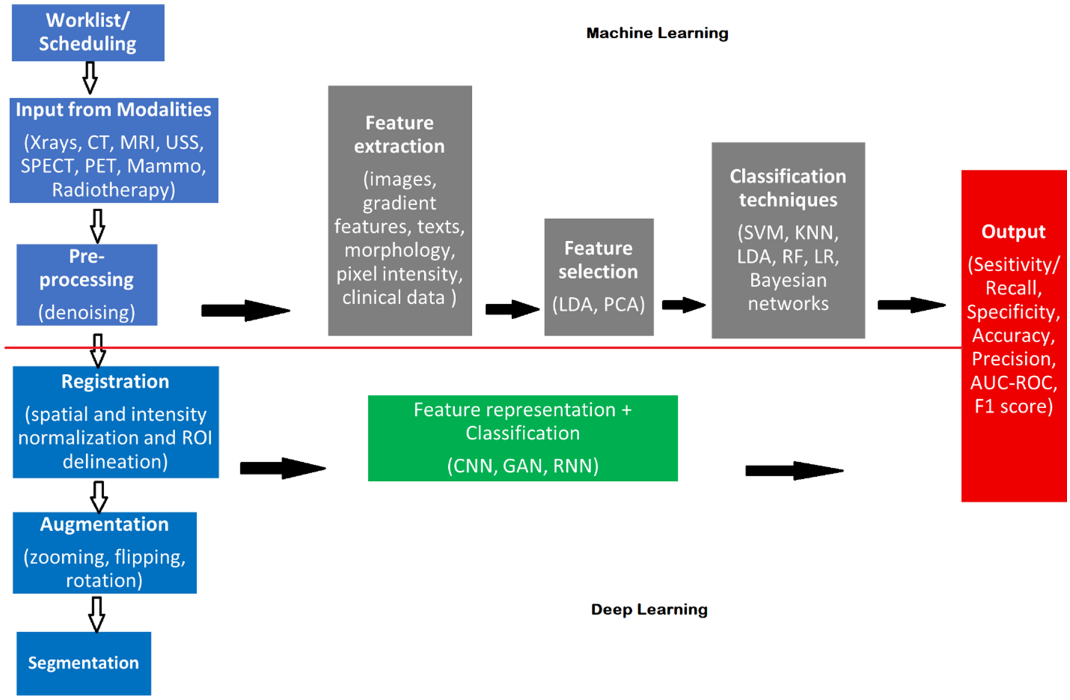

Figure 4. Summary of ML/DL algorithms and workflow in medical imaging

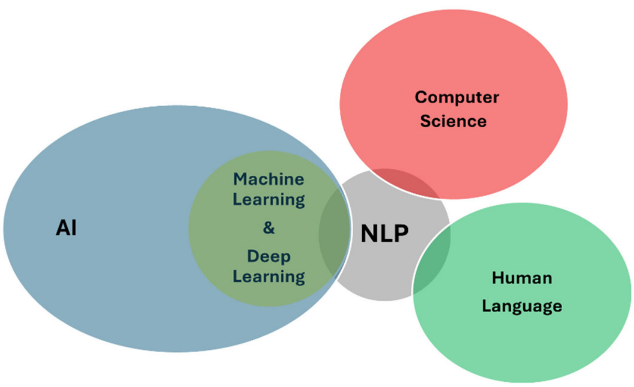

Figure 5. Relationship between NLP, ML/DL, human language, and computer vision

A walkthrough since the year 2000 records giant strides in NLP such as neural language modeling (2001), multitask learning (2008), word embedding (2013), NLP neural networks (CNNs, LSTM, RNNs, GRUs in 2013), sequence to sequence modeling (2014), attention mechanism (2015), and pre-trained language (2018) [50]. The application of the BERT model (Bi-directional Encoder Representations from Transformers) and succeeding models has been key in NLP advancement for text categorization/ summarization, information extraction, machine translation, and answering questions [51]. This has led to researchers building tools and systems such as chunking, semantic role labeling, emotion detection, parts of speech taggers, sentiment analyzer, and named entity recognition. Emerging NLP models are hidden Markov models, naive Bayes classifiers, and neural networks [49]. In medical imaging, NLP is primarily used to analyze and extract meaningful information from radiology reports, thus supporting automated tasks like providing textual descriptions of images, generating structured data from free text, identifying abnormalities (such as pulmonary embolism and fractures), and enhancing clinical decision support systems [52]. For example, in orthopedic trauma radiology reporting, the NLP BERT model achieved approximately 96% accuracy and 95% F1 score on simple reports and 93% accuracy and 83% F1 score on complex reports, while also outperforming traditional ML [53].

3.4. Robotics

Robotics refers to a system where robots are built and programmed to perform specific duties without further human intervention; tasks are predictable and repetitive and require no additional thought, subdivided into perception, planning, and execution.

