REVIEW Physics

Recent advances and future perspectives of artificial intelligence in medical imaging: a review

Akhil Raj.P, Kamalesh.C, Renisha Divina Dsouza, Vashist Baburao Mhalsekar
Unit of Medical Imaging Technology, Yenepoya School of Allied Health Sciences, Yenepoya (Deemed to be University), Mangalore, Karnataka India

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ABSTRACT

Radiology can benefit significantly from various new Artificial Intelligence (AI) tools. The application of machine learning algorithms and deep learning techniques to help radiologists interpret medical images more accurately and efficiently and to lower radiographers' human errors is known as AI in radiology. The goal of this review article is to provide an overview of AI applications in radiology for precise diagnosis and treatment, optimizing workflow and image quality while reducing radiation dose. Articles published related to the study were searched and evaluated from indexed journals on PubMed, Springer, and Elsevier databases from January 2000 to December 2023. With automation and process optimization for data collecting, including patient positioning and acquisition parameter settings. To enhance various aspects of image quality, such as reducing image noise and utilizing lower radiation doses for data collection, it is necessary to take steps such as collecting data, using advanced reconstruction algorithms, employing image denoising techniques, and optimizing image reconstruction parameters. In this review article, we discussed the current developments of AI in the field of medical imaging technology. We concluded that AI enhances diagnosis and treatment planning; it has the potential to transform the medical imaging and healthcare sector completely.

KEY WORDS

Artificial Intelligence (AI), Computer Assisted Diagnosis (CAD), Deep Learning, Deep Convolutional Neural Network (DCNN), Reconstruction

CORRESPONDING AUTHOR, GUARANTOR

Renisha Divina Dsouza, Assistant Professor, Unit of Medical Imaging Technology, Yenepoya School of Allied Health Sciences, Yenepoya (Deemed to be University), Mangalore, Karnataka India
E mail: renishamdb98@gmail.com

Introduction

Building computer programs with intelligent behaviour is the focus of the large field of Artificial Intelligence (AI) [1]. AI is becoming more prevalent in medicine, with the most applicability being within the radiology field [2]. AI has advanced perception, enabling computers to depict and comprehend complicated input [3]. Clinical AI is integrated into clinical practice. To improve quality, manage resources, and guarantee patient safety, governance structures supervise the adoption, upkeep, and observation of clinical AI algorithms [4]. AI and machine learning technologies help radiologists to analyze medical images [5]. AI in radiology promises to better patient care by expediting the interpretation process and increasing diagnosis accuracy. However, to guarantee that the technology is used efficiently and securely, collaboration with radiologists is crucial [6]. AI is anticipated to bring about significant changes. Machine learning evaluates doctors' performance in diagnosing and treating patients and improving their expertise [7]. The use of AI in clinical radiography is widely acknowledged [8]. AI is predicted to alter clinical work procedures significantly, necessitating the development of radiologist-specific additional abilities [9]. The study aims to conduct a literature review on recent advancements in the field of medical imaging. Using AI can help with treatment planning, outcome prediction, image analysis, detection, and diagnosis. The primary aim of this review article is to present a comprehensive survey of AI applications in radiology. These applications aim to enhance accuracy by providing precise diagnosis and treatment, optimizing workflow and image quality while reducing radiation dose.

Data Source:

Articles published related to the study were searched and evaluated from indexed journals on PubMed, Springer, and Elsevier databases from January 2000 to December 2023

AI Interpretation in Imaging:

AI software applications are developed using convolutional networks based on deep learning. Through an automated procedure, these algorithms acquire picture attributes from training datasets derived from radiologic images. After that, they divide and examine the structure seen in the pictures, summarising their findings [10]. Early automated software, such as computer-assisted diagnosis (CAD), was employed in different studies with differing degrees of effectiveness.

Computed Assisted Diagnosis:

CAD, an automated processing system, has the potential to aid radiologists in detecting and diagnosing the study. Computer-assisted diagnosis (CADx) systems and computer-assisted detection (CADe) systems are the two categories under which CAD systems are divided. While CADx systems aim to characterize the lesions, CADe systems are primarily used to locate lesions in medical imaging [11,12]. CADx systems use a classifier to assess the risk of malignancy after extracting some specified criteria from the images. However, with the advent of deep learning techniques, significant advancements in research and clinical AI applications have been made possible.

