RESEARCH PAPER

# Artificial Intelligence in Medical Imaging: Ethical Considerations and Clinical Applications in Radiology

**Vratika Arya[1], Himanshu[2], Neeshu Rani[3], Ms. Ankita Semwal[4], Sumit Singh[5], Pushpendra Kumar Rajput[6*]**

[1]Assistant Professor, Noida International University. Email: vratikaarya8@gmail.com, ORCID: https://orcid.org/0009-0001-8021-8223

[2]Assistant Professor, Glocal University. Email: himanshu007uc@gmail.com

[3]Master's Student, Santosh deemed to be University, Ghaziabad (Pincode - 201009). Email: nishuchauhan1011@gmail.com

[4]Assistant Professor, Maya Devi University. Email: Ankita.semwal@mdu.edu.in, ORCID: 0009-0001-3872-6611

[5]Assistant Professor, Rayat Bahra University, Mohali, Chandigarh, Punjab. Email: singhsingh789595@gmail.com

[6*]Co-responding Author: Assistant Professor, Department of Medical Radiology and Imaging Technology, Subharti College of Allied and Healthcare, Swami Vivekanand Subharti University, Meerut, UP, India. Email: Insapushpendra@gmail.com, ORCID: 0009-0005-0448-6006

*ABSTRACT*

**Introduction:** Artificial Intelligence (AI) has radically reshaped the field of medical imaging and radiology through advancements in diagnostic precision, efficient workflows, and evidence-based care. The incorporation of advanced technologies like deep learning, convolutional neural networks, and natural language processing has ushered in an era where diagnostics and patient outcomes have been radically enhanced.

**Aims:** In this paper, we aim to provide a comprehensive overview of AI integration within radiology practices, focusing particularly on image interpretation, disease detection using multiple modalities, and patient care systems that utilize AI support. The ethical considerations regarding the use of AI in radiology are considered, including privacy, biases in algorithms, accountability, and transparency.

**Methods:** A literature review was undertaken to identify relevant articles in the PubMed, Scopus, Web of Science, and IEEE Xplore databases, published between 2015 and 2024. Peer-reviewed papers concerning AI implementation in diagnostic radiology, ethical considerations, and sustainability of health AI systems were selected.

**Findings:** AI technologies show excellent results in diagnosing different conditions through the use of several imaging techniques, such as CT, MRI, PET, and digital radiography. Deep learning algorithms have shown the same effectiveness as that of experienced radiologists, and in some instances, have proven to be even more effective. Nonetheless, many ethical issues remain, among them being model transparency, bias in training data sets, risks for patients' privacy, and high carbon footprint due to extensive AI model training.

**Conclusion:** The potential of using AI in radiology is enormous; however, for the responsible use of AI in this field, it is essential to have adequate ethical guidelines, equal access to data, strict regulation, and sustainable methods for computations.

**Key Terms:** Artificial Intelligence; Medical Imaging; Radiology; Deep Learning; Algorithmic Ethics; Data Privacy; Explainable AI; Federated Learning; Sustainable Healthcare

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## 1. Introduction

For many years, radiology has been a field where the two domains – technology and medicine have met. Following Wilhelm Conrad Roentgen's discovery of the X-rays in 1895, each technological revolution ranging from ultrasonography through to MRI and PET has gradually improved the ability of physicians to visualize the interior of the human body non-invasively [1]. The advent of artificial intelligence technologies such as machine learning and deep learning is by far the most revolutionary change taking place in the field of medical imaging within decades, going way beyond simple computer-aided detection software packages [2].

Modern systems using the power of artificial intelligence algorithms, which were trained based on millions of annotated medical images, can detect patterns in the data provided in an independent manner with sensitivity and specificity comparable to, and in certain conditions superior to, experienced radiologists [3]. The applications range from detecting pulmonary nodules based on CT imaging through to automatic delineation of gliomas based on multiparametric MRI, from artificial intelligence-based mammographic screening to prediction of fractional flow reserve based on coronary CTA [4,5].

