AI applications in the medical field

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Abstract. In this paper we will discuss the advancements in AI uses in the medical industry as well as talk about a few of the medical scanning branches that are adopting AI or are made to aid in the scanning the human body.

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1. Introduction

Artificial-intelligence (AI) is a broad field of computer science focused on creating intelligent machines that can carry out tasks normally reserved for human cognition. It's uses span from visual-recognition systems and voice interfaces to autonomous decision engines and machine translation. Because it draws upon psychology, linguistics, statistics and more. AI sists at the crossroads of many disciplines.[1], [2], [3], [4], [5]

Since 2012, AI has exploded in medicine especially in radiology and pathology thanks to deep learning and convolutional neural networks. By 2022, a whopping 70% of FDA-cleared health AI tools were for radiology, reflecting the field's rapid publication boom.

Yet expectations that AI would outshine human radiologists haven't materialized yet. Most approved algorithms are narrow-scope helpers: they boost efficiency or quality but don't replace radiologists. They're split into interpretive (diagnosing images) and non-interpretive tools act before ("upstream") or after ("downstream") imaging to streamline workflows. As of right now AI systems are now a mainstay in medicine, diagnosing illnesses, accelerating drug discovery, enhancing doctor patient communication, transcribing prescriptions and even delivering remote care. While computers can already perform many tasks faster than humans, the latest algorithms match or sometimes beat the human experts on accuracy. This article will focus on the breakthroughs of AI in the Bio-scanning industry.[6].

2. AI in Bioscanning

Artificial intelligence (AI) and machine learning have quickly become essential tools in healthcare, with rehabilitation poised to reap significant benefits from their data-driven insights. By mining large datasets, AI helps clinicians spot patterns in patient progress, forecast treatment outcomes, and tailor interventions to each individual - supporting the modern shift toward patient-centered care.

Medical imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) play a pivotal role in providing clinicians with detailed and comprehensive visual information about the human body. These imaging modalities generate vast amounts of data that require efficient analysis and interpretation, and this is where AI steps in.

Predictive analytics is another key advantage: AI can anticipate potential setbacks and guide preemptive adjustments, especially valuable for chronic or complex cases. Reviews highlight that such foresight empowers therapists to refine strategies based on individual risk profiles and expected responses.[7], [8]

For this study two public sources were used. FDA's database of artificial-intelligence and machine-learning-enabled medical devices and the American College of Radiology Data Science Institute's AI Central to identify FDA-cleared radiology applications as of August 2022. They found a total of 241 in total, of which 101 were dedicated to body imaging (defined as scans from the thyroid through the pelvis while excluding head, other neck compartments, breast and extremities). After removing ten products used for radiation or surgical treatment planning, 91 body-imaging AI tools remained. Each Algorithm was categorized by it's primary subspecialty (abdominal, chest, cardiac, neuroradiology, etc.) per the American College of Radiology Data Science Institute database. Thyroid ultrasound applications were re-classified under "abdomen" because they are typically considered part of abdominal imaging in most practices. The authors recorded each tool's application type, target body area and modality, then organized these data by anatomical region (Fig 1) and radiology subspecialty (Fig. 2). [9], [10]