AI-rad Companion:

AI-rad companion is a support platform that has been approved by the FDA. It uses artificial intelligence algorithms to handle Computed Tomography (CT) image files. The program offers automatic image processing, evaluation, and display of structures on CT scans. The chest CT scan comprises all components.

1. The program identifies and differentiates lung abnormalities, determines the precise position of the abnormality, and provides measures of the lesion's size, including the maximum and lowest linear dimensions and multiplanar reformation.
2. Segmentation of the heart and detection of calcium.
3. Segmentation and measuring of the diameter of the aorta.
4. Vertebra body segmentation and density measurements [13].

Progress in both hardware and software has enabled the establishment of a platform that can evaluate complete datasets. Innovative research in this field mostly concentrated on representational learning, where the computer aimed to identify the fundamental features of the data [14]. Deep learning models treat a dataset as an ordered collection of features, with the number of levels in the hierarchy corresponding to the depth of the computational evaluation [15]. These novel methodologies have completely transformed the area of artificial intelligence and sparked a significant interest in the use of AI in medical applications.

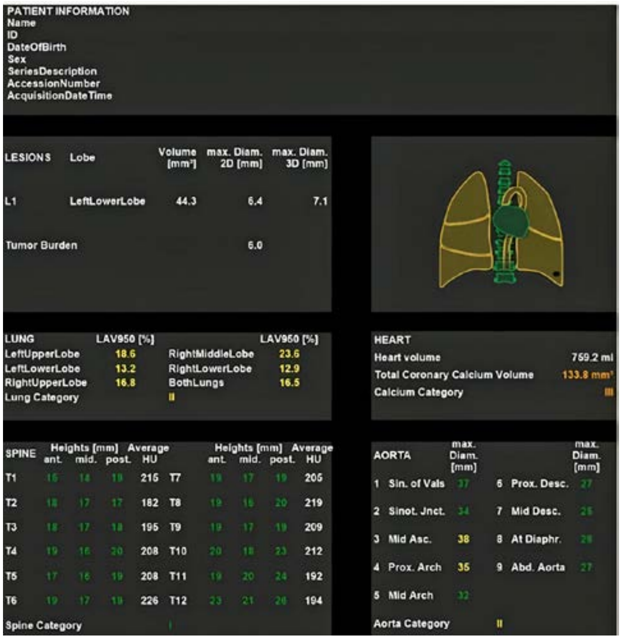

***Fig 1:** Shows a representative of the summary page from the AI platform. Source:[16]*

Fig 1 represents that all the algorithms are combined into a full multiorgan AI software solution that offers automatically generated summary results to be shown with AI-annotated photos to help with image interpretation [16]. Many of these algorithms were created to yield outcomes for certain anatomical structures. Some of these have been combined into multiorgan AI software systems that offer automatically generated summary data, which are presented with AI-annotated pictures to assist with interpreting the images [17,18].

Integrating AI into the therapeutic process has been proposed as a highly effective way to increase workflow efficiency, for example, by reducing report turnaround times and enabling faster scan interpretation.

AI in Computed Tomography

AI and Deep Learning in Reconstruction:

With the implementation of AI techniques, image reconstruction in the radiology field has considerably advanced. The optimization of image quality, reduction of artifacts, and improvement of diagnostic accuracy are achieved by the application of machine learning algorithms. Better visualization of anatomical features is made possible by the potential for high-quality picture reconstruction from low-dose scans through deep learning models, such as convolutional neural networks (CNNS) [19].

Filtered-back projection (FBP) is widely used as the preferred technique for reconstructing CT images because of its fast reconstruction time and efficient computational ability, allowing real-time image reconstruction while patients are being scanned. The primary disadvantage of FBP is that it deteriorates image quality in low-dose parameters and in patients with larger size of body because of increased image noise and beam hardening errors [20].

Iterative reconstruction is developed to get around the drawbacks of FBP-based image reconstruction. Iterative reconstruction is a computer technique that improves image quality by improving the reconstruction process. In contrast to classical FBP, iterative reconstruction reduces artifacts and improves spatial resolution by iterative optimization of images through mathematical frameworks. In low-dose CT scans, iterative image reconstruction techniques are useful for maintaining image quality while reducing patient radiation exposure [21]. Additionally, iterative reconstruction has certain drawbacks. The primary one is computational complexity; compared to conventional methods, it necessitates significant processing power and time, slowing down the reconstruction process. To properly control the reconstruction process and optimize settings, operators may need to possess a greater level of skill [22].