Perception creates an artificial sense of self-awareness in the robot, supporting interactions with the environment (social robotics) via integrated sensors or computer vision. Interestingly, the quality of sensing and vision has tremendously improved in the last decade, with perception being an integral element for planning [54].

Robotics and AI can be traced to the first robot car by Dickmanns in 1986, and for significant times later, self-driving cars in the AI industry (early automata and industrial robots). However, we have in recent times witnessed the evolution of technology and humanoid robots, with practical applications of robotics in our modern world such as enhancing efficiency and precision, assisting in healthcare and surgery, disaster response, space exploration, and AI modeled presenter/news anchor [55]. In the field of radiography, robotics increases productivity during X-rays, angiography, fluoroscopy, and 3D imaging by enabling precision and high-grade automation. Figure 6 shows an ORION robot that enables patient positioning with millimeter precision, well-suited for radiotherapy. Robotic navigation system is very useful in endovascular procedures, tumor ablation (rectal, lungs, kidneys, prostate, breast), and image-guided biopsies (abdominal and pelvis) across ultrasound (USS), CT, and MRI-guided interventions, achieving higher accuracy/precision in placement of

Figure 6. Robots

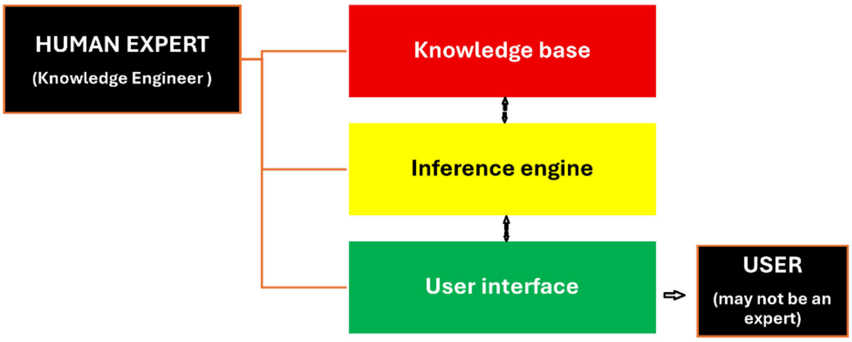

Figure 7. Components of an ES

needles, catheter navigation, reduced radiation exposure by 35%, and reduced procedural time by 30% compared to handheld techniques [56].

3.5. Expert system (ES)

ES denotes a computer program that learns and tries to reciprocate the judgment and decision-making ability of humans, complementing rather than replacing human experts. Its main components are a knowledge base, inference engine, and user interface (Figure 7).

ES works by accumulating experience and facts on a knowledge base, integrating them with an inference or rules engine (a set of rules for applying the knowledge base to situations provided to the program), and providing an answer to the problem [57].

In summary, ES was introduced by the Stanford project led by Feigenbaum, where researchers were trying to identify domains requiring expertise such as diagnosing infectious diseases (MYCIN), identifying unknown organic molecules (DENDRAN), and later rule-based systems (LISP). ES embodies knowledge of human experts in a particular domain so that users (who may not be experts) can use it to solve difficult problems. However, this knowledge or information may be inaccurate, incomplete, or fuzzy; thus, the performance of ES relies on having a good knowledge base. The field of ES has in the last years switched from a technology limited to research circles to one commercially utilized to aid human decision-making in the fields of environment, medicine, business, engineering, and education. Well-known ESs are MYCIN, PUFF, DENRAL, ELIZA, HEARSAY, XCON, MOLGEN, PXDES, and MACSYMA [58]. Medical imaging has witnessed the use of PHOENIX rule-based system as a useful and informative component of a radiology information system [59], and in conjunction with DL, it has been used to diagnose and predict the severity of COVID-19 using chest CT scan (F1 score of 0.94) [60], as well as automated screening for COVID-19 pneumonia (87% accuracy, 98% negative predictive value, 0.66–0.90 sensitivity) [61].

3.6. Fuzzy logic (FL)

FL refers to a mechanism of approximation (approximate reasoning) and inference (decision-making) adopted when true or false cannot be ascertained.

The four main parts of an FL architecture (Figure 8) are:

1) Rule base: comprises all rules and the if-then conditions to control the decision-making system.
2) Fuzzification: converts the inputs, such as crisp numbers, into fuzzy sets.
3) Inference engine: determines the degree of match between fuzzy inputs and rules, which rules need to be implemented, and combines these rules to develop the control actions.
4) Defuzzification: converts the fuzzy sets to a crisp value.