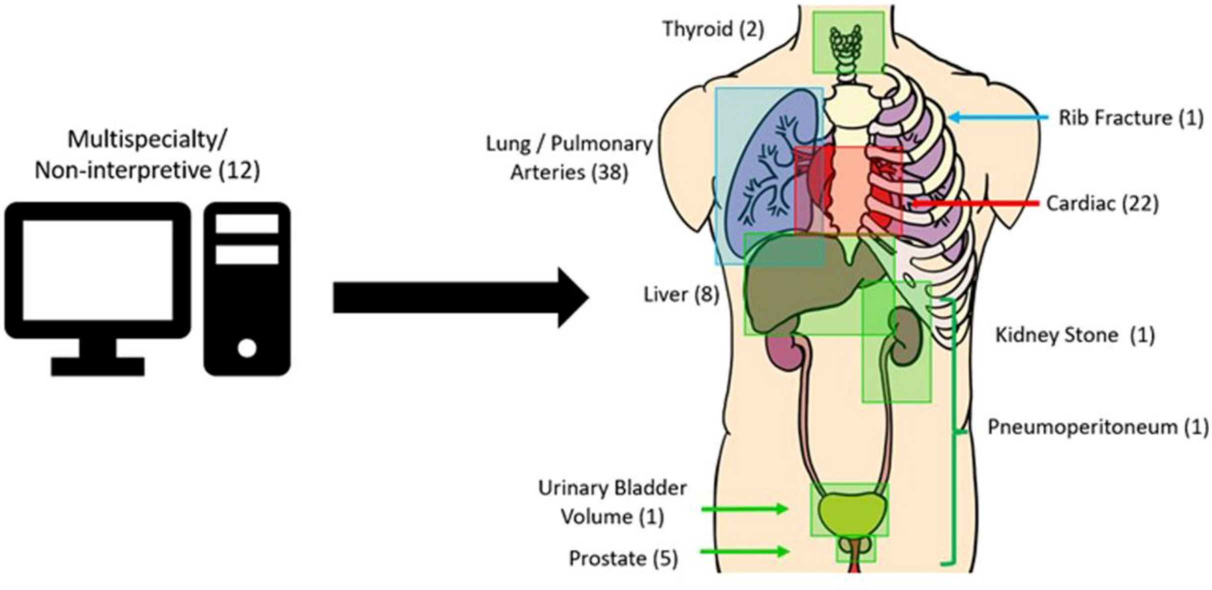

Fig. 1. (Fig. 1) This figure summarizes AI tools by both anatomical region and application type: each region's count is shown in parentheses, while multispecialty or non-interpretive applications are labeled "multispecialty/noninterpretive" Single-site or single-pathology tools such as those detecting rib fractures, kidney stones, or urinary bladder volume are listed by their specific finding. Visual cues indicate the anatomical domain: green boxes, arrows and brackets denote abdominal imaging; blue highlights represent chest imaging; red marks cardiac imaging. Notably, organ systems outside this model: e.g. gastrointestinal tract, spleen, pancreas, uterus which currently lack the dedicated FDA cleared AI applications.[11]