AI-based reconstruction techniques are introduced to eliminate the shortcomings of earlier systems. The primary objective of the AI-based reconstruction algorithm is to enhance the resolution of the image in a short amount of time with low dosage exposure [23].

Deep Learning Reconstruction (DLR) techniques that are sold commercially identify patterns of noise in images and eliminate them from raw data by utilizing a Deep Convolutional Neural Network (DCNN) [24]. Theoretically, artifacts like motion, truncation, cone beam, and other image reconstruction issues can all be resolved with DLR [25]. The training data sets used in a DCNN are essential to its performance because they teach the algorithm how to distinguish between anatomical structures and noise. DCNN training has been approached differently by each DLR developer, but the final reconstructed DLR picture is directly impacted by the type and quality of training data [26].

Low-noise picture pairing data is used to train DCNN algorithms. To optimize DLR accuracy and consistency, node weights and hyperparameters are chosen. Pre-trained DCNNs offer reliable results and rapid reconstruction [27].

The two main techniques that are available for purchase are vendor-specific, which operates in image space along with projection space, and vendor-independent, which operates the DLR algorithm in image space [28].

The vendor-independent method is mostly provided by third-party solutions positioned between PACS scanning and CT scanners. The CT scanner is used, and the reconstruction algorithm is used to initially reconstruct the data. After scanning, the picture is transferred to a separate server that handles cleaning up CT reconstructions [29,30]. Utilizing a vendor-specific strategy, which has access to projection space data, reduces picture noise mainly by improving object edge definition and spatial resolution [31]. In addition to methods like non-breath-hold scans and pre-scan breath-hold instructions, motion artifacts can degrade image quality. AI reconstruction algorithms can reduce 4D-CT artifacts and improve the geometric accuracy of structures [32].

AI in Dose Reduction:

An essential objective in radiology is to lower the radiation exposure during computed tomography imaging without sacrificing diagnostic quality [34].

Artificial intelligence-powered automatic positioning systems have surfaced as viable options for reducing radiation exposure while maintaining high-quality images [35]. Manually adjusting the scanner's parameters and the patient's position during traditional CT imaging might result in inconsistent image quality and increased radiation exposure [36]. By utilizing cutting-edge algorithms to optimize patient placement and scanner settings depending on numerous criteria such as patient anatomy, imaging protocol, and clinical indication, AI-driven autonomous positioning systems seek to address these issues [37].

During CT scans, technologists take great care to precisely choose the anatomic scan range and correctly center the patient to get high diagnostic image quality at a lower radiation dose. The method of manually centering and placing takes a lot of time, is technician-reliant, inconsistent, and is not optimal [38].

AI auto placement makes use of a fixed, off-the-shelf, 2D/3D video camera positioned on the ceiling that can measure distances to objects inside its range of vision. The gantry-mounted touchscreens of the CT systems show conventional RGB (Red, Green, Blue) video images. Details regarding the gantry and table installation geometry of each CT system, to ascertain the scout scans' starting and finishing points, and the locations of anatomical landmarks [39].

With the use of AI algorithms and a 3D infrared camera, precise landmarks on the patient's body were identified, and all anatomical areas were recorded, ensuring that no pathology was missed in the area of interest. Additionally, the system automatically moves the