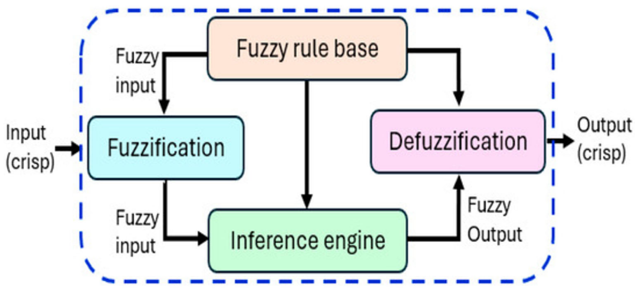

Figure 8. FL architecture

Since the 1980s, FL implementation has been reported in banking, hospitals, automatic control, manufacturing, and education. Recent studies in imaging have attested to the role of FL in predicting radiation protection awareness levels [62], recognition and segmentation of brain tumors in MRI scans (accuracy of 0.936 and 0.845, respectively) [63], enhancement of MRI images (entropy, peak signal to noise ratio, absolute mean brightness error), and image processing and analysis [64]. In 2024, a combination approach utilizing fuzzy CNN models produced a greater yield, achieving 99.31% and 99% classification accuracy for brain tumors and Alzheimer's disease in brain MRI, respectively [65, 66], including 97% classification accuracy for COVID-19 and viral and bacterial pneumonia in chest X-rays (CXR) [67]. However, as the number of variables increases, the number of rules exponentially increases, resulting in complexities. Several measures have emerged to address this challenge such as rule selection, feature selection, evolutionary algorithms, rule interpolation, singular-value decomposition-QR, rule learning, and hierarchical fuzzy systems (HFS). Of particular interest lately is HFS, which guarantees rule reduction and universal approximation and improves interpretability and balance between accuracy and interpretability [68].

4. Radiology Practice and Transformation

4.1. Technological evolution in medical imaging

Radiology is a branch of medical sciences that utilizes imaging technology and radiation (ionizing and non-ionizing) to diagnose and treat diseases. Since the discovery of X-ray technology in 1895 by Wilhelm Conrad Roentgen, tremendous advancements in imaging technology have been recorded. The fundamental concept of 2D X-ray production laid the groundwork for more complex and noninvasive imaging technologies. The creation of CT in 1973 by Sir Godfrey Hounsfield and Allan Cormack marked a milestone achievement, employing rotating X-ray sources and detectors with computational algorithms to produce 3D images of the body [69]. Somewhat around the 20th century, USS technology signified a shift away from ionizing radiation to the use of high-frequency sound waves to produce real-time images of the body [70]. The advent of MRI technology in the 1970s by Paul Lauterbur and Sir Peter Mansfield was a massive hit, utilizing a powerful magnetic field and radio waves to produce extraordinary, detailed images of soft tissues in the body [71]. A paradigm shift from film-based technology to digital radiography in the late 20th century, including the introduction of teleradiology, PACS (picture archiving and communication system), and DICOM (Digital Imaging and Communications in Medicine), tremendously improved image acquisition, storage, and easy transfer for reporting. This transformational process in medical imaging technology led to functional imaging techniques such as PET, which uses radiotracers that release positrons, and SPECT (single photon emission computed tomography), which uses gamma-emitting radionuclides [72]. Over time, the development of 4D imaging further pushed boundaries by incorporating the time element, permitting real-time monitoring of the physiological process. A combination of anatomical and physiological imaging resulted in hybrid technologies, PET/CT and SPECT/CT, further enhancing accuracy, location, and characterization of lesions. In interventional radiology, imaging has been vital for guidance in minimally invasive procedures by providing real-time visualization of the area concerned [73].

4.2. AI application in imaging tasks

AI use is gradually permeating radiology, integrated with imaging technologies to improve a range of tasks and revamp practice in the following aspects listed below. Table 1 provides a summary of the impact of AI techniques in radiology.

