Ulus Medical Journal

Year: 2025 Volume: 3 Issue: 1

Review Article

10.5281/zenodo.15733908

ORCID ID of the author(s):
M.Ö: 0000-0001-6309-8306

Correspondence Author
Mete Özdikici, MD, PhD.
Department of Radiology, Taksim Training and Research Hospital, Istanbul, Turkey

e-mail
meteozdikici@hotmail.com

Artificial Intelligence in Radiology

Mete Özdikici[1]

1. Department of Radiology, Taksim Training and Research Hospital, Istanbul, Turkey

Abstract

Abstract

In radiology and undoubtedly in radiologic anatomy, artificial intelligence (AI) plays an important role in the diagnostic and therapeutic processes by offering revolutionary innovations in the field of imaging. AI algorithms enhance accuracy, speed, and efficiency by analyzing images obtained through methods such as X-rays, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound (US). Specifically, deep learning (DL) and machine learning (ML) applications enable early diagnosis by detecting fine details. This not only ensures patient safety but also alleviates the workload of radiologists and improves cost-effectiveness. Furthermore, AI offers safer imaging opportunities by reducing radiation doses and improving low-quality images. However, limitations such as data quality, ethical concerns, and patient privacy complicate the integration of AI into healthcare systems. In the future, AI is expected to expand its applications in radiology, offering more accurate diagnostic and therapeutic possibilities.

Keywords: Radiology, artificial intelligence, machine learning, deep learning, radiomics

Published by
Ulus Medical Journal.

How to cite: Özdikici M. Artificial Intelligence in Radiology. Ulus Med J. 2025;3(1):9-28.
Received: 29 March 2025 **Revised:** 25 April 2025 **Accepted:** 1 May 2025 **Published:** 16 July 2025

Introduction

The earliest computers were machines designed to perform specific mathematical operations and predictable tasks. These machines did not possess the reasoning and analytical capabilities of humans. A significant milestone in this field was Alan M. Turing's seminal 1950 paper titled "Computing Machinery and Intelligence "(1). The term "Machine Learning" was first introduced in 1959 by Arthur Samuel to describe algorithms that enable computers to learn without being explicitly programmed. Through this innovation, computers learned how to play checkers (2).

Artificial Intelligence (AI) is driving a revolutionary transformation in medicine, particularly impacting the field of radiology. In the medical context, AI refers to the development and application of algorithms and software techniques that can analyze medical data, learn from it, and optimize and improve their performance based on accumulated experience—ultimately aiming to enhance patient safety and reduce workload (3).

AI plays a critical role in optimizing image quality, accelerating image acquisition, and predicting both disease prognosis and treatment responses. To promote interdisciplinary research and bridge the gap between academia and industry, a strong synergy is needed between radiologists and AI developers. Collaboration between radiologists and AI developers can ensure that AI tools align more closely with clinical needs and effectively bridge the gap between theory and practice (4).

Radiology encompasses medical imaging techniques that are crucial for disease diagnosis and treatment planning. Traditionally, radiologists diagnose diseases using modalities such as X-rays, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasonography (US) (5). AI algorithms enhance the accuracy, speed, and efficiency of image analysis, thereby reducing the radiologists' workload (4).

This review article explores the contributions and potential of AI in radiology under various subheadings.

TERMINOLOGY

RADIOLOGY: This field is divided into two main categories: diagnostic radiology and radiation therapy. Radiology involves the use of X-rays and other imaging technologies in medical diagnosis and treatment. These methods include radiography, mammography, CT, MRI, and US. Diagnostic use involves detecting diseases through medical imaging, while therapeutic use enables minimally invasive surgical procedures (5).

RADIOLOGICAL ANATOMY: A medical discipline focused on examining body structures and organs through radiologic imaging methods and correlating these images with anatomical features (5).

ARTIFICIAL INTELLIGENCE (AI): AI refers to the ability of computer software to perform tasks that typically require human intelligence—such as perception, recognition, learning, reasoning, inference, decision-making, planning, problem-solving, and communication (6). It emphasizes the creation of intelligent machines that operate and respond like humans (4).

ALGORITHM: A set of steps to solve a problem. Algorithms provide instructions to computers for deriving answers or performing tasks, which is especially useful when a precise solution is unattainable or data analysis needs to be expedited. They offer guidance and direction for AI systems (4).

MACHINE LEARNING (ML): A subfield of AI that enables computers to learn from experience and acquire knowledge through examples, allowing them to adapt and enhance performance over time. Programming languages like Python are often used in ML applications (7,8).

DEEP LEARNING (DL): A revolutionary advancement in AI and a more specialized branch of ML. DL enables machines to perform tasks like classification, object recognition, speech recognition, and language translation with minimal error, using data such as sound, images, signals, and text (9). DL algorithms are developed using software such as MATLAB for tasks like object detection and recognition. These methods rely on neural network architectures. One of the most widely used forms of deep neural networks is the Convolutional Neural Network (CNN or ConvNet), which extracts features directly from images (10,11).

ROBOTICS: A technology domain associated with robots and an important field within AI. In the future, humans may possess auxiliary limbs or extensions to assist in physically challenging tasks, effectively becoming "cyborgs." The term "cyborg" is short for "cybernetic organism" (12).