Despite all of the potential that has been seen to be held within artificial intelligence in radiology, several challenges have arisen. First among these has been a concern for how difficult it has been to interpret some of the black-box AI algorithms used to analyze images. Another problem concerns the possibility of bias within the datasets, thereby exacerbating existing demographic disparities [6,7]. Patient privacy within the new age of digital health records remains an issue within radiology AI. Finally, there is the issue of where liability should lie when AI systems make errors that can be attributed to their use [8].

Another aspect of the impact that AI is having on healthcare that has been overlooked concerns that of its environmental impact. The energy needs of training deep learning algorithms are considerable, resulting in a considerable carbon footprint and strain on data centers [9]. As healthcare organizations around the world aim to meet various sustainability targets, the time has come for the field of AI to become cognizant of SDGs.

This paper conducts a comprehensive review of the clinical application of AI in medical imaging and radiology, along with an equally critical assessment of the need for ethics, regulation, and sustainability when developing applications for AI. Using results obtained from peer-reviewed sources published in top journals listed in Scopus, this manuscript attempts to give the radiologist, clinician, health informatics specialist, and policymaker guidance on implementing AI ethically in their practice.

## 2. Overview of AI Technologies in Medical Imaging

### 2.1 Machine Learning and Deep Learning Fundamentals

Artificial intelligence in medical imaging essentially depends on the capabilities of machine learning techniques in detecting complex and non-linear relationships in high dimensional imaging data [10]. Previous ML algorithms such as support vector machines (SVM), random forest, and gradient-boosting decision trees were dependent on a large number of handcrafted features and did not necessarily work well with raw pixel data. Deep learning approaches, specifically convolutional neural networks (CNNs), have solved these shortcomings by performing automatic feature extraction using raw imaging data [11].

CNNs consist of several convolutional layers through which filters learn to extract high-level information from low-level texture features of input images. Some of the most prominent CNN architectures are AlexNet, VGGNet, GoogLeNet, ResNet, DenseNet, and Vision Transformer (ViT) [11,12]. One approach that has greatly facilitated medical imaging analysis by addressing the lack of data in training is transfer learning, which involves using a pretrained model fine-tuned on specific data [13].

### 2.2 Imaging Modalities and AI Integration

#### *2.2.1 Computed Tomography (CT)*

The volume of data that is produced by CT scans is suitable for analysis using AI techniques. Deep learning methods have proved to be very efficient when it comes to detecting nodules in lungs, as their sensitivity reaches 94.4%, which makes them even more efficient than a group of six radiologists [12]. AI techniques are used in the evaluation of liver lesions based on CT data, for measuring aortic aneurysms, for vertebra fractures detection, and to predict cardiovascular disease risk through coronary artery calcium score assessment [4].

#### *2.2.2 Magnetic Resonance Imaging (MRI)*

The ability of MRI to analyze various parameters and its excellent soft tissue differentiation makes it the most suitable modality for AI-assisted image processing, especially in neurological imaging, musculoskeletal radiology, and tumor staging. The performance of deep learning-based brain tumor segmentation systems, such as the Multimodal Brain Tumor Segmentation (BraTS) challenge, demonstrates that AI can obtain Dice similarity coefficients greater than 0.85 in the whole tumor segmentation task [13]. In addition, MRI scan time reduction with AI-assisted k-space undersampling and deep learning reconstruction (fastMRI) can be performed fourfold faster without compromising diagnostic accuracy [20].

#### *2.2.3 Digital Mammography and Breast Imaging*

Breast cancer screening has been shown to be among the most promising examples of the application of AI technologies within radiology. Several prospective trials have shown that using AI helps reduce the workload of radiologists by identifying mammograms without abnormalities, focusing human expertise on those that need closer examination. One significant Swedish study showed that the use of AI for breast cancer screening helped identify 20% more cancerous lesions than double reading did but reduced radiologist workload by 44% [21]. Screening mammograms evaluated via deep learning algorithms had an AUC above 0.87 [14].