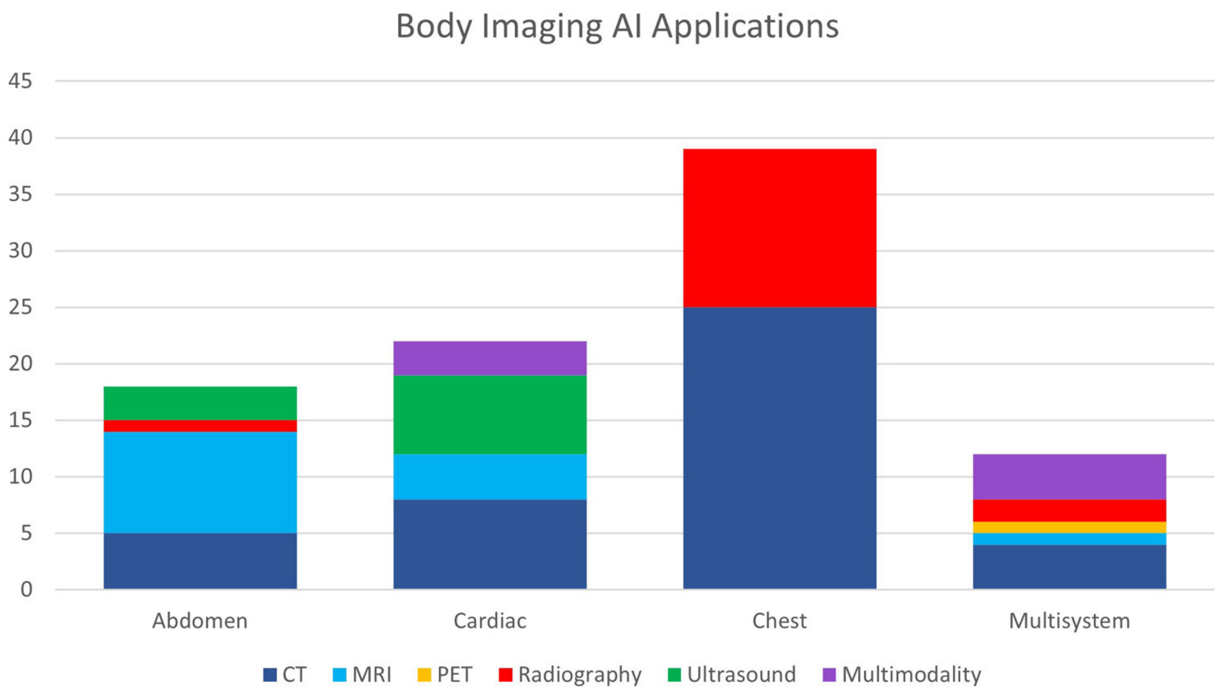

Fig. 2. Body imaging AI application by subspecialty and modality.[11], [12]

FDA cleared radiology AI products were grouped into three functional classes, image processing, segmentation/qualification and computer aided diagnosis (CAD) though in reality these categories overlap considerably (Fig. 3). For instance, lesion segmentation or quantitative imaging tools feed directly into the diagnostic workflow yet rarely labeled as CAD, while many CAD systems rely on image-processing steps to flag findings but ultimately serve to aid interpretation. The authors assigned each product to a category based on descriptions in the AI Central database and the vendors own websites.

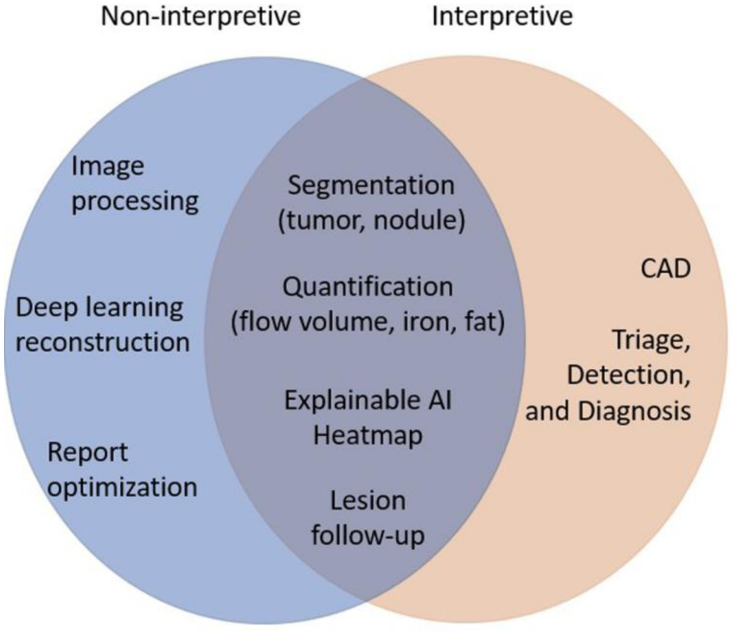

Fig. 3. A Venn diagram illustrating how AI applications combine interpretive and non-interpretive capabilities.

The CNN's mimic's how animals see starting with raw pixel grids, they apply stacked convolutional layers to pull out edges, textures, then shapes and objects. After each convolutional block a ReLU activation injects non-linearity, while pooling shrinks the map but keeps the key info. As you go deeper, the network learns higher-level, abstract patterns. The output of this journey is a set of deep features: compact, discriminative vectors that carry semantic meaning far beyond the original pixels. These low-dimensional representations save compute, simplify downstream tasks and it's letting us skip the tedious hand-crafted feature engineering. Plus, because they capture only what matters, they naturally curb overfitting and boost generalization exactly what you need when wrestling with huge imaging datasets.