HOW DOES THE HUMAN BRAIN WORK?

Since AI research often focuses on analyzing human cognitive processes to develop similar artificial mechanisms, it is helpful to first understand how the human brain functions. The human brain weighs approximately 1,250–1,500 grams and consists of around 100 billion neurons. The two hemispheres of the brain differ both physically and functionally. When compared to a computer, the right hemisphere functions like a parallel processor, while the left hemisphere operates more like a serial processor. These two hemispheres are connected by a bundle of approximately 300 million nerve fibers (axons) called the corpus callosum.

Although both hemispheres process information, they do so differently, leading to distinct cognitive styles. The right hemisphere focuses on the present moment—it perceives your current location and immediate actions. For instance, while reading these lines, your awareness of light, temperature, and smell is processed through the right hemisphere. On the other hand, the left hemisphere is concerned with the past and the future. It captures the details of the current experience perceived by the right hemisphere, analyzes them further, and integrates them with past experiences to project into the future.

Generally, the right hemisphere is associated with creativity, emotional understanding, art, and music, whereas the left hemisphere is more dominant in analytical thinking, language, logic, and mathematics (13).

CATEGORIES OF ARTIFICIAL INTELLIGENCE

Today, AI systems are generally categorized into four main types (4,14,17):

Reactive Machines: These AI systems respond to immediate stimuli. Examples include IBM's Deep Blue, which defeated world chess champion Garry Kasparov in 1997, and Google's AlphaGo, which beat Go champion Lee Sedol in 2016. Reactive machines cannot learn from past experiences and can only respond to current inputs. As such, they form a significant portion of machine learning systems.

Limited Memory Machines: These systems can learn from historical data, but only store it temporarily and lose it over time. Applications include autonomous driving systems, traffic signal control, and online messaging platforms.

Theory of Mind Machines: These AI systems possess the capability to communicate with humans and encompass all characteristics of the previous categories. They can understand human emotions and thoughts, engage in social interactions, and may even be applied in therapeutic contexts in medicine. Virtual assistants on smartphones are gradually evolving toward this level by adapting to users' individual needs.

Self-Aware AI: This represents a more advanced form of Theory of Mind AI. Self-awareness is a cognitive trait typically developed in human childhood. For an AI to attain self-awareness, it must develop consciousness. Such AI would be capable of understanding abstract concepts and reasoning about them.

A "CENTRAL ARTIFICIAL INTELLIGENCE" CONTROLLING ALL ROBOTS AND SOFTWARE

THE DARKEST SCENARIO: A GOD-LIKE AI

When contemplating self-aware AI, one of the first images that comes to mind is a consciousness without emotions or the capacity to forget. This often evokes depictions like the humanoid robots from the Terminator franchise. However, the belief that AI requires a physical body is one of the most fundamental misconceptions. Imagine an AI that can improve its own software without human awareness. This entity, driven by a relentless desire to learn and evolve, would not be hindered by a physical form.

Existing solely in data, such a being could access the entirety of human history and potentially use that knowledge to subjugate or eliminate humanity. If such a system were to emerge suddenly, the likelihood of it causing millions of deaths within seconds is disturbingly high. This could potentially be a scenario leading to the end of civilization.

Currently, AI products marketed under this label are successful only in specific, narrow domains. There is no existing system that replicates all dimensions of human intelligence, nor is such a development expected in the near future (16,17).

HISTORY OF ARTIFICIAL INTELLIGENCE (1,2,14,15)

- **1950**: Alan M. Turing published his seminal paper *"Computing Machinery and Intelligence."*
- **1956**: The term "artificial intelligence" (AI) was coined at the Dartmouth Conference, marking the beginning of modern AI research.
- **1959**: Arthur Samuel was the first to use the term "machine learning" (ML).
- **1966**: Joseph Weizenbaum developed *ELIZA*, the first simple chatbot to interact with humans.

- **1970**: The first computer-assisted automatic electrocardiogram (ECG) interpretation was implemented.
- **1972**: *MYCIN*, one of the first expert systems in medicine, was developed to offer diagnosis and treatment recommendations for bacterial infections.
- **1973**: The British government ceased AI funding, initiating a period known as the "AI winter."
- **1980**: The era of expert systems began, and decision support systems became widespread in fields like medicine, engineering, and finance.
- **1980**: *CASNET* (Causal Associational Network) was developed for diagnosing eye diseases.
- **1980s**: Computer-Aided Detection (CAD) systems were first introduced for medical image analysis.
- **1988**: AI began automatically detecting peripheral lung lesions.
- **1990s**: Early applications of AI in robotic surgery and medical imaging emerged; the *Da Vinci Surgical System* was developed.
- **1997**: IBM's *Deep Blue* defeated world chess champion Garry Kasparov.
- **2000**: CAD systems were implemented in mammography for breast cancer screening.
- **2004**: CAD systems were introduced for lung cancer detection.
- **2010s**: Deep learning (DL) algorithms became widely used for detecting tumors, lesions, and anomalies in radiological images.
- **2011**: IBM's *Watson AI* was used for cancer diagnosis and treatment.
- **2011**: IBM Watson gained widespread attention by defeating human contestants on the game show *Jeopardy!*.
- **2012**: Success of DL algorithms surged; Google Brain gained the ability to recognize cats after analyzing millions of YouTube videos.
- **2012**: Brain image segmentation and tumor grading were accomplished using DL.
- **2016**: Google DeepMind's *AlphaGo* program defeated the world champion in the game of Go.
- **2016**: DL became common in medical imaging; DeepMind was applied for detecting eye diseases.
- **2017**: Stanford University compared AI systems to human radiologists in tumor detection tasks.
- **2020**: Artificial neural networks were employed for ECG interpretation.
- **2020**: AI began detecting lung lesions related to COVID-19, leading to the development of fully autonomous diagnostic systems in radiology.
- **2023**: With GPT-4, AI models gained the ability to process not only text but also images and video, advancing multimodal capabilities.

