http://jhmi.sums.ac.ir
Health Man & Info Sci
2026, 13(3), 166–183

HMIS
Health Management and Information Science

Review Article

Deep Learning-Based Object Detection in Oncology: A Systematic Scoping Review of CT, MRI, and PET/CT Applications

Mahdie Jajroudi[1,2], Mohammad Reza Afrash[3], Fateme Yadegari[1], Seyyed Ali Najafi Fadafen[4], Ali Akbar Movassagh[5], Ashraf Alnattah[1,2], Parham Geramifar[6,*], Saeid Eslami[1,2,*]

[1]Department of Medical Informatics, Faculty of Medicine, Mashhad University of Medical Sciences, Mashhad, Iran.
[2]Pharmaceutical Research Center, Mashhad University of Medical Sciences, Mashhad, Iran
[3]Artificial Intelligence in Medical Sciences Research Center, Smart University of Medical Sciences, Tehran, Iran
[4]Faculty of Medicine, Mashhad University of Medical Sciences, Mashhad, Iran
[5]Department of Medical Physics and Biomedical Engineering, School of Medicine, Tehran University of Medical Sciences, Tehran, Iran.
[6]Research Center for Nuclear Medicine, Tehran University of Medical Sciences, Tehran, Iran.

Abstract:

Introduction: The global rise in cancer incidence highlights the urgent need for more effective diagnostic tools to support early detection and optimize treatment planning. Deep learning-based object detection (OD) has emerged as a major advance in medical imaging, automating lesion identification and classification. By improving the analysis of CT, MRI, and PET/CT scans, OD reduces interpretation time, enhances diagnostic accuracy, and promotes more consistent clinical decision-making in oncology. This review maps the clinical applications of deep learning-based OD in cancer imaging, evaluates the diagnostic performance of various architectures, and identifies barriers to routine clinical adoption.

Methods: Following the Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines, PubMed and Scopus were systematically searched for studies published between 2014 and January 2026. Peer-reviewed studies applying deep learning-based OD models to cancer imaging using CT, MRI, or PET/CT were included. Study quality was assessed using the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool.

Results: Of the 46 included studies, 27 utilized one-stage detectors, 11 used two-stage detectors, and 5 employed both approaches. One-stage models were favored for their efficiency, while two-stage models demonstrated superior detection of small or low-contrast lesions. Applications included early cancer detection, lesion classification, and evaluation of treatment response.

Conclusion: Deep learning-based OD demonstrates high diagnostic accuracy and potential to optimize oncologic imaging workflows. However, challenges such as validation, generalizability, and integration into clinical practice limit widespread adoption. Addressing these barriers is critical to realizing the full potential of OD in improving cancer management.

Keywords: Object Detection, Deep Learning, Cancer, Magnetic Resonance Imaging, Computed Tomography, Positron Emission Tomography - Computed Tomography

Article History:
Received: 20 March 2026
Accepted: 31 May 2026

Please cite this paper as:
Jajroudi M, Afrash MR, Yadegari F, Najafi Fadafen SA, Movassagh AA, Alnattah A, Geramifar P, Eslami S. Deep Learning-Based Object Detection in Oncology: A Systematic Scoping Review of CT, MRI, and PET/CT Applications. Health Man & Info Sci. 2026; 13(3): 166-183. doi: 10.30476/jhmi.2026.110527.1354.

***Correspondence to:**
Parham Geramifar, Saeid Eslami
Research Center for Nuclear Medicine, Tehran University of Medical Sciences, Tehran, Iran. 2Pharmaceutical Research Center, Mashhad University of Medical Sciences, Mashhad, Iran
Email:
pgeramifar@sina.tums.ac.ir
EslamiS@mums.ac.ir

Introduction

Cancer remains a significant global health challenge, accounting for millions of deaths each year and imposing a substantial burden on societies worldwide. The World Health Organization (WHO) estimates that by 2040, the annual incidence of cancer could reach 27.5 million cases, resulting in approximately 16.3 million

deaths. These statistics emphasize the urgent need for further research and the implementation of improved strategies for the management of cancer (1,2).