1) Workflow: ML and NLP algorithms enable scheduling of patients via a scheduling software and optimize workflows by predicting appointment delays/no shows, thereby eliminating tedious aspects of the workflow and burnout of imaging professionals. AI has been validated to automate the triage of imaging studies, prioritizing radiological studies (X-rays, CT/MRI scans) based on urgency and managing incidental finding follow-ups [74]. According to Kapoor et al. [75], its seamless integration into the electronic health record (EHR) system has tremendously reduced unwarranted variation in radiologist follow-up recommendations, thereby improving the quality of radiology reports. In a case study to better manage worklist and flow of patients during MRI scans, AI showed great potential in predicting patients with the highest probability of missing their appointments and, following a phone call reminder, impressively decreased patient no-show rate from 19.3% to 15.9% [76]. Again, AI supports the concept of radiology electronic round trip, streamlining information flow from the point of making a request to EHR and then PACS, with no need for manual entry of data [77]. Furthermore, ML has the potential to rearrange the worklist and to report based on urgency levels as opposed to first-in-first-out. A typical scenario was in chest radiography, reportedly prioritizing abnormal cases in a simulated workflow, reducing turnaround time by 7–28% [78]. It also resulted in a reduction in the average report turnaround time for all critical findings on CXR [79]. According to a recent study in 2023, the NLP tool Chat GPT has greatly streamlined various radiology workflow steps, including patient registration, scheduling, patient check-in, image acquisition, interpretation, and reporting. It has further enhanced patients' preparation for radiological investigations by providing personalized instructions to patients based on specific needs such as dietary restrictions, medications, and specific preparations for specialized imaging procedures [80]. In oncological imaging, AI has been established to condense the planning process and outcome via precise radiation dosing, enhancing workflow efficiency [81].
2) Image segmentation and classification: DL technologies, particularly CNNs, have been very useful in image segmentation and classification tasks, owing to feature extraction and semantic segmentation features, further enhancing precision and speed of diagnosis. They demonstrated superior performance in segmentation of lung nodules from CT scans, outperforming six radiologists and achieving 94.4% AUC [82]. Similarly, they have been integral in the segmentation of brain tumors in MRI and retinal images analysis, underscoring their broad versatility and applicability in imaging [83]. They have further aided image classification, distinguishing normal from abnormal in mammography, evident in their ability to distinguish benign from malignant tumors at a comparable level with radiologists [84]. This is consistent with the studies of Wang et al. [85] and Kowalewski et al. [86], in which DL models and CNNs classified lung nodules on CT and differentiated real carcinoma subtypes on MRI with a very high accuracy, matching the expertise of radiologists. Similarly, CNNs have performed automatic segmentation of left ventricular myocardium in MRI comparable

Table 1. Summary of AI's radiology impact

Study	AI technique	Modality	Task	Performance
Dung *et al*. (2014)	ML	CT, MRI, PET	Classification (reportable and non-reportable cancer cases)	98.25 sensitivity, 96.14 specificity
Jeanny *et al*. (2023)	ML (unsupervised)	CT	Prediction (idiopathic pulmonary fibrosis progression)	83% accuracy
Li *et al*. (2018)	ML (unsupervised and radiomics)	Radiotherapy and oncology	Prediction (lung cancer treatment response)	Significant differences in survival ($p = 0.003$) and freedom from nodal failure ($p = 0.038$).
Jie *et al*. (2023)	DL (MLP)	X-rays	Prediction (X-ray spectrum from tube voltage)	100% accuracy
Wang *et al*. (2024)	DL (MLP-radiomic)	MRI and oncology	Prediction (rectal cancer treatment response)	AUC values 0.718 and 0.810
Srigiri and Yepuganti (2023)	DL (CNN)	MRI	Classification (brain tumors)	99.48% accuracy
Mukesh *et al*. (2023)	DL (CNN)	X-rays	Diagnosis (thoracic pathologies)	AUROC values 0.9450 and 0.9120.
Md *et al*. (2022)	DL (CNN-RNN)	X-rays	Diagnosis (COVID-19)	99.86% accuracy, 99.99% AUC, 99.78% recall, 99.78% F1 score
Fatih (2021)	DL (LSTM)	X-rays	Diagnosis (COVID-19, pneumonia, normal)	100% success rate (accuracy, sensitivity, specificity, and F1 score)
Rajeev *et al*. (2023)	DL(CNN-LSTM)	MRI	Classification (brain tumor)	97.94% validation accuracy
Mahati *et al*. (2023)	DL (CNN-LSTM transfer based)	Mammography	Classification (benign and malignant)	99% binary accuracy and 92.5% for subtypes
Yuping *et al*. (2024)	DL (Autoencoders)	MRI	Image retrieval	99.09% accuracy
Mohammed *et al*. (2023)	DL (Autoencoders)	MRI	Image denoising	Validation loss of 0.0001
Olthof *et al*. (2021)	NLP/ML	X-rays	Diagnosis (Pneumothorax)	96% and 93% accuracy and 95% and 83% F1 score for simple and complex reports, respectively
Sylvain *et al*. (2024) Carolina *et al* (2023)	Robotics	CT, MRI, USS, radiotherapy	Minimally invasive procedures	35% and 30% reduction in radiation dose and operating time, respectively
Wajid *et al*. (2022)	Expert system	CT	Diagnosis and severity prediction (COVID-19)	F1 score of 0.94
Prashant *et al*. (2021)	Expert system/DL	X-rays	Diagnosis (COVID-19 pneumonia)	87% accuracy, 98% negative predictive value, 0.66–0.90 sensitivity
Mandong *et al*. (2021)	FL	MRI	Segmentation and prediction (brain tumor)	0.845 accuracy
Huda *et al*. (2023)	FL /DL	MRI	Classification (brain tumors)	99.31% accuracy
Alessandro *et al*. (2022)	DL	Ultrasound	Segmentation and classification (breast cancer masses)	82% and 91% accuracy, respectively
Jayasutha *et al*. (2024)	FL/DL	MRI	Classification (Alzheimer's disease)	99% accuracy
Yadlapalli and Dokku (2023)	FL/DL	X-rays	Classification (COVID, viral and bacterial pneumonia)	97% accuracy
Chong *et al*. (2020)	ML/NLP	MRI	Workflow	No-show rate decrease from 19.3% to 15.9%
Nabulsi *et al*. (2021)	DL	X-rays	Workflow	Turnaround time decrease by up to 28%
Ardila *et al*. (2019)	DL	CT	Segmentation (lung nodules)	94.4% AUC
Wang *et al*. (2022)	DL/NLP	CT	Classification (lung nodules)	70.92% sensitivity, 93.17 specificity, 0.862% AUC