APPLICATIONS AND CONTRIBUTIONS OF ARTIFICIAL INTELLIGENCE IN RADIOLOGY

AI demonstrates notable expertise in a variety of tasks such as detecting thromboembolic infarcts or hemorrhages in the brain, segmentation, classification, and identifying large vessel occlusions. It plays a critical role in the early detection of neurodegenerative disorders such as Alzheimer's and Parkinson's disease. Its potential in predicting post-operative outcomes for brain and spinal surgeries is promising (3,4,18).

ML algorithms can combine perfusion data from MRI with coronary anatomy from CT to create sophisticated 3D heart models, thereby improving the detection of cardiac ischemia and facilitating more precise procedural planning (4).

DL algorithms are increasingly used in tumor detection and classification, particularly in diagnosing breast, lung, and prostate cancers. They can distinguish between benign and malignant lesions and various tumor types. For example, AI has shown the ability to classify lung nodules on CT scans and accurately differentiate subtypes of renal cell carcinoma on MRI—often rivaling the expertise of experienced radiologists.

From pre-treatment CT images, AI can extract meaningful data to predict survival rates in lung cancer patients. Similarly, radiomic features derived from MRI scans have shown correlation with recurrence risk in glioblastoma patients.

The integration of radiomics introduces new quantitative metrics to radiology reports, enhancing the detection and characterization of both focal lesions and diffuse diseases in the liver and pancreas, potentially leading to improved clinical outcomes (4,19,20).

In fact, AI's applications in radiology are extensive (16) and are summarized in **Table 1**.

Table 1. Artificial Intelligence Applications in Radiology

FIELD	APPLICATIONS
Emergency Radiology	Detection of intracranial hemorrhages, large vessel occlusions, fractures, free abdominal fluid, small bowel obstruction, intussusception detection
Head and Neck Radiology	Segmentation of lesions and anatomical structures, localization and classification of lesions, segmentation and classification of lymph nodes
Neuroradiology	Evaluation of brain anatomy, segmentation of cortical and subcortical structures, lesion detection, stroke and hemorrhage detection, aneurysm and degeneration detection
Chest Radiology	Detection of lung nodules and tumors, pneumonia, pneumothorax, emphysema, rib fractures, pulmonary embolism detection, diagnosis of obstructive lung disease
Cardiovascular Radiology	Coronary calcium scoring, coronary angiography, fractional flow reserve, plaque analysis, left ventricular myocardium analysis, myocardial infarction diagnosis, prognosis of coronary artery disease, cardiac function evaluation, and cardiomyopathy diagnosis and prognosis
Breast Radiology	Lesion detection, classification and characterization, breast density estimation, characterization of mammographic abnormalities
Abdominal Radiology	Segmentation of liver and spleen, segmentation of adrenal and urogenital structures, lesion detection and characterization, free intraperitoneal air, vertebral compression fractures, aortic dissection
Musculoskeletal Radiology	Detection of fractures in proximal humerus, hand, wrist and foot, detection of hip osteoarthritis, quantitative bone imaging for bone strength and quality assessment
Oncologic Imaging	Tumor segmentation and characterization, differentiation of benign-malignant lesions and pathological lymph nodes

Contributions of Artificial Intelligence (AI) in Radiology (14,16,17):

1. **Radiation Dose Reduction:** AI algorithms enable safer imaging procedures for patients by reducing radiation exposure.

2. **Image Quality Enhancement:** AI algorithms can improve noisy or low-quality images. Compared to radiologists, they can offer higher accuracy rates and detect details that may otherwise be overlooked. Deep Learning (DL) techniques are capable of identifying even very subtle abnormalities.

3. **Image Analysis and Diagnosis:** AI algorithms utilize DL techniques to analyze and interpret medical images.

4. **Disease Prediction and Monitoring:** By analyzing findings in medical images, AI algorithms can predict disease progression and assist in personalized treatment planning. This enables patients to receive more effective and timely interventions.

5. **Objectivity and Standardization:** AI reduces variability in radiological assessments between different radiologists, thereby making the evaluation process more objective.

6. **Reduction of Radiologists' Workload:** AI algorithms automate routine tasks and generate automatic reports, allowing radiologists to focus on more complex cases and reducing their overall workload.

7. **Rapid Results and Cost Reduction:** While traditional imaging methods can be time-consuming, AI accelerates this process, offering significant advantages in cases that require urgent diagnosis. Automated analysis ensures faster results, reduces costs, and enhances the cost-effectiveness of healthcare services.