The integration of 3D imaging techniques, such as CT and MRI, significantly enhances the visualization of anatomical and physiological information. This capability complements non-invasive imaging by providing comprehensive insights into disease progression at both organ and whole-body levels. Clinical evaluations demonstrate 3D imaging's value in diagnostics and therapeutics, particularly in oncology for improved treatment precision and response monitoring via crucial tumor characteristics (3,4). Manual interpretation of medical images is challenging due to subjectivity, labor intensity, and inter-observer variability. Inconsistent interpretations arise from varied training, and fatigue from high workloads increases error risks. These limitations necessitate technological solutions like computer-aided diagnosis (CAD) to improve accuracy and efficiency (5,6).

Deep learning, an AI method, enhances medical image interpretation. It automatically detects and classifies cancerous lesions, reducing subjectivity and improving the speed and accuracy of clinical decisions (7). The standard approach for object localization in 3D medical imaging uses segmentation models to create voxel-by-voxel annotations. While enabling high model accuracy, this approach has drawbacks. Voxel-by-voxel annotation in 3D medical imaging is time-consuming, requires expert verification, and suffers from inter-annotator variability, leading to imprecise boundaries. Segmentation models encounter these imprecise labels and often need post-processing, making them costly and limiting their predictive power (8,9).

Object Detection (OD), a deep learning-based technique crucial in modern computer vision, addresses the complex challenge of identifying and analyzing objects within images. Facilitated by advancements in algorithms and computational power, OD determines precise object locations and boundaries within an image (object localization) by delineating them with bounding boxes and categorizes each object into its corresponding class (object classification) by assigning class labels (8, 10-13).

It enhances early diagnosis, postoperative monitoring, and metastatic disease tracking with high sensitivity and specificity by optimizing workflows and supporting timely interventions (4, 14-18).

This review surveys the development of deep learning-based OD in medical image-based cancer diagnosis, aiming to provide researchers with a comprehensive overview of the latest techniques. Focusing on CT, MRI, and PET/CT imaging, we explore recent advancements in OD models, highlighting their ability to automatically detect and classify lesions, tumors, and other abnormalities with high accuracy. This review addresses the following research questions: (1) which cancer types and clinical applications have benefited most from deep learning-based OD techniques? (2) How do one-stage and two-stage OD models perform across different imaging modalities in cancer diagnosis? (3) What are the key challenges preventing the widespread clinical adoption of deep learning-based OD in oncology?

Materials and Methods

We adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines to ensure clarity, consistency, and transparency. The methodology was designed to systematically identify, select, and synthesize relevant studies on deep learning-based object detection in cancer imaging, with a specific focus on CT, MRI, and PET/CT modalities.

Data Sources and Search Strategies

A structured literature search was conducted across PubMed and Scopus, covering publications from 2014 up to January 1, 2026. The search strategy utilized both Medical Subject Headings (MeSH) terms and relevant keywords in titles and abstracts, focusing on three main areas: cancer, object detection, and imaging techniques (CT, MRI, and PET). Supplementary Table S1 provides a detailed overview of the search strategy. All database references were imported into EndNote 20 software to identify and remove duplicates before final screening.

Inclusion and Exclusion Criteria

This study includes articles published in English that focus on deep learning object detection algorithms applied to a specific cancer type using CT, MRI, or PET imaging. Included studies also report quantitative performance metrics such as sensitivity, specificity, or accuracy, and are published in peer-reviewed journals. Excluded from the review are articles related to segmentation, machine learning methods not involving human subjects, and studies not published in peer-reviewed journals. Additional exclusion criteria included studies employing semi-automatic image processing

methods, those not conducted for cancer research, and those involving material detection (e.g., prostate seed detection), as well as all types of reviews, books, and conference papers.