#### *2.2.4 Chest Radiography*

Chest X-ray is by far the most common diagnostic modality and its interpretation through the use of AI techniques is one of the most researched topics. In this regard, CheXNet, a DenseNet with 121 layers that was trained using the ChestX-ray14 data set, which consists of more than 100,000 images, performed better than four radiologists in detecting pneumonia [22]. More recently, there have been attempts to create multi-disease classifiers capable of diagnosing 14 different conditions, including cardiomegaly, pleural effusion, and pneumothorax, where AUC was above 0.80 [5].

#### *2.2.5 Pathological and Nuclear Medicine Imaging*

Applications of artificial intelligence technology have been increasingly used in nuclear imaging, whereby deep learning models have been found to exhibit excellent sensitivity in the diagnosis of bone metastasis from bone scintigraphy and in the localization of metabolic abnormalities in 18F-fluorodeoxyglucose positron emission tomography-computed tomography images. The field of digital pathology has seen tremendous advances in recent years, whereby machine learning tools allow for the automated assessment of prostate carcinoma (Gleason score), lung carcinoma subtyping, and sentinel lymph node metastasis [23].

### 2.3 Generative AI and Synthetic Data

With Generative Adversarial Networks (GANs) and diffusion models, there has been the introduction of synthesizing realistic medical images that help overcome the problem of insufficient data, as well as cross-modality image transformation such as MRI-to-CT synthesis [15]. The use of synthesized images may be useful for adding to training data sets, helping eliminate demographic biases, and even making the data more private when being shared across institutions. Nevertheless, these images need to be validated before use.

### 2.4 Natural Language Processing in Radiology

Natural Language Processing (NLP) can enhance image analysis through the automation of information extraction from radiology reports, report structuring, and decision-making support [16]. Multi-modal approaches that utilize both image and text processing have emerged as promising areas in clinical applications. Recent developments in LLMs such as GPT-4 and BioMedLM have shown capabilities to provide initial radiology report generation, detection of incidental findings necessitating further action, and extraction of structured information for population studies.

***Table 1. Representative AI Applications Across Imaging Modalities and Clinical Tasks***

| AI Application | Imaging Modality | Disease/Task | Key Reference |
|---|---|---|---|
| CNN-based detection | CT | Pulmonary nodule detection | Ardila et al., 2019 [12] |
| Deep learning segmentation | MRI | Brain tumor delineation | Bakas et al., 2018 [13] |
| Transfer learning (ResNet) | Fundus photography | Diabetic retinopathy grading | Gulshan et al., 2016 [14] |
| GAN-based synthesis | MRI / CT | Data augmentation & reconstruction | Yi et al., 2019 [15] |
| NLP + imaging fusion | Multi-modal | Radiology report generation | Zhang et al., 2020 [16] |
| Federated learning | Multi-site CT/MRI | Collaborative model training | Rieke et al., 2020 [17] |
| Explainable AI (Grad-CAM) | X-ray | Pneumonia localization | Selvaraju et al., 2017 [18] |

*CNN = Convolutional Neural Network; GAN = Generative Adversarial Network; NLP = Natural Language Processing*

## 3. AI in Disease Detection and Diagnosis

### 3.1 Oncological Imaging

Detecting and characterizing cancers is by far one of the most extensively investigated applications of AI in radiology. AI has shown comparable diagnostic accuracy as that of radiologist specialists in the detection of pulmonary nodules, colorectal polyps by CT colonography, hepatocellular carcinomas by dynamic contrast-enhanced MRI, and prostate cancer by multiparametric MRI [4,12]. Radiomics, which involves large-scale analysis of medical images using computer algorithms, has helped in creating AI models that can predict the biological behavior of the tumor, including its histology, molecular subtype, response to treatment, and survival outcome [24].

Datasets used for the I-ELCAP (International Early Lung Cancer Action Program) and National Lung Screening Trial (NLST) initiatives have served well in developing and testing out AI systems for lung cancer detection. The use of AI for augmenting nodule management systems in combination with validated risk models like Lung-RADS holds the potential to lower false positives without affecting the sensitivity of malignant nodules.