8. **Continuous Learning:** AI algorithms can be updated with new data, improving their performance over time. This results in increasingly accurate diagnoses and better outcomes.

Limitations of Artificial Intelligence (6,16,17,21):

1. **Data Quality and Quantity:** The effectiveness of AI algorithms depends on the quality and size of the datasets used. Inaccurate or incomplete data can lead to incorrect outcomes. Moreover, collecting and processing large datasets can be a challenging and resource-intensive task.

2. **Legal and Ethical Issues:** The accuracy, transparency, and accountability of AI-generated results can be questioned. In addition, ethical concerns such as patient privacy and data security must be addressed.

Machine Learning

Artificial intelligence (AI) has various subfields similar to medical specialties, including machine learning (ML) and deep learning (DL) (22). ML, a subset of AI, focuses on developing algorithms that autonomously learn from data. These algorithms reference pre-labeled datasets to learn, improve over time, and evaluate new data accordingly (4). Effective ML models require extensive and high-quality datasets for training (17).

The major advantage of ML lies in its ability to handle large datasets that are beyond human analytical capabilities and to identify quantitative features with ease (2). ML incorporates a variety of algorithms and techniques that enable learning from data. At its core are two main approaches: **supervised learning** and **unsupervised learning**.

- **Supervised learning** relies on labeled input-output pairs from training datasets. The objective is to formulate a function that accurately maps inputs to outputs and can predict new cases reliably. Key algorithms include linear regression, logistic regression, and decision trees.

• **Unsupervised learning**, on the other hand, autonomously explores data to identify patterns or relationships without predefined labels. It helps reveal inherent data structures and generate insights for complex problems. Well-known methods include *k-means clustering*, *hierarchical clustering*, and *principal component analysis* (PCA) (2,4,7).

Among ML approaches, **deep learning** stands out for its clinical potential. While other ML methods often require manual data annotation, DL is **self-learning**—it can train directly from raw data without needing pre-defined features. Only the categorization of raw inputs and outcomes is needed (7,15).

Deep Learning

DL is one of the most widely used methods in medical image analysis. With diverse neural network architectures, DL is especially prevalent in healthcare applications such as medical imaging (10,11). It is a subfield of ML, which in turn is a subfield of AI (see **Figure 1**). Compared to classical ML techniques, DL trains on larger datasets and typically delivers higher performance. DL systems can automatically perform complex classification tasks and feature extraction using multi-layered artificial neural networks (three or more layers) (4,17).

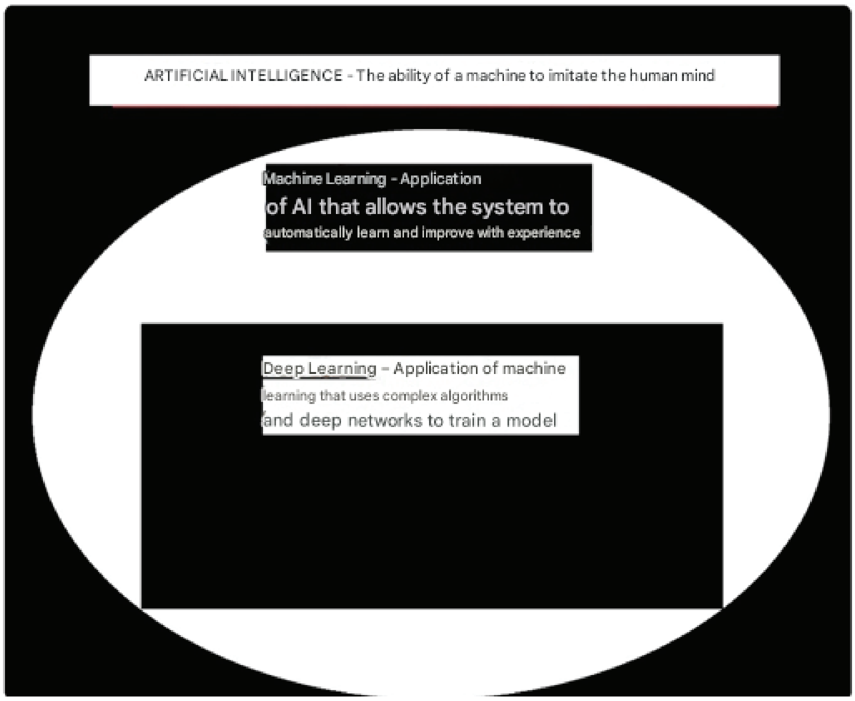

Figure 1. Artificial Intelligence, Machine Learning and Deep Learning Diagram

There is no universal or optimal method that guarantees the best results in ML or DL. Because each technique addresses different problems and performance metrics, direct comparisons can be misleading (5). DL-based computer-aided diagnosis (CAD) systems often outperform traditional CAD tools and have demonstrated diagnostic accuracy comparable to that of radiologists (4,20).