Data extraction and synthesis

Two independent reviewers, M.J. and A.N., systematically evaluated each identified study, adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines to ensure a transparent and reproducible methodology. They independently screened titles and abstracts to exclude irrelevant articles, followed by a thorough full-text review of the remaining papers to confirm eligibility based on predefined inclusion and exclusion criteria. In cases of disagreement regarding study relevance or eligibility, the reviewers engaged in a structured discussion to resolve discrepancies. If consensus could not be reached, a third reviewer (S.E.) was consulted to arbitrate and make a final decision, ensuring consistency and reliability in the study selection process.

A standardized data extraction form was employed to systematically collect critical details, including the first author, publication year, sample size, dataset source (public or local), object detection algorithms, imaging modality, performance metrics, and significant findings. Any discrepancies were resolved through consensus or consultation with a third reviewer, ensuring consistency and reliability in the data extraction process.

Quality Assessment

To evaluate the methodological quality of the included studies, we employed the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool to assess the risk of bias and applicability across the 46 studies. Our QUADAS-2 assessment evaluated four key domains—patient selection, index test, reference standard, and flow and timing specifically in the context of the diagnostic accuracy of deep learning-based object detection models in cancer imaging. Two independent reviewers conducted this evaluation, resolving any disagreements through consensus, with a third professional reviewer providing arbitration for unresolved discrepancies. The inter-rater agreement was quantified using Cohen's kappa, which demonstrated substantial agreement.

Results

Study Selection and Characteristics

This scoping review, conducted per PRISMA-ScR guidelines, included 46 studies identified through a systematic search of PubMed and Scopus (2014-2025). The PRISMA flow diagram (Figure 1) details the study selection process. The included studies focus on deep learning-based object detection within cancer imaging, encompassing diverse cancer types and utilizing CT, MRI, and PET/CT modalities.

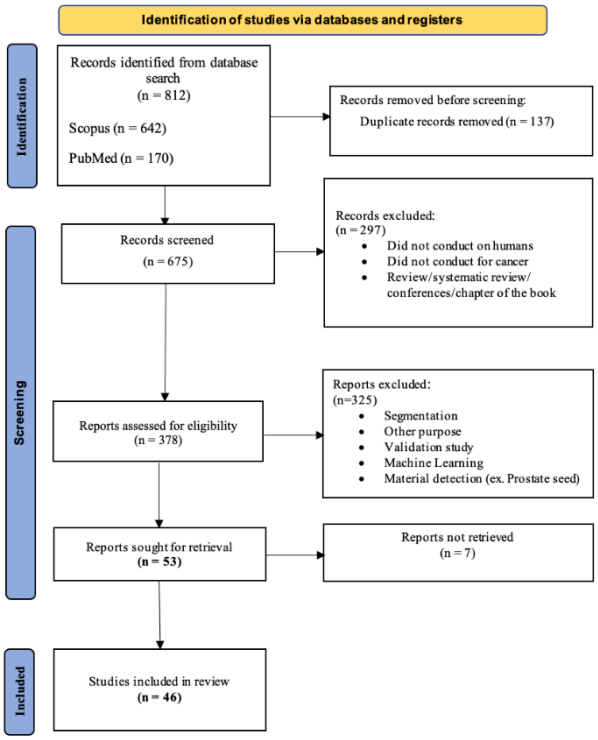

Figure 1: PRISMA-ScR Flow Diagram of Study Selection Process.

This diagram illustrates the systematic screening and selection process of studies included in the scoping review. Out of 812 records identified from PubMed and Scopus, 46 studies met the inclusion criteri

focusing on deep learning-based object detection applied to CT, MRI, and PET/CT cancer imaging. Reasons for exclusion at each stage are detailed.

Figure 2 diagrammatically overviews the included studies, showcasing the diverse landscape of cancer types (e.g., brain, lung, breast, prostate), imaging modalities (CT, MRI, PET/CT), and deep learning models investigated. This visual overview highlights the extensive research leveraging object detection in cancer imaging, underscoring its increasing importance for improving diagnostic accuracy, enabling earlier detection, and supporting clinical workflows through automated lesion localization and classification across various anatomical regions and imaging contexts. Table 1 summarizes the extracted fields.