3. Financial benefits.

When deciding if a new radiology software is worth buying, three things have to be considered:

1. Clinical value – Does it actually improve patient care? Look for gains in quality, accuracy, error reduction, screening, triage, or reporting.
2. Simplicity – Is it easy to install, train on, plug into existing workflows, maintain, and upgrade? A user friendly tool keeps the team moving.
3. Financial ROI – Will it generate new billable services, boost throughput, or cut radiologist workload enough to bring measurable revenue?

In practice, the strongest investments are those that combine concrete simplicity with a clear financial upside, even if clinical benefits are only partially proven yet.[13], [14], [15]

1) Image-quality improvement (MIMPS)

Using deep-learning reconstruction on PET and MRI scans, this application increases image clarity while lowering contrast agent or radiation dose. The software is easy to install, but making the scanner schedule more efficient requires substantial operational changes. Because it can raise patient throughput and offer new billable services, the financial return is high.

2) Faster scan times (MIMPS)

The same reconstruction technique cuts acquisition time, again with minimal technical setup. However, freeing up scanner slots demands major workflow adjustments. Faster exams boost throughput, improve image quality, and reduce both contrast and radiation exposure—generating strong ROI through higher patient volume.

3) Finding detection & segmentation (CADe)

A computer-aided detection system for CT scans flags pulmonary nodules and other lesions. It improves lesion spotting with minimal extra training or workflow disruption. By decreasing radiologist workload and exam turnaround, it can cut interpretation time and improve productivity, giving a modest but clear financial benefit.

4) Acute/incidental triage (CADt)

This CT-based tool spots urgent incidental findings such as pulmonary emboli and prioritizes them in the worklist. Implementation is relatively straightforward but still needs some training, IT support, and quality assurance. The primary benefits are patient safety and medicolegal risk mitigation, which can translate into better referral patterns and a moderate financial upside.

5) Quantitative assessment (MIMPS)

Applied to MRI, this algorithm automatically measures liver iron concentration and other metrics that would otherwise be labor-intensive. Deployment is mildly demanding—technologists need training and the protocol may require hardware tweaks—but it adds new billable services, extends the radiologist's role, and can attract more referrals, offering a solid ROI.

6) Interpretation support (MIMPS)

On prostate MRI, the system improves segmentation of the gland and lesions and standardizes PI-RADS scoring. Integration requires moderate training and IT setup. The result is higher radiologist performance and shorter interpretation times, which together deliver measurable financial gains through increased efficiency.