### 3.2 Neurological Disorders

The development of AI solutions in the field of neuroimaging has greatly evolved in recent years to support medical diagnosis of patients with stroke, neurodegenerative disease, and psychiatric illness. AI algorithms that can detect automated intracranial bleeding without the use of contrast material can identify cases needing clinical attention within seconds of image acquisition; this technology has been validated in more than one prospective study and boasts a high sensitivity of over 90% [25].

Deep learning solutions trained on a dataset of longitudinal magnetic resonance imaging scans of patients collected by the Alzheimer’s Disease Neuroimaging Initiative (ADNI) have been able to predict conversion from mild cognitive impairment to Alzheimer’s disease six years before diagnosis, thus facilitating timely intervention. Other AI technologies used in neuroimaging, including convolutional algorithms that process diffusion tensor imaging results, have proven useful in diagnosing neurological diseases such as multiple sclerosis and traumatic brain injury.

### 3.3 Cardiovascular Imaging

Examples of cardiovascular applications of artificial intelligence include echocardiography, cardiac magnetic resonance imaging, and coronary computed tomography angiography (CCTA). Deep-learning-based automated left ventricle ejection fraction quantification by echocardiography has already been able to produce reproducible results that surpass human observers' inter-observer variability, where the average absolute error is around 4% [27]. FDA-approved FFRCT by HeartFlow is an example of the application of computational fluid dynamics and artificial intelligence to compute fractional flow reserve from CCTA [28].

### 3.4 Musculoskeletal and Trauma Radiology

Radiological fracture detection applications for plain X-ray images have shown sensitivity increases of between 10% and 20%, compared to emergency department physicians not specialized in radiology. This is especially true for fractures that are difficult to detect, such as those of the wrist, hip joint, and ribs. Bone age prediction software trained using hand radiographs has demonstrated accuracy on par with pediatric radiologists; additionally, the report generation process has been completed in a much shorter period of time. AI-assisted osteoporosis detection based on opportune CT scans uses previously captured images to evaluate bone mineral density.

## 4. AI-Assisted Clinical Workflow and Decision Support

### 4.1 Worklist Prioritization and Triage

Intelligent worklist management using AI technology would be one of the most promising uses of AI in the immediate future. Using this technique, examinations requiring urgent attention can be sorted by the AI system and prioritized accordingly, resulting in considerable reduction in diagnosis time for these critical conditions. A proof-of-concept implementation of this technology has resulted in a substantial decrease in time-to-report of critical CT scans from over 60 minutes to less than 12 minutes.

### 4.2 Automated Reporting and Structured Reporting

AI-generated preliminary reports of imaging examinations, using standardized language vocabularies like RadLex and SNOMED CT, are now being considered for use in radiologists' productivity aids. Automated systems employing natural language processing can generate structured interpretations of standardized imaging studies (such as chest CT for PE or knee MRI), which can then be reviewed and finalized by the radiologist [16]. Such an approach, sometimes referred to as AI-assisted interpretation instead of AI replacement, follows the general principle of radiology professional organizations that AI must assist and not replace the radiologist [31].

### 4.3 Federated Learning and Multi-Institutional Collaboration

This is considered a breakthrough in the development of collaborative AI models where federated learning has allowed institutions to develop AI models using data sets from multiple institutions without collecting patient data at a single location [17]. The federated learning approach involves training of a model by exchange of parameters and not the actual image data, thereby protecting patient privacy, but still allowing a model to generalize across different patients and machines. Federated approaches such as FeTS (Federated Tumor Segmentation) and the NVIDIA FLARE framework have shown that federated models perform on par with those developed using centralized approaches.

## 5. Ethical Considerations in AI-Driven Radiology

### 5.1 Data Privacy and Security

Medical imaging databases have highly sensitive patient information that is exclusive to medical records. Apart from textual EHR, there is added vulnerability to re-identification when considering radiological imagery, especially head CT and MRI images for which facial reconstruction has been proven accurate through commercially available software, thus undermining traditional anonymization methods [32]. In the US, the HIPAA and in Europe, the GDPR lay down fundamental legal guidelines, but the applicability of these laws to AI training datasets, specifically with regards to cross-border de-identified medical image databases, is a new realm of regulatory consideration.