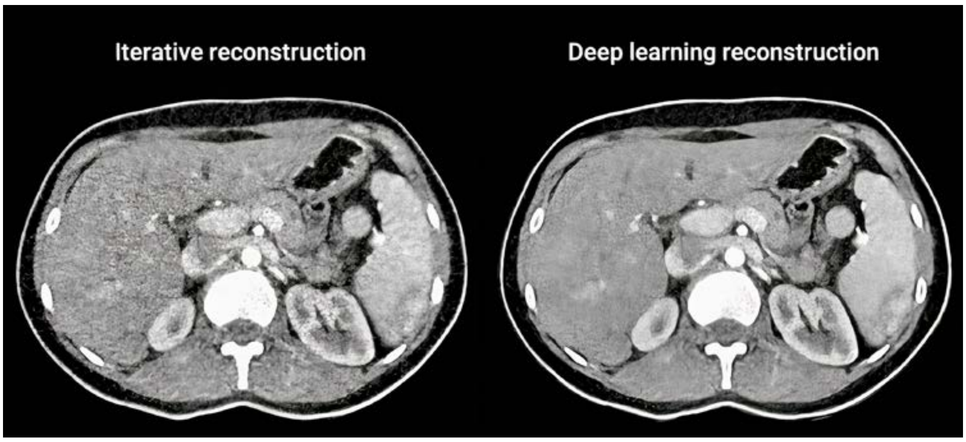

Fig 2: *Comparative analysis of CT image quality between iterative reconstruction and deep learning-based reconstruction. Source: [33]*

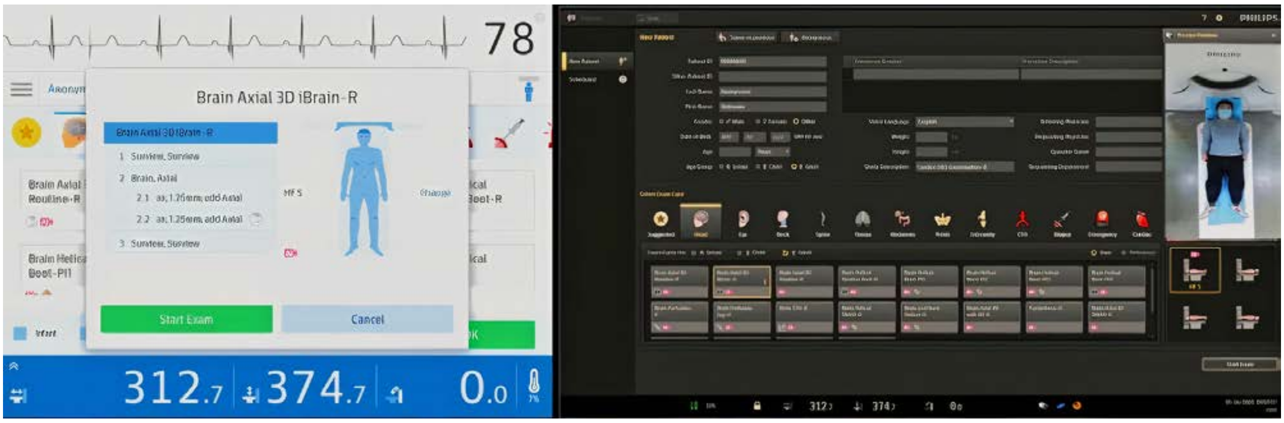

***Fig 3:** The flexibility of the camera workflow, both on the console and at the gantry, allows for fast and consistent positioning. Source:[44]*

couch vertically so that the isocenter is where the majority of the anatomical regions of interest are found. By preventing incorrect patient centering, it lowers the radiation doses that the patient receives [40].

The AI positioning algorithm identifies anatomical landmarks and reference points required for precise placement after it has analyzed the scout photos. The AI algorithm determines how to modify the patient's posture within the CT scanner to maximize its efficiency based on the examination of the scout images and predetermined placement criteria. These adjustments could involve tilting, rotating, and translating the patient table. Using input from the CT scanner's imaging equipment, the AI program continuously tracks the patient's location in real-time while the modifications are being performed. To guarantee ideal alignment throughout the scan, the algorithm can dynamically modify the placement parameters [41,42].

When the X-ray tube is positioned underneath the patient's table, the system can perceive the patient as being either extremely thick or thin, depending on how they are positioned about the isocenter. This is because the isocenter is where a CT system's spatial calibration occurs [43].

Although manufacturers have implemented AEC (Automated Exposure Control) systems in somewhat diverse ways in their industrial equipment, the fundamental concepts remain the same. Thus, the number of photons required for each projection through the patient is automatically determined by the system. This suggests that for the system to achieve the desired examination quality and finish the assigned clinical task, it will need to use an additional number of photons for very large individuals. The patients are not homogeneous cylinders; therefore, during a single gantry rotation, the tube current typically oscillates up and down, increasing through thicker body portions and reducing over thinner body regions on average [45].