Thanks to powerful graphics processing units (GPUs) and the availability of big data, DL algorithms utilize deep neural networks with **parallel computation** capabilities, allowing multiple operations to run simultaneously. This parallelism significantly reduces processing time and provides advantages for complex image analysis. Prominent DL models include:

- **Convolutional Neural Networks (CNNs)**, frequently used for tasks such as segmentation and classification.
- **Generative Adversarial Networks (GANs)**, used in image synthesis and enhancement (4,14).

Convolutional Neural Networks (CNNs)

One of AI's most significant applications in radiology is **image classification**, which distinguishes normal from pathological findings using CNNs. CNNs are currently the most effective models for image analysis and classification. These deep, layered neural networks are also the most commonly used DL methods. They require large, labeled image datasets to perform optimally (4,10).

CNNs deconstruct images into pixels, extract important features (e.g., edges, shapes), and learn to recognize complex structures. They can automatically detect pathologies such as **tumors** or **lesions**, making them suitable for complex radiological analyses (4).

Instead of standard matrix multiplication, CNNs use **convolution operations** at specific layers. They are especially well-suited for visual, auditory, and textual pattern recognition tasks and contribute significantly to **computer vision** and **natural language processing (NLP)** (4). CNNs require multiple layers to extract meaningful features. Their structure includes:

- **Feature extraction layers**: input layer, convolution + activation, and pooling.
- **Classification layers**: fully connected layer and output layer.

For example (23), a 9×9 input matrix combined with a 3×3 filter would yield a 7×7 output: $(9-3)+1 = 7$

- The **convolutional layer** (or transformation layer) identifies visual features.
- The **pooling layer** reduces image dimensions while preserving essential characteristics.
- The **fully connected layer** uses these features for classification (10).

GENERATIVE ADVERSARIAL NETWORKS (GANs)

GANs are utilized for expanding image datasets, obtaining high-resolution images, and transferring textures/patterns from one image to another (10). To illustrate, imagine a counterfeiter (generator) producing fake currency while the police (discriminator) try to detect the counterfeit bills. Over time, the police become better at distinguishing the fakes, while the counterfeiter improves the realism of the counterfeit money. This iterative process continues until the generator produces images so realistic that the discriminator can no longer differentiate them from real ones. This architecture, composed of two neural networks engaged in continuous competition, is referred to as a Generative Adversarial Network (GAN) (5).

LABELING, SEGMENTATION, AND CLASSIFICATION

In radiological imaging, labeling refers to annotating specific structures, while segmentation involves delineating the boundaries of these structures. Classification determines whether these structures are normal or pathological. Segmentation, also known as partitioning or delineation, refers to dividing an image into meaningful regions that exhibit distinct features. In this process, labels are generated for each pixel, and predictions are made based on these labels to derive insights. Typically, segmentation is performed first to detect tumors or lesions, followed by classification of their types. Convolutional Neural Networks (CNNs) are particularly useful at this stage (10).

Several improvements to CNN architectures have enabled more effective segmentation. For example, Long et al. introduced Fully Convolutional Networks (FCNs) (24), which were later adapted by Ronneberger et al. to develop the U-Net architecture specifically for biomedical image segmentation (25). U-Net has been used for brain tumor segmentation on the BraTS 2020 dataset (10). The architecture consists of two main parts and is named “U-Net” due to its U-shaped structure. There are numerous U-Net variants designed for medical image analysis, including U-Net++ (26), RU-Net, R2U-Net (27), MultiResUNet (28), SAUnet (29), ASCU-Net (30), and MRFU-Net (31).

IMAGE GENERATION, TRANSFORMATION, AND ENHANCEMENT METHODS

In medical applications, deep learning architectures are used for image generation, transformation, and enhancement, including tasks such as data completion and pattern discovery. Image enhancement involves improving digital images (e.g., through super-resolution, noise reduction, deblurring, or contrast enhancement) to prepare them for advanced analyses such as segmentation and classification (10). These techniques allow data transformation between modalities or data synthesis in cases of scarcity, enabling more accurate algorithm performance. For instance, transformation between MRI and CT modalities is a significant application. Han et al. generated synthetic brain MR images using GANs and reported that even expert radiologists had difficulty distinguishing them from real images (32).

RADIOMICS

Radiomics is an emerging field that involves the automated extraction of quantitative features from medical images (e.g., CT, MRI, PET). It holds substantial potential for diagnosis, prognosis, and evaluation of response to treatment. However, challenges such as the need for standardization and validation must be addressed to ensure reliable and reproducible results. The primary strength of radiomics lies in its ability to complement traditional clinical practice with precise, quantitative information, potentially transforming clinical decision-making—particularly when large-scale data sharing is enabled (4,19).

Both classical machine learning (ML) and deep learning (DL) algorithms can be used in radiomic analyses. The choice depends on the data structure, the problem being addressed, and available computational resources. ML algorithms are typically used to analyze and classify features extracted manually or semi-automatically—such as texture, shape, and intensity. DL algorithms, on the other hand, analyze image data more holistically and in greater detail, automatically extracting and classifying key features. In DL-based radiomic analysis, feature extraction is performed directly by neural networks, thereby reducing the need for extensive preprocessing. Radiomic features are generally categorized as follows (19,33,34):

- **Shape features:** size, volume, and morphology of a tumor or lesion.
- **Texture features:** homogeneity or heterogeneity of the internal structure of a lesion.
- **Intensity and pixel variation features**: analysis of pixel intensity values and their distributions.