The concept of differential privacy, which involves adding controlled amounts of statistical noise to data or predictions from models to make sure they cannot be used to identify any records, is an advanced technical approach for ensuring privacy during AI training. Unfortunately, such approaches can sometimes come with accuracy penalties, and the balance between privacy protection and performance is currently under investigation [33].

**5.2 Algorithmic Bias and Health Equity**

Algorithmic bias, which refers to the unfair and systematic disparity in model performance between different demographic groups, stands out as one of the most urgent ethical issues in clinical AI [6]. For example, in radiology, the causes of bias could be an imbalanced representation of minority racial, ethnic, or socio-economic groups within the data set used in training, variations in image protocols and imaging devices between different institutions, as well as the biases of the labels created by annotators who may themselves come from an unbalanced distribution of clinical experience. Indeed, a seminal study showed how AI algorithms approved by the FDA for dermatology had a notably poor performance on images of people with darker skin, while the same was also found concerning AI models in thoracic and abdominal imaging trained using data primarily from North America and Europe [34].

Methods of addressing this issue include the careful selection of demographically balanced and geographically diverse training sets, algorithmic fairness constraints during model development, and the use of standardized bias evaluation tools like the Aequitas and Fairlearn packages.

**5.3 Transparency and Explainability**

This issue of the opacity of deep learning models, which can be referred to as "black boxes," raises serious questions about clinical trustworthiness, regulation, and medico-legal liability [35]. Radiologists need more than just an answer; they also require explanations so that they can assess whether the machine's output is appropriate and relevant within a broader clinical picture. Methods such as Explainable AI (XAI) attempt to explain what deep learning algorithms do in a way that humans can understand.

The gradient-weighted class activation map (Grad-CAM) technique creates visual heatmaps that show the parts of the image that are most significant to a model's decision-making process [18]. While the SHAP method (SHapley Additive exPlanations) allows us to attribute a certain value to a feature in tabular data formats, attention techniques in transformers give us some interpretability out of the box. It must be mentioned that XAI approaches approximate, rather than explain the mechanistic workings of models, and need further human factors testing.

**5.4 Accountability and Legal Responsibility**

AI integration into clinical decision-making brings up many difficult questions concerning the issues of professional and legal responsibility that current medico-legal frameworks do not cover [7]. In cases when AI plays a role in making incorrect diagnostic decisions, be it by providing a false negative result for malignancy or a false positive leading to unnecessary procedures, it becomes challenging to attribute responsibility to one party—whether it is the developers of the technology, the health institutions implementing it, or the radiologists who use AI-driven results in their practice. Some legal experts propose frameworks where AI can be considered a 'sophisticated medical device' under product liability law, while others offer innovative approaches based on shared responsibility, which implies all parties involved in AI implementation bear some level of responsibility.

Radiological associations like RSNA, ESR, and ACR are unanimous in recognizing that it is always the radiologist's ultimate responsibility to interpret the data, even if AI is used in the process [8]. This notion of 'human-in-the-loop' review is explicitly incorporated into the European AI Act, classifying AI in medicine as high-risk AI that must be subject to human review and transparent reporting mechanisms.

**5.5 Informed Consent and Patient Autonomy**

Whether it would be ethical to disclose the use of AI in diagnosis, and provide a choice to patients regarding whether they wish for AI to be involved, is a growing debate in both the fields of ethics and law. Survey responses show that there are significant percentages of patients who do not know about or have concerns regarding the involvement of AI in the process of medical treatment; however, some of these patients say they would be willing to have AI used in diagnosis, provided that the reason behind its use is clear, and that radiologist guidance is assured [36]. Informed consent, an essential element in biomedical ethics discussed in the Belmont Report and Declaration of Helsinki, applies in this case.