To ensure proper operation of these computational methods, the patient has to be at the center of the isocenter of the system. However, due to the wide variations in patient anatomy, this can be difficult to do [46].

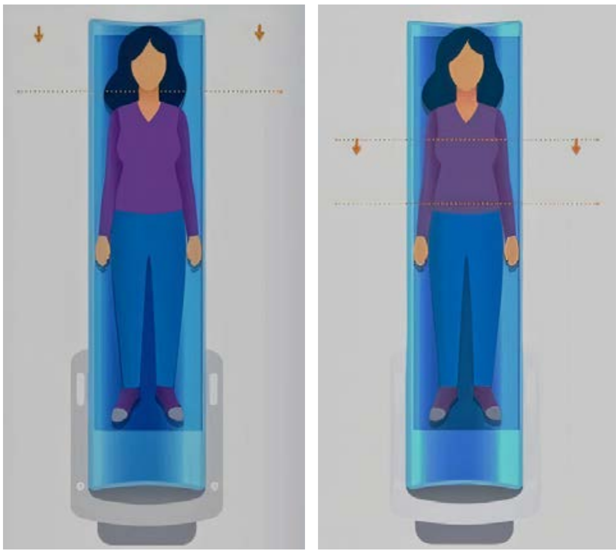

Fig 4: Automated planning of preview start and end positions for a head (left) and abdomen (right) scan. Source: [44]

Parameter Selection:

Several factors need to be carefully selected for the particular type of imaging technique and diagnostic indication to maximize the CT examination. These features are related to the radiation therapy the patient is receiving, the way the X-ray tube and patient table are moved, and the use of additional specialized methods (such as cardiac gating) throughout the data collection procedure. Currently, some AEC systems use simple machine-learning algorithms to determine the optimal tube current and potential. One of the most difficult decisions is setting up the contrast administration and image acquisition time such that, throughout data collection, the iodine enhancement is maximal over the area of interest [47].

To accomplish this, data were gathered on a sizable number of patients at different times when the contrast was injected and circulated throughout their bodies. With the use of this data, an algorithm may predict the ultimate dimensions of the aortic contrast enhancement curve. The system can forecast the whole contrast enhancement curve in patients who follow once the training data is exceeded. Using only a few data points on the ascending portion of the curve, it is possible to estimate the best time to perform the scan while the contrast is traveling through the patient's body [48].

Research has shown that there is a decrease in the amount of iodinated contrast medium needed in conjunction with improved consistency of contrast enhancement throughout the scan range. Slashing the injection rate lowers the chance of damaging the vein that the material is injected into, hence reducing the amount of iodine [49].

AI in MRI:

Magnetic resonance imaging (MRI) is a valuable tool in clinical medicine since it can visualize human organs and tissues to aid in follow-up diagnosis. However, MRI has always faced the difficulty of long scan times. Before the emergence of deep learning, two common methods for accelerating MRI were used: compressed sensing (CS), which uses picture compressibility, and parallel imaging, which uses redundant information between coils. Although these methods have made significant accomplishments, they still confront the challenges of extended iteration time and low acceleration rate [50].

Deep learning has recently emerged as an MRI acceleration approach. When compared to previous approaches, it not only enhances image quality but also provides the benefits of real-time imaging. The peak signal-to-noise ratio (PSNR) and mean structure similarity index measure (MSSIM) are used to thoroughly evaluate image quality. Higher PSNR indicates less noise, while higher MSSIM indicates better structure resemblance to the ground truth. Meanwhile, real-time imaging is vital for some clinic applications, such as deep learning, which can enable real-time adaptive magnetic resonance imaging (MRI)-guided radiation by obtaining larger acceleration factors to reduce total delays [51].

AI can impact all phases of the Magnetic Resonance Imaging (MRI) process, including image acquisition and reconstruction, image analysis and interpretation, and diagnosis and prognosis. If realized, the intelligent imaging revolution will result in faster acquisition times, less effort for physicians, lower healthcare costs, and more personalized treatment decisions for patients [52].

- *Acquisition and Reconstruction*

Artificial intelligence is being integrated into the MRI acquisition process, which normally entails the collecting of raw data from the MRI scanner. AI can address difficulties like acquisition time, SNR, balancing spatial and temporal resolutions, and artifacts. The acquisition is improved by optimizing scanning parameters, lowering scan duration, and motion correction, and by providing real-time feedback [53].