Table 1: Summary of Included Studies: Cancer Type, Imaging Modality, Dataset, Model Architecture, and Clinical Aim

First Author /Year	Cancer Type	Sample Size (cases or scans)	Public or Local	Imaging Modality		Aim of Articles	Object Detection Algorithms	Object Detection Architecture
Ahsan,R 2025 (23)	Brain Tumor	44,155 images (patients/scan: 285/155	Public	BraTS[1] 2018	MRI	Diagnosis	Faster R-CNN YOLO[2]v5 SSD[3]	One-Stage and Two-Stage Detectors
Aishwarya,K 2025 (28)	Lung Cancer (Pulmonary Nodules)	a total of 1190 images representing CT scan slices of 110 cases	Public + Local	(IQ-OTH/ NCCD[4], SRM Hospital)	CT	Screening	YOLOv8, Mask R-CNN	One-Stage and Two-Stage Detectors
Chaudhary,A 2025 (41)	Brain Tumor	255 scans (3,000 brain MRI images)	Public	BR35H[5]	MRI	Diagnosis	CNN[6]	Two-Stage Detectors
Dai, J.2025 (37)	Pancreatic Cystic Neoplasm	448 cases	Local		CT	Diagnosis	Mamba YOLOv10	One-Stage Detectors
Gui, H.2025 (47)	Breast Cancer	687 cases (internal), 98 (external)	Local		MRI	Screening	YOLOv9	One-Stage Detectors
Jiang, C.2025 (31)	Lung Cancer (Pulmonary Nodules)	888 scans	Public	LUNA16[7] TIANCHI[8]	CT	Diagnosis	Kans Net[9]	Two-Stage Detectors
Muksimova, S .2025 (30)	Brain Tumor	233 patient/3064 images	Local		MRI	Diagnosis	YOLOv5m	One-Stage Detectors
Qasem, A.2025 (29)	Head and Neck Cancer	48 patients	Local		PET/ CT	Diagnosis	YOLOv4	One-Stage Detectors
Saidani,T..2025 (48)	Brain Tumor	1956 Total Images	Public		MRI	Diagnosis	YOLOv11	One-Stage Detectors
Tang, C.2025 (22)	Lung Cancer (Pulmonary Nodules)	1,018 scans	Public	LUNA16, LIDC-IDRI[10]	CT	Diagnosis	YOLOv6	One-Stage Detectors
Zamanidoost, Y.2025 (36)	Lung Cancer (Pulmonary Nodules)	888 CT scans	Public	LUNA16, PN9[11]	CT	Diagnosis	Faster R-CNN	Two-Stage Detectors
Zhang, M..2025 (24)	Lung Cancer (Pulmonary Nodules)	888 scans	Public	LUNA16	CT	Screening	SPC-UNet[12]	One-Stage Detectors
Abdusalomov A.2024 (11)	Brain Tumor	233 patients/3064 images	Local		MRI	Diagnosis	YOLOv5	One-Stage Detectors
Ahmadyar, Yasha,.2024 (49)	Lung Cancer	888 scans	Public	LUNA16	CT	Diagnosis	YOLOv5	One-Stage Detectors
Anari, P.2024 (25)	Renal Cell Carcinoma	1084 Patients/ 5657 scans	Local		MRI	Diagnosis	YOLOv7	One-Stage Detectors
Chai, Y.F..2024 (43)	Lung Cancer (Pulmonary Nodules)	1,018 scans	Public	LIDC-IDRI, LUNA16	CT	Diagnosis	YOLOv8	One-Stage Detectors
Hikmah, N.F,.2024 (34)	Brain Tumor (Meningioma)	233 patients/3064 images	Local		MRI	Diagnosis	SSD	One-Stage Detectors
Liu, Y.2024 (26)	Lung Cancer (Pulmonary Nodules)	888 scans	Public	LUNA	CT	Diagnosis	YOLOv7	One-Stage Detectors
Manokaran, Jenita.2024 (50)	Lung Cancer	60 patients	Public		CT	Diagnosis	YOLO	One-Stage Detectors
Pandey, S.K.,.2024 (51)	Brain Tumor	1251 scans	Public	BraTS 2021	MRI	Diagnosis	YOLOv5	One-Stage Detectors
Piao, Z,.2024 (52)	Adrenal Adenoma	235 patients	Local		CT	Classify	YOLOv5	One-Stage Detectors
Suryawanshi, 2024 (53)	Brain Tumor	255 scans (3,000 brain MRI images)	Public	BR35H	MRI	Diagnosis	YOLOv5 Faster R-CNN	One-Stage and Two-Stage Detectors
Randar, S..2024 (54)	Liver Tumor	131 cases	Public	LiTS[13]	CT	Diagnosis	YOLOv8	One-Stage Detectors
Song, Wen.2024 (45)	Lung Cancer	888 cases	Public	LUNA16	CT	Diagnosis	M3N[14]	One-Stage Detectors
Gao, Z..2024 (55)	Lung Cancer	888 cases	Public	LUNA16	CT	Diagnosis	FULFIL[15] +Graph Convolution Network	One-Stage Detectors
Ito, Sadayuki,.2023 (39)	Brain Tumor	195	Local		MRI	Diagnosis	YOLOv4	One-Stage Detectors
Terzi, Duygu Sinanc.2023 (56)	Brain Tumor	293 cases Test:100 cases	Public	Gazi Brains 2020 BraTS 2020	MRI	Diagnosis	Mask R-CNN, YOLOv8	One-Stage and Two-Stage Detectors
Terzi, Ramazan,.2023 (40)	Brain Tumor	19,176 slices	Public	Gazi Brains 2020 Brains 2020	MRI	Diagnosis	Retina Net YOLOv3 FCOS NAS-FPN ATSS VFNet	One-Stage and Two-Stage Detectors