(*Continued*)

Table 1. (*Continued*)

Study	AI technique	Modality	Task	Performance
Aravind (2022)	DL	X-rays	Classification (14 chest anomalies)	87% accuracy and 0.78 AUC
Shadi and Noor (2021)	DL	MRI	Classification (brain tumors)	96.56% accuracy
Ravi *et al.* (2021)	DL	Mammography, USS, CT, MRI, X-rays	Diagnosis (breast imaging, lung nodules)	AUC values 0.868–0.909 (mammography, USS, MRI) Accuracy of 0.937 (CT) and 0.864 (X-rays)
Reabal (2023)	DL	X-rays	Diagnosis (musculoskeletal)	0.87 accuracy. 0.93 specificity, 0.93 AUC in 3 out of 7 anatomic regions
Yasir *et al.* (2025)	DL	MRI	Diagnosis (brain tumor, including Alzheimer's disease)	99% accuracy
Nafiseh *et al.* (2023); Meghavi and Megha (2023)	ML/DL	X-rays	Diagnosis (COVID-19 and heart failure)	98.91% accuracy and 82% accuracy, respectively
Nwaiwu and Das (2024)	ML	X-rays	Image acquisition	16% reduction in radiation and contrast doses
Atita *et al.* (2024)	ML/DL	MRI	Image acquisition	Shorten scan time to less than 1 minute
Felix *et al.* (2024)	DL	MRI	Image acquisition	Scan time reduction by 44.4%
Lennart *et al.* (2023)	ML/DL	CT	Image acquisition	71% reduction in radiation dose
Richard *et al.* (2019)	ML/radiomics	Radiotherapy and oncology	Prediction (nasopharyngeal carcinoma)	AUC value 0.80
Jean-Emmanuel *et al.* (2018)	DL/radiomics	Radiotherapy and oncology	Prediction (rectal cancer)	80% accuracy
Yung-Shuo and Yen (2021)	ML/radiomics	Radiotherapy and oncology	Prediction (esophageal cancer)	AUC value 0.813
Daniel *et al.* (2020)	ML/radiomics	Ultrasound and oncology	Prediction (breast cancer)	91% sensitivity, 83% specificity, 87% accuracy
Almir *et al.* (2020)	ML/radiomics	MRI and oncology	Prediction (breast cancer)	97.4% and 83.9% accuracy for three and six parameters, respectively

with manual analysis [87]. They also achieved a competitive performance of about 82% and 91% in segmentation and classification of breast cancer masses, respectively, sonographically [88]. In chest radiography, DL classifier output models classified 14 anomalies with an accuracy of 87% and an AUC value of 0.78 [89]. A newly designed CNN model attained an impressive classification accuracy of 96.56% for brain tumors in contrast-enhanced magnetic resonance images [90].

3) Diagnosis: Integration of AI into computer-aided detection systems has redefined the nature of CT, USS, X-ray, and MRI image interpretation by improving diagnostic accuracy, reducing false positives, and eliminating fatigue-based errors or inconsistencies due to varied expertise levels [91]. DL models in a recently conducted systematic review and meta-analysis achieved high performance in the diagnosis of diabetic retinopathy, glaucoma, and age-related macular degeneration (AUC values: 0.933–1). It also has shown good accuracy in detecting lung nodules/cancer in both CXR and CT scan (AUC values of 0.864 and 0.937, respectively). Under breast imaging (mammography, breast tomosynthesis, ultrasound, MRI), several included studies were found to produce high accuracy in detecting cancer, with AUC values ranging from 0.868 to 0.909 across these modalities [92]. A combination of DL models showed promising signs in musculoskeletal reporting using X-rays, outperforming radiologists in three out of seven anatomical regions (AUC 0.93, accuracy 0.87, specificity 0.93) [93]. Research has asserted that ML/DL algorithms (CNN, RF, SVM) can detect COVID-19 from CXR (accuracy 98.91%) [94]; DL algorithms, in particular, are useful in diagnosing heart failure (accuracy, sensitivity, and specificity of 82%, 95%, and 74% respectively) [95]. Interestingly, in MRI scans, these models have achieved an accuracy of almost 99% in diagnosing brain tumors, including detecting Alzheimer's disease [96]. In an experimental study in the diagnosis of various heart diseases, SVM and ANN models were integral in the early, accurate diagnosis of arrhythmia, cardiomyopathy, and coronary heart disease in the ratios of 89.1%, 80.2%, 83.1%, and 85.8%, 85.6%, 72.7% respectively [97]. Elsewhere, SVM has proven to surpass ANN and DT algorithms, with an accuracy of 92.1% for coronary heart disease [98]. A combination of different AI algorithms (genetic and random forest) produced an accuracy of 95.58% in the early diagnosis of Parkinson's disease, the best result so far [99].
4) Image measurements and assessment: AI algorithms can detect voxel-level patterns, characterize specific biomarkers, and analyze quantitative assessments in MRI. They have also been integral in the volumetric analysis of brain tissue, intracranial hemorrhage/hypertension, ischemic stroke and cerebrospinal fluids, and malignant lesions in CT and MRI scans [100]. The incorporation of radiomics in abdominal and pelvic imaging introduces quantitative metrics into radiology reports, enhancing clinical outcomes, for example, a case of hepatocellular carcinoma (AUC of 0.79 with the validation