AI algorithms can automatically modify scanning parameters (such as magnetic field intensity, gradient settings, and pulse sequences) to optimize image quality for each patient and clinical task. This lowers the time and effort required for manual corrections, resulting in a faster and higher-quality scan. AI can accelerate data collection by employing techniques such as compressed sensing (CS) and parallel imaging. These technologies reduce the number of measurements required for high-quality photos, allowing patients to spend less time in the scanner. Furthermore, AI-driven algorithms can aid in the recovery of missing data, hence enhancing image quality [54-56].

Patient movement during an MRI scan can cause image artifacts. AI systems can detect and adjust for these motions in real time, increasing the quality of the collected data. AI can help technologists provide real-time feedback, enabling dynamic modifications during scans to ensure optimal data gathering, particularly in difficult circumstances (e.g., pediatric or elderly patients).

Once the raw data has been gathered, it must be rebuilt into meaningful images that radiologists can analyze. Traditional reconstruction approaches, such as the Fourier transformation, use complicated mathematical techniques to convert data into images. AI is increasingly being utilized to improve or perhaps replace traditional approaches [57,58].

Compressed sensing is a technique that allows for the reconstruction of high-quality images from fewer data points, resulting in shorter scan durations. Artificial intelligence models, particularly deep learning techniques like convolutional neural networks (CNNs), can significantly enhance the quality of reconstructed images by learning how to retrieve missing information and decrease noise. AI can help improve the usage of multi-coil arrays (many receiver coils) and parallel imaging techniques, which are intended to speed up image acquisition and increase image quality by minimizing the number of data points acquired from each coil. AI algorithms can speed up and improve the quality of these reconstructions [59,60].

• *Image Analysis and Interpretation*

AI can automatically separate and delineate regions of interest in MRI images. This makes it possible to quantify and track illness progression more precisely. Objectively measure factors such as tissue density, volume, and lesion progression, providing information that is sometimes difficult to get manually. AI algorithms are being developed to help detect abnormalities such as tumors, plaques, cysts, and other pathological diseases. AI can identify regions of interest in MRI data, allowing radiologists to concentrate on potentially troublesome areas. AI may be trained on massive datasets to recognize patterns linked with various diseases. For example, it can assist in detecting early signs of Alzheimer's disease by analyzing brain scans for typical abnormalities, such as atrophy, that may not be immediately obvious to the naked eye. AI can use MRI scans in conjunction with clinical data to forecast the evolution of diseases like cancer or neurodegenerative disorders. For example, AI models can monitor tumor growth over time or assess how a patient's health is reacting to treatment. By analyzing longitudinal MRI data, AI can anticipate how patients will respond to various medications, allowing for personalized treatment plans that optimize patient outcomes [61,62].

• *Clinical Workflow Optimization*

AI models can provide early reports based on MRI data, identifying important abnormalities and summarising the images. This not only reduces radiologists' workloads but also speeds up the reporting process, especially in busy hospitals or radiology departments.

AI systems can reduce human error in interpretation, particularly when dealing with enormous datasets or complicated imagery. For example, AI systems might help radiologists by highlighting tiny indications of disease that might otherwise go unnoticed, thereby enhancing diagnostic accuracy.

AI models can be incorporated into existing healthcare systems, adding a layer of decision support. AI can suggest diagnoses or notify healthcare practitioners of important issues by merging MRI data with other patient information contained in Integration with Electronic Health Records (HER) systems.

AI has improved the value of functional MRI (fMRI), which monitors brain activity by detecting blood flow. AI can help identify brain activity patterns associated with specific tasks or cognitive processes, which can benefit in the research of neurological disorders such as epilepsy, Alzheimer's, and Parkinson's disease [63-65].

• *Future Prospects*

AI in MRI has huge potential for personalized medicine, allowing tailored treatment plans based on individual patient data. By evaluating MRI scans and other medical data, AI can predict how a patient's illness will proceed and how they will respond to various therapies.