## 6. Environmental Impact of AI in Healthcare Imaging

### 6.1 Energy Consumption and Carbon Footprint

The computing requirements of training deep learning models are enormous and increasing rapidly. Training one such large transformer model can be expected to produce greenhouse gas emissions on par with the lifetime emissions of five ordinary cars in the US [9]. Although the medical imaging AI models are smaller than their counterparts in natural language processing, the total energy expenditure incurred by training and retraining these diagnostic models in thousands of hospitals and clinics is not insignificant in terms of the healthcare industry's carbon footprint.

Medical imaging equipment consumes a lot of energy. For instance, a CT scanner uses about 30 kW of power. MRIs need superconducting electromagnets that are kept at low temperatures using large amounts of energy. The additional requirement of GPUs for inference adds to this cost. The energy usage of data centers, which store enormous amounts of medical images in DICOM format, is another factor contributing to the problem.

### 6.2 Sustainable AI Practices

Green AI, the development of AI technology that is energy-efficient as well as capable of delivering high performance on assigned tasks, is a novel paradigm with applications in healthcare [37]. Methods such as pruning, quantization, and knowledge distillation are among several approaches to model compression that result in significant reduction in the size and latency of the model inference process while retaining diagnostic accuracy. Carbon-aware computing, which involves scheduling of machine learning jobs during peak hours of renewable electricity in the grid, has been shown to significantly reduce carbon footprint of model training by up to 75 percent without impacting model accuracy.

In terms of infrastructure considerations, hospitals and other health-care facilities must undertake an energy audit of AI deployments in their organizations, apply PUE metrics for data centers, and choose cloud providers that have a proven track record of carbon-neutral operations. The notion of 'model sharing,' whereby different facilities jointly develop AI models using the technique of federated learning, allows for energy savings as well as privacy protection.

Consistency with UN Sustainable Development Goal 3 (Good Health and Well-Being) and SDG 13 (Climate Action) necessitates that the AI for health sector clearly measure, disclose, and reduce its environmental footprint as part of AI governance best practices [38].

***Table 2. Ethical Challenges and Proposed Mitigation Strategies in AI-Driven Radiology***

| Ethical Domain | Challenge | Proposed Mitigation Strategy |
|---|---|---|
| Data Privacy | Re-identification risk in imaging datasets | Federated learning; differential privacy; GDPR compliance |
| Algorithmic Bias | Underrepresentation of minority groups | Diverse training data; bias auditing frameworks |
| Transparency | Black-box model decisions | Explainable AI (XAI); Grad-CAM; SHAP values |
| Accountability | Unclear liability in AI-assisted diagnosis | Clear regulatory frameworks; human oversight mandate |
| Environmental Impact | Energy-intensive model training & data storage | Green AI practices; carbon-aware computing; model compression |
| Informed Consent | Patient unawareness of AI involvement | Mandatory disclosure protocols; patient education programs |

## 7. Regulatory Frameworks and Governance

However, the regulatory environment of AI medical devices is quite heterogeneous across nations and changes very rapidly. The US FDA considers AI medical devices, particularly radiological AI software, as Software as a Medical Device (SaMD). As of 2023, more than 600 medical devices employing artificial intelligence and machine learning have been authorized by the FDA, of which the majority are classified under radiology [39]. Moreover, the FDA's proposed regulation model for AI/ML-based SaMD includes a system of a 'predetermined change control plan' according to which AI algorithms can adjust after being launched without receiving approval again.

In addition, the world's first law regulating the use of AI is the EU's Artificial Intelligence Act (2024). This act includes an extensive set of criteria and regulations related to the use of AI technologies. According to this act, AI systems deployed for healthcare purposes should be technologically sound, accurate, and subject to human supervision. Among other things, the use of AI technologies that take advantage of patients' vulnerable status or produce biased estimates based on particular features of a patient is prohibited.

For instance, the Change Programme on Software and AI as a Medical Device by MHRA in the United Kingdom is designed to offer greater clarity and flexibility in guiding AI medical software regulation. Another example in the UK is the NICE Evidence Standards Framework for Digital Health Technologies which offers an evidence pathway for the evaluation of clinical and cost effectiveness before any implementation within the NHS [40]. Furthermore, the IMDRF has issued guidelines in the form of global harmonization principles for regulating AI/ML medical devices.