dataset) [101]. In echocardiography, AI techniques have enhanced functional evaluations such as ejection fraction measurements (98% of studies, with an average analysis time of 8 ± 1 s/patient), further improving accuracy and less reliance on the physician's experience [102]. In oncological imaging, AI algorithms can assess tumor size and metabolic changes and perform granular analysis of image pixels/voxels to monitor treatment outcomes. These DL strategies have streamlined cancer diagnosis and prognosis (equaling expert readers and also as second readers for breast/lung cancer, brain tumors, and pancreas imaging), allowing for efficient tracking of tumor progression and significantly enhancing overall treatment assessment and patient care (>80% of approved devices regarded the complex area of cancer diagnostics) [103, 104]. A significant breakthrough is the integration of data from multi-modality imaging (from any of echocardiography, CT angiography, PET, SPECT) utilizing ML approaches (ANN, SVM, KNN, DT) to provide holistic information for complex assessments and procedural planning in cardiac imaging [104].

5) Image acquisition and reconstruction: AI has been pivotal in optimizing image quality and study protocol for MRI/CT scans [100, 101]. In X-rays, Nwaiwu and Das [35] demonstrated the ability of ML to accelerate image acquisition by the use of positioning, noise reduction, DL algorithms, and specific anatomic ML algorithms that allow for an increase in receptor sensitivity. This proof has been associated with a decrease in radiation and contrast doses by 16%. Moreover, DL algorithms have proven useful in image rotation, flipping, cropping, labeling, making measurement, image comparison, and monitoring in busy practice [105]. Furthermore, studies have reported ML/DL to be very effective in removing artifacts, reconstruction, and analysis in cross-sectional imaging such as rapid accelerated MR imaging to shorten scan time to just 1 minute without compromising quality and still giving accurate brain volume measurements (enhances patient throughput) [106]. Similar results were obtained in Schlicht et al. [107], where advanced DL techniques in lumbar spine MRI reduced acquisition time by 44.4%, with better signal contrast, resolution, and accessibility of the spinal canal and neural foramen in comparison to conventional techniques. In CT, DL, when compared to filtered back projection and hybrid iterative reconstruction conventional techniques, provides improved image quality and a reduction in radiation dose up to 71% [108]. Numerous studies assert the great relevance of DL techniques for image reconstruction and functional analysis in MRI scans, ultralow intravenous contrast protocol MR imaging, ultralow radiation dose CT, and nuclear medicine acquisitions [109, 110].

6) Prediction: ML and radiomics have been useful in predicting response and outcomes of disease to treatment, mainly in the field of radiotherapy and oncology. The rationale behind radiomics use in prediction is to utilize algorithms that are able to identify patterns within images, beyond what the human eye can perceive, and to explore them to make predictions. Examples of its applications include ML/MRI radiomics predicting the response of nasopharyngeal carcinoma to intensity-modulated radiation therapy (AUC value of 0.80) [111], DL/CT radiomics in predicting neoadjuvant treatment response to rectal cancer (80% accuracy) [112], meta-analysis in investigating the predictive power of radiomics in esophageal cancer (AUC value of 0.813) [113], KNN/USS radiomics for breasts cancers (sensitivity of 91%, a specificity of 83%, and an accuracy of 87%) [114], and ML/MRI radiomics for pathologic response in breast cancer (accuracy of 97.4% and 83.9% for three and six MRI parameters, respectively) [115]. Additionally, it has demonstrated its capability in predicting postoperative outcomes (brain and spine surgeries) and survival rates and chances of complications to enable surgeons in treatment planning and managing patients' expectations such as predicting survival rate of lung cancer utilizing radiomics features in CT ($p = 0.04$ following radiotherapy) [116], predict recurrence of glioma patients in brain MRI (good discriminator, with c-index 0.7578 and 0.6925 in the training and validation cohort, respectively), and predict modeling/decision support for angiography procedures [117, 118]. Radiomics, although highly promising, has not yielded widely generalizable results, hence limiting its current use and implementation in clinical practice.