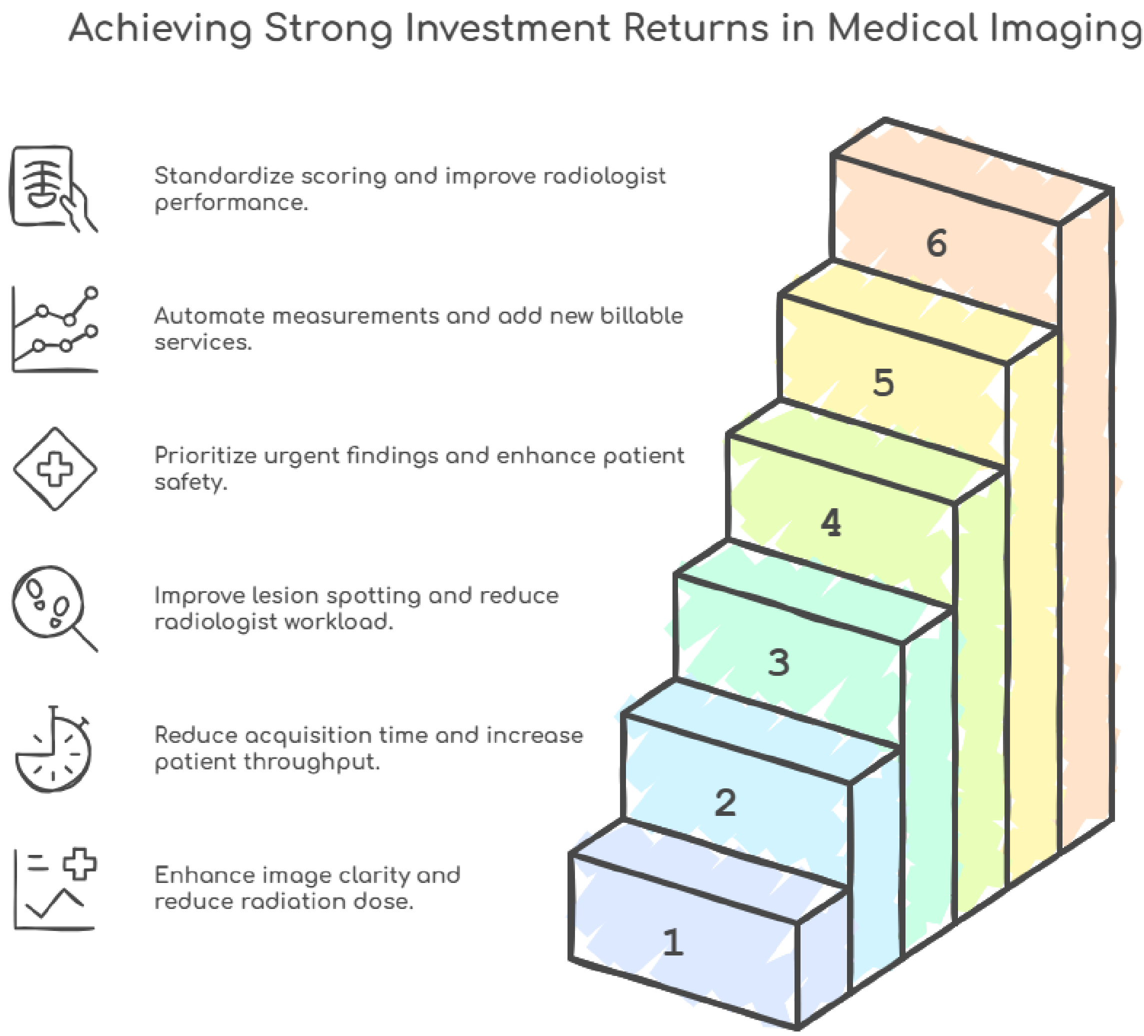

Fig. 4. Investment return in medical imaging

In short, each application delivers a mix of clinical value (better imaging or detection), simplicity of adoption (ranging from minimal to moderate effort), and potential for financial return often driven by higher throughput, new services, or improved workflow.

4. Bottom line take away

The body imaging AI market is booming, with most tools falling into two camps: interpretive (CAD) and non interpretive (segmentation/quantification/image processing).

• Interpretive CAD focuses on single, high volume pathologies—think pneumothorax or pulmonary embolism on chest radiographs or CTs—and is designed to speed up detection, reduce errors, and improve turnaround. They’re most valuable when they can demonstrably cut review time, boost diagnostic accuracy, or add measurable patient care benefits, otherwise the ROI is hard to justify.

• Non interpretive AI (segmentation, volume calculation, image quality enhancement) automates laborious measurements for e.g., liver iron, cardiac ejection fraction, thyroid nodule TI RADS and delivers consistent, reproducible numbers that are useful for serial follow up. These tools can shave minutes off table time or scanner time, but their value depends on whether the practice actually frees up slots to generate new revenue.

Chest imaging dominates because datasets are plentiful and protocols highly standardized. Around half of all commercially available products are segmentation/quantification apps; image processing solutions cut across specialties.[10], [16], [17]

Looking ahead, the next wave will likely be multimodal AI that fuses EHR, imaging, and biometrics to give a more holistic diagnostic picture. The road is still long issues of generalizability, interpretability (“black box”), and bias remain hurdles before such systems can enter routine practice.

In short, the marketplace offers a wide range of narrow focus tools; their success hinges on clear clinical benefit, ease of integration, and a demonstrable return on investment. Radiologists who stay informed about the specific type of algorithm (CADt vs CADe vs CADx) and its intended workflow role will be best positioned to pick the right solutions for their practices.[12], [18], [19], [20].

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