First Author /Year	Cancer Type	Sample Size (cases or scans)	Public or Local	Imaging Modality		Aim of Articles	Object Detection Algorithms	Object Detection Architecture
							Faster R-CNN, Dynamic R-CNN Cascade R-CNN	
Xie, Fei,.2023 (57)	Small Intestinal Tumor	267 cases	Local		CT	Diagnosis	Faster R-CNN, Mask R-CNN, Retina Net RepPoints Cascade R-CNN	One-Stage and Two-Stage Detectors
Xu, Di .2023 (31)	Prostate Cancer	88 Patients	Local		PET/CT	Metastases Diagnosis	Mask R-CNN	Two-Stage Detectors
Zhang, S..2023 (33)	Hypopharyngeal Cancer	1800 T2 MRI slices	Local		MRI	Diagnosis	CCS-Net	Two-Stage Detectors
Mehralivand, Shabnam,.2022 (27)	Prostate Cancer	1390 patient	Local and Public	PROSTATEx	MRI	Diagnosis	Cascaded Deep Learning	Two-Stage Detectors
Oh, Jin Huh,et al.2022 [58]	Brain Tumor	113 scans	Local		MRI	Metastases Diagnosis	YOLOv2	One-Stage Detectors
Shelatkar, Tejas,et al.2022 [59]	Brain Tumor	482 scans	Public	BraTS 2021	MRI	Diagnosis	YOLOv5	One-Stage Detectors
Son, Jeong Woo,et al.2022 [38]	Lung Cancer	515 Patients 888 scans	Local and public	LUNA16	CT	Diagnosis	YOLO, Efficient Net	One-Stage Detectors
Swinburne, Nathaniel C.,et al.2022 [46]	Brain Tumor	58334 images	Local		MRI	Diagnosis	Retina Net, Mask R-CNN	One-Stage and Two-Stage Detectors
Wang, Han,et al.2022 [44]	Lung Cancer	593 scans	Local		CT	Diagnosis	Faster R-CNN, YOLO	One-Stage and Two-Stage Detectors
Xu, Jun,et al.2022 [60]	Lung Cancer	1186 scans	Public	LUNA16	CT	Diagnosis	Faster R-CNN	Two-Stage Detectors
Chegraoui, Hamza,et al.2021[61]	Brain Tumor	330 cases	Public	BraTS 2021	MRI	Diagnosis	YOLOv5	One-Stage Detectors
Gunasekara, Shanaka Ramesh,et al.2021[62]	Brain Tumor	233 patients/3064 images	local		MRI	Diagnosis	R-CNN	Two-Stage Detectors
Ito, Sadayuki,et al.2021 [63]	Spinal Schwannoma	50 patients	Local		MRI	Diagnosis	YOLOv3	One-Stage Detectors
Peng, Xian,et al.2021 [64]	Liver Tumor	1,000 CT scans	Public	Decathlon	CT	Diagnosis	Proposed model	One-Stage Detectors
Takao, Hiroshi,et al.2021 [65]	Brain Tumors	127 patients (696 brain metastases)	Local		CT	Metastases Diagnosis	SSD	One-Stage Detectors
Adachi, Mio,et al.2020 [66]	Breast Cancer	371 scans	Local		MRI	Diagnosis	Faster R-CNN	Two-Stage Detectors
Su, Ying,et al.2020 [67]	Lung Cancer	1,018 patients	Public	LIDC-IDRI	CT	Diagnosis	Faster R-CNN	Two-Stage Detectors
Zhao, Z.,et al.2019 [68]	Thyroid Nodules	500 scans	Local		CT	Classify	Modified U-Net + CNN-Fs	Two-Stage Detectors