**8. Proposed Framework for Responsible AI Integration in Radiology**

Based on the above ethical, legal, regulatory, clinical, and environmental perspectives outlined in the previous paragraphs, the following manuscript offers a multi-dimensional model—CLEAR-AI Framework—for AI adoption in radiology practice:

C – Clinical Validation: AI systems must be prospectively clinically validated on representative patient samples prior to any implementation in their performance, stratified according to various demographic groups, modality types, and indications.

L – Legal and Regulatory Compliance: AI implementation should comply with all relevant national and international legal requirements related to data protection laws and regulations of software as medical device (SaMD) and other sector-specific AI governance rules, as well as ensure appropriate accountability structures.

E – Explainability and Ethics: Each adopted AI system must be explainable for radiologists and use XAI techniques while respecting the institutionally adopted ethics of AI governance principles, which are based on the concept of beneficence, non-maleficence, autonomy, and justice.

A – Accountability and Audit: The mechanisms of continuous performance monitoring and algorithmic audit, as well as incident reporting, need to be institutionalized, along with human oversight by qualified radiologists.

R – Responsibility to Sustainability: An assessment of the environmental footprint associated with each AI application should become a standard step in decision-making in AI procurement and deployment.

**9. Future Directions**

The future direction of artificial intelligence in medical imaging includes several key trends that could revolutionize the field of radiology in the next decade. First, foundation models which are high-capability AI systems trained on multiple types of multi-modal medical data before being fine-tuned for individual applications have the potential to democratize AI by allowing organizations to leverage such capabilities without developing their own algorithms [41]. Moreover, AI systems that incorporate data from multiple sources including radiological imaging, genomics, EHRs, and real-world evidence could bring about precision medicine on a massive scale.

Second, digital twin technology refers to patient-specific computer models built from medical image data and allows performing simulations of diseases, surgical procedures, and assessing treatment response. Lastly, although quantum computers are still in the early stages of development, they could eventually overcome current computational limitations in developing massive AI models [42].

For ethical reasons, globally agreed-upon guidelines for the governance of AI, culturally sensitive methods of AI bias testing for low- and middle-income countries' health care context, and the use of patient-centered design frameworks when designing AI systems to make sure that their benefits are distributed equitably among different patients would become necessary. Participatory approaches to co-designing AI systems taking into account patient needs have emerged as one such key concern for health AI [43].

**10. Conclusion**

The development of artificial intelligence has had a profound impact on the field of medical imaging and radiology, bringing unprecedented advances in diagnostic accuracy, operational efficiency, and the information that can be gleaned from imaging studies for clinical purposes. From deep learning models for detecting lung nodules to federated learning algorithms used to segment brain tumors at multiple institutions, artificial intelligence is showing remarkable efficacy across all areas of radiology.

However, to fully capitalize on the promise of artificial intelligence in radiology, an unwavering dedication to ethical considerations must go hand in hand with innovation. Data security must be ensured using technical safeguards and regulations tailored to the vulnerabilities of medical imaging information. Algorithmic bias must be actively assessed, measured, and mitigated so that artificial intelligence technology improves the quality of care while minimizing health disparities. AI systems must be inherently transparent and interpretable so that radiologists can make critical assessments of their recommendations and remain the key decision-makers.

The environmental component of health care AI, albeit less publicized, requires immediate consideration. Responsible AI use will be characterized by efficient models, carbon-aware computing, energy-efficient infrastructure, and model sharing, and should become a standard expectation for any future acquisition and development of AI.

The CLEAR-AI framework put forth in this review presents an integrated approach to adopting AI responsibly in medicine in consideration of its clinical potential and ethical considerations. With AI poised for greater adoption within radiology and across the entire health care system, it becomes the duty of all stakeholders to see that it develops in accordance with ethics and principles of conscientiousness.

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