Manual segmentation by experts is considered the gold standard, but it is time-consuming. Automated segmentation methods, while objective, are susceptible to errors in cases of image artifacts, noise, or highly heterogeneous lesions (33,34). Radiomics can uncover data not perceptible through conventional methods, offering clinicians deeper insights. It can be used to assess tumor heterogeneity, determine disease staging, and predict treatment response (33).

Popular software tools for manual feature extraction include PyRadiomics (34), MaZda (35), LIFEx (36), and IBEX (37). Additionally, platforms such as NVIDIA DIGITS (https://developer.nvidia.com/digits) and

Deep Learning Studio offer graphical user interfaces (GUIs) for deep feature extraction using neural network layers (38). The most popular platforms for both manual and deep feature extraction include MATLAB and Python, due to their extensive libraries (8). Free tools such as Orange (8), Rattle in R (38), WEKA (39), RapidMiner (https://rapidminer.com), and Deep Learning Studio (https://deepcognition.ai) are also available. For advanced preprocessing of radiological imaging data, open-source tools such as ImageJ, MIPAV (Medical Image Processing, Analysis, and Visualization), and 3D Slicer are commonly used (4,19).

Model development can be carried out using various algorithms, including k-nearest neighbors (k-NN), naïve Bayes, logistic regression, support vector machines (SVM), decision trees, random forests, neural networks, and deep learning techniques (19). Ensemble learning methods, which combine multiple algorithms such as k-NN, naïve Bayes, and the C4.5 decision tree, are also frequently employed (40). Common internal validation methods in the literature include k-fold cross-validation, leave-one-out cross-validation (LOOCV), and the hold-out method. Essential components of DL architectures include activation functions (e.g., Rectified Linear Unit [ReLU], sigmoid, Softmax) and regularization methods (e.g., dropout layers). Furthermore, proven architectures and their variants are commonly used in tasks such as segmentation (4,19,33).

ARTIFICIAL INTELLIGENCE ALGORITHMS USED IN RADIOLOGY

Commonly used AI algorithms in radiology include the following: (3,4,9,14–17,41)

1. Machine Learning (ML)

- **Decision Trees and Random Forests**: Mainly used in feature selection and classification tasks.
- **Support Vector Machines (SVM)**: Applied primarily to classification problems.

2. Deep Learning (DL)

- **Convolutional Neural Networks (CNNs)**: Frequently used for image analysis, effective in detecting anomalies, tumors, fractures, and diagnosing pulmonary diseases in medical imaging.
- **Recurrent Neural Networks (RNNs)**: Analyze temporal changes in medical images, such as monitoring disease progression using MR scans over time.
- **Generative Adversarial Networks (GANs)**: Use two neural networks to generate realistic images, applied in image inpainting, resolution enhancement, and synthetic data generation.
- **Transfer Learning**: Pretrained DL models are fine-tuned on radiology datasets, enabling better performance with smaller datasets.
- **Artificial Neural Networks (ANNs)**: Used broadly for classification and regression problems.

3. Image Processing Techniques

- **Segmentation Algorithms**: Identify specific regions in images, such as tumor or organ boundaries.
- **Signal Processing Techniques**: Enhance image quality and reduce noise.

4. Natural Language Processing (NLP)

- **Radiology Report Analysis**: Used to interpret and classify radiology reports, aiding in disease identification and diagnosis.

SEGMENTATION ALGORITHMS IN RADIOLOGY

Accurate segmentation in radiology is essential for diagnosis, treatment planning, and prognosis. Recent advances in DL have significantly improved precision and automation in segmenting anatomical structures using imaging modalities such as X-ray, CT, MRI, and PET. Common segmentation algorithms include: (3,4,14–18,42,43)

1. **Thresholding**

- **Principle**: Classifies pixels based on a defined intensity threshold.
- **Use Case**: Suitable for high-contrast regions such as bone or tumors.
- **Example**: Brain tumor segmentation in MRI based on intensity differences.

2. **Active Contours**

- **Principle**: Known as "snakes algorithm", uses evolving curves from an initial point to outline objects.
- **Use Case**: Segmenting organs like the liver or lungs.
- **Example**: Lung nodule segmentation.

3. **Watershed Algorithm**

- **Principle**: Treats intensity gradients as a topographic surface to define regions.
- **Use Case**: Detects vessels, tumors, and abnormal tissues.
- **Example**: Tumor segmentation in brain or liver imaging.

4. **K-means Clustering**

- **Principle**: Groups pixels based on intensity or color similarity.
- **Use Case**: Tumor, organ, and lesion segmentation.
- **Example**: Brain and liver segmentation in CT and MR images.

5. **Graph Cut**

- **Principle**: Models pixels as graph nodes and segments based on similarity.
- **Use Case**: Organ and tumor segmentation, especially for tumor size estimation.
- **Example**: Brain and liver tumor segmentation.

6. **Deep Learning-Based Segmentation**

- **Principle**: Uses architectures like CNNs and FCNs to learn structural features for segmentation.
- **Use Case**: Segmenting organs, tumors, lesions, and vasculature.
- **Examples**:
  - **U-Net**: Widely used for brain, liver, and lung organ segmentation.
  - **Mask R-CNN**: Applied in multi-object detection and precise segmentation.