AI will most likely be used to integrate MRI with other imaging modalities to provide a more complete picture of a patient's condition. This could increase diagnostic accuracy and allow for more targeted treatment delivery. The combination of AI and robotic technology could improve MRI operations. For example, AI-powered robots could help with patient placement or guide MRI scanners to appropriate locations, boosting operation accuracy and comfort [66].

AI in Ultrasound:

Ultrasonography (USG) is the most widely used radiologic method because it is widely accessible, reasonably priced, and radiation-free. The global USG surveillance rate is still low despite several benefits [67]. The availability of qualified personnel, such as inadequate radiologists and ultrasoundographers who can effectively serve for cancer surveillance, is one of the main obstacles to surveillance, especially in rural areas. Because USG depends on the operator, the results of the examination may be interpreted incorrectly. However, these obstacles might be addressed by creating an assisted ultrasound system that aids in the identification and categorization of focal liver lesions (FLLs) during a real-time USG scan [68].

AI has become more widely used in healthcare, particularly to improve the sensitivity and accuracy of medical picture interpretation, as a result of the quick development of deep learning algorithms and their great capacity to analyze complicated data. Healthcare workers and non-radiologist physicians would greatly benefit from an AI-assisted USG image analysis system to improve the precision of USG inspection and interpretation. One possible tactic to raise overall liver cancer surveillance rates is this system. Despite the limitations of the detection, artificial intelligence (AI) models that were recently developed for diagnosing and detecting FLLs in ultrasound images showed promising performance with increased sensitivity and specificity for detecting and classifying FLLs typical in clinical practice. For example, a lack of differentiation and characterization skills resulted in incorrect categorization [69-71].

AI in deep learning and detection:

Real-time object detection in photos is better suited for a more recent class of AI models called "YOLO," which has demonstrated superior performance over Convolution neural network models in object detection tasks. Using the model as a framework, distinct kinds of FLLs in USG still images may be identified and distinguished.

• *AI Model*

The AI model used for the study was YOLOv5 framework. Because of its tiny size and quick processing performance, YOLO has gained popularity as a real-time object identification method since its initial release in 2015. The most recent version at the time of the investigation was YOLOv5, which had far better capabilities than the earlier YOLOv4; that is, it had a lighter model size, more adaptability, and a significantly faster training pace. It offers data augmentation features that effectively identify small objects, which was the previous YOLO mode's most troublesome drawback [72,73].

In order to obtain a high-level feature map that represents the input image, YOLO's methodology entails processing the entire input image through a deep neural network.

After that, this feature map is divided into an N×N grid, where N is a number that the user defines. The job assigned to each cell in this grid is to identify objects whose centers lie inside its borders. Each cell is projected to have numerous bounding boxes to accommodate objects with different dimensions and aspect ratios [74].

YOLO makes a lot of bounding box predictions during the inference stage. Bounding boxes with no liver lesions, however, receive poor confidence scores in every class and are eventually removed. Be aware that a single FLL may have several bounding boxes created by YOLO. A post-processing method called "non-maximum suppression" (NMS) is used to lessen this redundancy. This approach uses the intersection over union (IoU) metric to estimate the similarity of groups of proximal bounding boxes. Only the bounding box with the greatest confidence score within each group is kept.

The NMS algorithm's confidence threshold and IoU threshold are essential for regulating the YOLOv5 model's performance. An IoU threshold of 0.3 and a confidence threshold of 0.25 were used as criteria for accurate detection in order to assess detection rates and maximize model performance. The class posterior probabilities were created by aggregating and normalizing the confidence scores from each of the seven differential diagnoses in order to replicate real-world clinical situations that can arise during a USG examination. These odds were then shown for each FLL in descending order, resulting in a prioritized list of possible diagnoses that closely mimics the clinical practice decision-making process.

With this new AI model, YOLOv5, we can demonstrate a good performance in detecting and diagnosing malignant focal external liver lesions, including Hepatocellular carcinoma and Cholangiocarcinoma, and benign FLLs on Ultrasound still images. More external validation and real-time clinical performance are required to enhance its applicability [75].