4.3. Challenges and prospects of AI use in radiology

Despite AI's huge impact in radiology, it does come with several challenges that must be overcome to ensure a successful implementation. This can be broadly grouped into three categories:

1) Technical: AI algorithms require large storage with high computational power to analyze medical images and identify anomalies. Lack of access to large-scale storage solutions (especially in remote or underserved areas) due to cost and hardware limitations remains an uphill struggle, and combating these technical challenges does not come cheap. AI development often requires substantial upfront costs, including hardware (powerful servers, GPUs), software, and data infrastructure. In fact, AI systems require continuous updates, maintenance, and monitoring, which adds to the long-term cost. Advanced AI models, especially DL, require specialized expertise and can be very expensive to develop and train [119]. Such a high cost of AI development and implementation, taking into consideration both the initial investment and the long-term operational costs, makes it difficult for radiology units to adopt AI solutions, potentially exacerbating existing inequalities and creating a divide between those who can leverage the technology and those who cannot. The quality and quantity of data are crucial for the performance of AI algorithms. Hence, the availability of an adequate amount of data with accompanying accurate labels to train models must be taken into full account, as training data should be a representative of the intended population of AI applicability [120]. There are ongoing issues of data quality in radiology, as medical images can be noisy, incomplete, or inconsistent. This makes it even harder for AI algorithms to learn accurately, due to no standardization of the process [121, 122].

2) Human: Training of users to effectively use AI appropriately and safely in radiology presents a significant hurdle. Considering the evolving nature of the technology field and new discoveries, such education and training have got to be an ongoing one that will enable radiology professionals to effectively integrate AI into practice, understanding its capabilities and limitations. This demands great awareness and technical ability, which in itself could be quite challenging due to varying levels of expertise among professionals [123, 124]. Interdisciplinary collaboration with AI experts in developing and refining AI tools to ensure their safe use in conformity with ethical principles, including participation in continuous professional development to stay informed with advancements in AI and best practices, is a huge task [125]. In addition, there are ongoing fears that AI will

automate certain tasks, leading to a shift or replacement of the radiologist role in the near future. Such an impact of AI, including on the workload, responsibilities, and professional development of radiologists, is one to be considered very closely, with a potential for deskilling [126].

3) Ethical: AI systems often require access to large datasets, including sensitive information like biometric data and healthcare records, which raises concerns about unauthorized access, misuse, and the potential for data breaches. Data privacy, also known as information privacy, is the principle that a person should have control over their personal data. The collection and processing of these sensitive data raise significant privacy concerns, especially if robust security measures are not in place. Besides, data shared for one purpose might be used to train an AI system for another, potentially without the individual's knowledge or consent, in this case. Also, AI models can be vulnerable to attacks where sensitive information from the training data is revealed through the system's outputs, in some cases, inadvertently disclosing sensitive information about individuals. Therefore, such re-identification attacks, unintended data memorization, and the use of sensitive data without proper consent are some of the issues contributing to data privacy challenges. Central to data ethics in AI use are principles of informed consent, privacy, data protection, and transparency [127].

Protecting patient data is paramount, as AI system ought to be designed and implemented in a way that guarantees patient confidentiality and compliance with relevant regulations. It is imperative to point out that AI algorithms process and analyze sensitive medical images, and this is a bit worrying because privacy and data protection concerns, if not tackled, could lead to a potential breach in professional practice. Breaches of sensitive data can have serious consequences, including identity theft and discrimination. Informing patients about the use of AI in their care to obtain informed consent, particularly when data are used for AI training, sounds reasonable yet could be demanding [128].

Furthermore, the "black box" nature of most AI models would mean that the decision-making process is not transparent, making it difficult in getting trust from healthcare professionals and patients. Black box AI models arise for one of two reasons: Either their developers make them into black boxes on purpose, or they become black boxes as a by-product of their training. Users cannot understand how a black box model makes decisions that it does including the factors it weighs and the correlations it draws. Even if the model's outputs seem accurate, validation can be difficult without a clear understanding of the processes that lead to those outputs. Sometimes, black box models can arrive at the right conclusions for the wrong reason (a phenomenon known as "Clever Hans effect"), and this can have serious consequences when models are applied in real-world radiology settings. Hence, transparency in algorithms and explainability of AI outputs are essential for responsible use [118].

Again, unfairness caused by bias in data sources is a frequent problem. This can be traced to the current absence of regulatory oversight as algorithms are mostly not trained on diverse and representative datasets, limiting generalization. There is also a chance that AI algorithms can perpetuate or amplify existing biases in data, which leads to unfair or discriminatory outcomes for certain patient groups. A closer look at available evidence supports that while high-quality data are essential for training accurate AI models, diverse data are necessary to avoid bias and overfitting. Data diversity is crucial for mitigating bias in AI systems by ensuring that training data accurately represent the population and include diverse perspectives, achieved by using diverse data sources, data augmentation, and careful data cleaning. This will result in AI models that are less likely to perpetuate or amplify existing societal biases, thus fostering equitable outcomes for all users [118, 119].