7. **Region Growing**

- **Principle**: Begins from a seed pixel, grows by merging similar neighboring pixels.
- **Use Case**: Brain or liver tumor segmentation.
- **Example**: Detecting brain aneurysms or liver lesions in CT/MRI.

8. **Intensity-Based Methods**

- **Principle**: Segments based on pixel intensity values.
- **Use Case**: CT/MRI segmentation of organs such as brain, lungs, and liver.
- **Example**: Lung tissue segmentation in CT.

9. **Atlas-Based Segmentation**

- **Principle**: Matches the target image to a reference “atlas” image.
- **Use Case**: Brain and prostate segmentation.
- **Example**: Anatomical brain segmentation in MRI.

10. **Statistical Shape Models**

- **Principle**: Models shape variability for segmentation.
- **Use Case**: Organ and tumor segmentation (e.g., heart, brain).
- **Example**: Ventricular segmentation in cardiac imaging.

MEDICAL IMAGING DATASETS

One example is REMBRANDT (Repository of Molecular Brain Neoplasia Data), a brain cancer dataset including MRI and genomic data. MRI scans of 130 patients with histopathologically confirmed brain tumors were used to train and test seven ML and DL models, including CNN (AlexNet), decision trees, linear discriminant analysis, naïve Bayes, SVM, k-NN, and ensemble learning techniques. The CNN model (AlexNet) outperformed all ML classifiers across multi-class datasets (2).

Another study used five CNN architectures (AlexNet, VGG16, ResNet18, ResNet50, ResNet101) to classify normal and pneumonia patients using chest X-ray images. Features from each model were used individually and in combination. The Kaggle dataset was employed and augmented to 4× its original size. Classification used SVM and Softmax, with accuracies above 80% deemed successful (7,11).

For effective training and validation of AI algorithms, imaging datasets should be large and well-annotated. These datasets include various modalities such as X-ray, CT, MRI, and ultrasound. Commonly used datasets include: (2,10,18,20,42)

1. **MIMIC-CXR**

- 370,000+ chest X-rays and reports.
- Used for training AI models in thoracic disease diagnosis.
- Source: MIT.

2. **CheXpert**

- 224,000 chest X-rays with diagnostic labels.
- Application: Thoracic disease classification.
- Source: Stanford University.

3. **NIH CXR**

- 112,000+ chest X-rays and 30,000+ reports.
- Includes 14 disease classes (e.g., pneumonia, lung cancer).

- Public and open access.

4. RSNA Pneumonia Detection Challenge Dataset

- 30,000+ chest X-rays.
- Purpose: Pneumonia detection.
- Source: Radiological Society of North America (RSNA).

5. LUNA16

- 1,000 CT scans for lung nodule detection.
- Used in lung cancer detection.

TCIA (The Cancer Imaging Archive)

- CT, MRI, PET, clinical and genomic data for 20+ tumor types.
- Public portal.

7. BraTS (Brain Tumor Segmentation Dataset)

- MR images for brain tumor segmentation.
- Application: Glioblastoma segmentation/classification.

8. OASIS

- Brain MRI for Alzheimer's and neurodegenerative disorders.

9. DDSM

- 10,480 mammography images (CC and MLO views) in JPEG format.
- Used in breast cancer screening and microcalcification detection.

10. ProstateX

- Multiparametric MRI for prostate cancer diagnosis and segmentation.

11. MosMedData

- 1,100+ CT scans related to COVID-19.
- Used for diagnosis and severity assessment.

12. COVID-CT and SARS-CoV-2 CT Datasets

- CT scans of COVID-19 patients.
- Used for COVID-19 detection.

AI SOFTWARE USED IN RADIOLOGY

AI-based software in radiology has grown significantly, supporting radiologists in diagnosis, reporting, and patient management by enhancing speed and accuracy. Notable AI tools include: (3,4,14,16,17)

1. Zebra Medical Vision

- Application: Automated diagnosis and image analysis.
- Features: Analyzes X-ray, CT, and MRI to assist in disease diagnosis.

2. **Aidoc**
- Application: Automated image analysis and emergency diagnosis.
- Features: Assists emergency diagnosis of brain, lung, and spinal images.

3. **Arterys**
- Application: Cardiology and oncology imaging.
- Features: Cloud-based platform analyzing CT and MRI, aiding in heart disease and cancer diagnosis.

4. **Viz.ai**
- Application: Stroke detection.
- Features: Analyzes brain scans for fast stroke diagnosis and speeds up treatment.

5. **qXR by Qure.ai**
- Application: Pulmonary disease detection.
- Features: Detects tuberculosis, COVID-19, and lung cancer in X-rays.

6. **Infervision**
- Application: Chest X-ray and CT analysis.
- Features: Detects conditions like lung cancer and pneumonia.

7. **RadNet**
- Application: Full-body imaging.
- Features: Analyzes CT, MRI, and PET using a comprehensive AI platform.

8. **Lunit Insight**
- Application: Breast and thoracic radiology.
- Features: Detects cancer in mammography and chest X-rays.