AI in Positron Emission Tomography (PET):

One of the initial implementations of AI in PET imaging has been to facilitate picture reconstructions, utilizing either the individual counts captured by the PET detectors in the form of a sinogram or an existing reconstruction generated by conventional methods. The most comprehensible technique for PET reconstruction is filtered back-projection; however, this approach has predominantly been replaced by iterative reconstruction approaches such as ordered subset optimization maximization (OSEM) [76]. The initial presentation of direct sensor-to-image translation was conducted by Zhu et al., who termed it AUTOMAP [77]. In this model, a neural network that is completely linked is positioned between the intended reconstruction and the sensor signals. Haggstrom et al. [78]. introduced a technique they refer to as "Deep PET," which had several benefits, such as shorter processing time and noise reduction.

The technique was trained on simulated data, where it was comparable to an ideal reconstruction, and it was implemented to real human data, but it seemed to produce images that resembled OSEM but with less noise. Since DL models frequently take an extended time to train but are relatively quick to apply once trained (a procedure called “inference"), it would be expected that such a technique could facilitate quick image creation at the scanner and enhance patient workflow.

Discussion:

The benefits of technological advancements in radiology and the newly emerging domain of radiomics parallel those experienced in other sectors that have transitioned to digital systems. However, challenges persist, particularly regarding the assumption that machines and computers displace human employment, often viewed as a limitation to the widespread utilization of AI in radiology [79]. It has been expected that a significant portion of the duties performed by anatomic pathologists and radiologists would be achievable by machine learning in the future, affecting human employment in these fields. Furthermore, machine learning methodologies will probably advance significantly in the next 5–10 years, thereby affecting radiology as a thriving human profession [80]. Approval of AI results may lead to numerous consequences. AI algorithms are supposed to improve the results, rather than substitute for radiologists. The next risk is that dependence on technology generally affects human intelligence and may lead to declining human capabilities [81].

Advantages of artificial intelligence for radiologists

Radiomics analysis is significantly more powerful than the human eye or brain since it can identify more than 400 characteristics from CT, MRI, or PET scans and connect these features with other data. These characteristics might be utilized to forecast treatment response and prognosis [82,83].

AI can facilitate the standard reporting process, correlate words, photos, and quantitative data, and ultimately provide the most likely diagnosis. CDE (Common Data Elements) consists of AI software programs like computer-assisted reporting systems, and radiology case reports for clinical research. CDE can serve as an AI language for creating a customized, organized report for a patient [84]. AI can compare the present and past examinations, particularly in the oncologic follow-up that collects the data and will help the radiologist to prepare the final report [85]. It can rapidly identify normal studies which will benefit radiologists and they can report only the abnormal studies and save time [86].

Deep learning algorithms can recognize pictures to identify the presence of a fracture and subsequently employ segmentation to evaluate the pattern of fracture [87]. AI has demonstrated comparable or superior performance to experienced radiologists in identifying fractures on radiographs and serves as a possible resource for healthcare professionals to reduce faults and alleviate burnout [88]. Another benefit of AI in radiography includes computerized measurements, such as implant placement, joint direction, leg length, or leg alignment [89-92].

One significant advantage of AI in clinical practice is its ability to handle at emergency situations.AI can identify a fracture before radiologists report it. Prioritizing reading studies with possibly favourable findings allows radiologists to minimize the time between initial nonexpert reading and final report, thus enhancing patient care. Another possible advantage of AI is reduced examination times. Radiologists may read 200–300 radiographs a day, thus even a small decrease in reading time, even by a few seconds for each radiographic examination, can add up to significant time savings. AI-assisted fracture detection also holds promise for improving radiologists' and non-radiologists' diagnostic skills by avoiding errors brought on by human exhaustion or satisfaction bias in image reporting in addition to identifying subtle findings that are hard for human eyes to see. [93,94].

Conclusion:

The impact of AI technology on radiology has been extensively addressed in the field. AI interpretation takes a major step ahead with AI-RAD companion, which pretends to be a major advancement in interpretation. As a way, AI deep learning reconstruction methods are considered to be advanced reconstruction methods that gradually reduce the radiation dose to the patient. Automated AI positioning and advanced parameter selection thus eventually work to reduce the radiation dose. This review concludes that AI enhances diagnosis and treatment planning, potentially transforming the medical imaging and healthcare sector completely. **R**

Abbreviations:

Artificial Intelligence (AI), Computer Assisted Diagnosis (CAD), Deep Convolutional Neural Network (DCNN), Filtered back projection (FBP), AEC (Automated Exposure Control)

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