4.4. Future research directions

The future of AI in radiology demands addressing these challenges. One of the ways is via extensive model training and testing and rigorous data scrutiny/validation. With current models trained and validated on specific datasets, this does not promote data diversity, as earlier mentioned, crucial for building fair, robust, and effective AI systems. Employing a variety and representation of different types of data to train AI models is vital to mitigating bias, improving accuracy across diverse populations, and enhancing the generalizability of AI models. Thus, there is a need for future research to utilize large, diverse datasets to reflect the diversity and complexity of real-world clinical data. In addition, intensified efforts should be channeled into exploring methods for robust validation of AI tools on diverse, unseen datasets to ensure reliable performance in various clinical settings. Studies have projected hybrid approaches such as deploying cloud computing and edge computing for training and validation [119].

As has been highlighted, there is a need for regulatory oversight and for AI applications to adhere strictly to ethical guidelines to guarantee the responsible handling of patient data in radiology. This involves a robust multidisciplinary approach that prioritizes patient safety, data privacy, and equitable AI use. Therefore, developing ethical guidelines, regulatory frameworks, and quality assurance measures for safe and responsible use of AI in radiology is crucial to sustainability. Emerging key aspects of regulatory landscape to include data governance (quality, security, and privacy of data used to train and validate AI models), risk management, explainability (transparency in the development, validation, and performance of AI algorithms, including addressing potential biases), cybersecurity (protecting AI systems from cyber threats to prevent data breaches and ensure patient safety), ethical considerations (ethical concerns related to AI bias, fairness, trust, benefits in healthcare, and the potential impact on healthcare disparities), and post-market surveillance (ongoing monitoring of AI-enabled devices in clinical use to detect and address potential safety issues) [129].

Another key feature to look into should be the "black box" concern already mentioned, an occurring issue for most AI models, which makes it difficult to comprehend how intelligent systems arrive at decisions. Creative research by way by developing methods that make the decision process of AI systems more transparent will increase trust and adoption, essential in advancing AI use in radiology practice. This involves designing a framework that balances technological innovation, ethical considerations (including data privacy), and legal integrity in developing more transparent and interpretable AI models, combining doctrinal, comparative, and public policy research to gain a detailed understanding, spanning beyond simple algorithmic improvements.

Preparing the radiology team for an AI-infused clinical scenery is an aspect most often overlooked, achievable through mandatory extensive staff trainings and capacity building sessions. This has significantly addressed knowledge gaps and increased hands-on skills by 75% while calming fears, as it was initially thought that AI would displace radiologists in reporting, when not the case [130]. Therefore, research into developing AI-powered tools for medical interpretation training and competency assessment is vital. Where possible, the radiology team should be engaged in every step of the AI process, from the development of the model to deployment.

Planned efforts should be targeted at integrating AI with virtual reality (VR) and augmented reality (AR) to improve AI models' robustness, while creating an immersive and interactive environment for medical imaging visualization and analysis. Future studies could explore VR and AR in enhancing image interpretation and patient education [131].

Lastly, fostering interdisciplinary collaborations among medical, technological, and academic fields is paramount in this technologically advancing era [132]. Studies should look into these lines in strengthening collaborations, cultivating a future where AI and radiology can work pari passu to reshape the healthcare landscape, enhance patient care, and improve clinical outcomes.

4.5. Strengths and limitations

This review engages with up-to-date and a wide range of academic sources to offer a comprehensive account of the history of AI and its applications in radiology, tracing the development of AI from its early days and covering key milestones from the 1940s to 2025. A detailed overview of AI techniques and their revolutionary impact in the broad field of radiology was provided, exploring both diagnostic and therapeutic aspects. Potential challenges were identified, and suggestions on future research directions were made. However, due to the large number of studies considered from different locations, population groups, and AI models, generalization of findings could be challenging, as well as the tendency of bias in AI applications.

5. Conclusion

This article provides a chronological account of AI and techniques, with AI making major progress in almost all its sub-areas, laying the path for explorations, extensive research, and future discoveries. Despite the onward movement and rapid advancements in AI witnessed till date, its applicability in radiology does come with some limitations. While this study proposes actionable steps and road map for AI adoption in radiology departments (AI strategy, AI engineering, stakeholders' engagement, case studies, AI in practice, regulatory/ethical considerations, future research directions), it is important to recognize and address these challenges following AI's continuing breakthroughs.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Victor Chigbundu Nwaiwu: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Sreemoy Kanti Das:** Validation, Resources, Data curation, Writing – review & editing, Supervision, Project administration.

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