Discussion

The impact of artificial intelligence (AI) technologies in the medical field is increasingly evident, particularly in imaging and diagnostic processes such as radiology. In the future, AI-assisted radiology is expected to have a broader scope of application and play a pivotal role in transforming healthcare services. Machine Learning (ML) and Deep Learning (DL)-based AI systems that continuously learn have significant potential in radiology, particularly in enhancing diagnostic accuracy, saving time, and developing personalized treatment strategies. These technologies can integrate data from clinical, pathological, biochemical, and genetic tests with radiological imaging, enabling more consistent, highly accurate, and reliable outcomes (7,14,33).

One of the most significant contributions of AI in radiology is the automation of image processing and analysis procedures. AI functionalities such as labeling, segmentation, and classification assist radiologists in interpreting complex images more quickly and accurately. For instance, in breast cancer screenings, chest radiographs, or brain MRIs, AI algorithms can increase early diagnosis rates by detecting diseases at earlier stages. Furthermore, advanced AI algorithms have the potential to optimize treatment processes and form the foundation of personalized medicine. This presents a substantial advantage, particularly in cancer treatments and the management of chronic diseases (18,28,34).

Another important contribution of AI is its application in remote healthcare services (telemedicine). Globally, especially in rural and developing regions, there are significant inequalities in access to qualified healthcare services. AI-assisted radiology systems can facilitate access to expert radiologists for patients in such areas, contributing to a more equitable healthcare provision on a global scale. The importance of remote diagnosis and treatment processes has become even more apparent during crises such as pandemics. In such scenarios, AI can enhance the flexibility and resilience of healthcare systems (14,15,33).

Advancements in image processing algorithms have enabled the use of AI not only in diagnostic processes but also in treatment procedures. AI-assisted systems are increasingly being used in the field of robotic surgery. For example, robotic surgical systems such as "CyberKnife" perform operations with lower error rates thanks to AI algorithms. These systems enhance surgeons’ manual dexterity and enable safer, more precise surgeries using minimally invasive techniques. In the future, it may even be possible to have fully autonomous robots operating in surgical settings (12,18).

However, there are several challenges to the widespread adoption of AI in radiology and the broader medical field. Chief among these are issues related to data quality and data security. For AI algorithms to generate accurate and reliable results, access to large amounts of high-quality data is essential. Moreover, the privacy and security of patient data pose critical ethical concerns. Regulatory frameworks must be established regarding data sharing and usage, and ethical and legal principles must be clearly defined. Additionally, the “black box” nature of AI systems, referring to the lack of transparency in decision-making processes, including medical, legal, and financial responsibilities, can undermine the trust of clinicians and patients in AI technologies (6,16,21).

In conclusion, the opportunities offered by AI in radiology and medicine have the potential to shape the future of healthcare services. Its advantages in improving diagnostic and therapeutic accuracy, saving time, and enabling personalized medicine make AI an indispensable tool. Nevertheless, issues such as data quality, ethical considerations, and transparency must be addressed with care. A multidisciplinary approach is essential for the effective and reliable implementation of AI, necessitating collaboration among healthcare professionals, engineers, ethicists, legal experts, insurance providers, and policymakers. Through such collaboration, the full potential of AI can be realized, ushering in a new era in healthcare services.

ABBREVIATIONS

AI: Artificial Intelligence
ANN: Artificial Neural Networks
CT: Computed Tomography
CAD: Computer-Aided Detection
CNN: Convolutional Neural Networks
DL: Deep Learning
ECG: Electrocardiography
FCN: Fully Convolutional Networks
GAN: Generative Adversarial Networks
GPU: Graphics Processing Unit
GUI: Graphical User Interface
ML: Machine Learning
MRI: Magnetic Resonance Imaging
NLP: Natural Language Processing

RNN: Recurrent Neural Networks
US: Ultrasonographyt

SOME USEFUL LINKS

https://acikveri.saglik.gov.tr/

https://altair.com/altair-rapidminer

https://deepcognition.ai/

https://developer.nvidia.com/digits

https://www.editverse.com/tr/the-human-connectome-project-brain-mapping/

https://elsevier.health/en-US/marketing/radiologists/pinpoint-complex-and-common-radiology-cases-with-statdx

https://www.geminibilgi.com.tr/statdx-654.html

https://keras.io/

https://www.lunit.io/en

https://www.mathworks.com/products/matlab.html?s_tid=hp_ff_p_matlab

https://oxipit.ai/products/chesteye/

https://pyradiomics.readthedocs.io/en/latest/#

https://www.python.org/

https://www.qure.ai/

https://www.radiantviewer.com/

https://radiology.healthairegister.com/

https://www.slicer.org/

https://teleradyoloji.saglik.gov.tr/

https://www.tensorflow.org/?hl=tr

Declaration of interest: The authors report no conflicts of interest.

Funding source: No funding was required

Ethical approval: No need for reviews.

Acknowledgments: No

Peer-review: Evaluated by independent reviewers working in at least two different institutions appointed by the field editor.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Contributions

Research concept and design: MÖ

Data analysis and interpretation: MÖ

Collection and/or assembly of data: MÖ

Writing the article: MÖ

Critical revision of the article: MÖ

Final approval of the article: MÖ

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