This table provides a detailed overview of the 46 studies included in the scoping review. It summarizes key study characteristics, including cancer type, sample size, dataset origin (public or local), imaging modality used (CT, MRI, or PET/CT), the primary clinical aim (e.g., diagnosis, screening, classification), object detection algorithms applied, and whether the models followed a one-stage or two-stage architecture.

Figure 2 provides a visual summary of the 46 included studies categorized by imaging modality (CT, MRI, PET/CT), associated cancer types, and deep learning-based object detection models used. It highlights the diversity of applications across anatomical regions and model architectures.

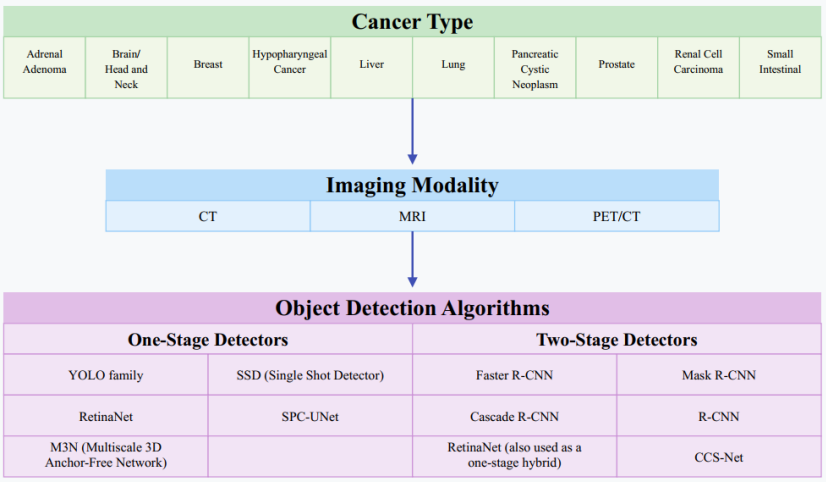

Figure 2: Overview of Included Studies by Imaging Modality, Cancer Type, and Object Detection Models

Public and Local Datasets in Cancer Imaging

Public datasets are widely utilized in deep learning-based object detection for cancer imaging due to their large, standardized, and accessible imaging collections, enabling robust model training across diverse cancer types. In contrast, local datasets, often derived from single-institution cohorts, provide tailored, high-quality annotations but are limited by smaller sample sizes and privacy constraints, potentially reducing model generalizability. As illustrated in Figure 3 and Table 1, the scoping review identified a variety of public datasets utilized in the 46 included studies on deep learning-based object detection in cancer imaging. The frequency of dataset usage reflects their prominence and accessibility within the research community. In addition to public sources, local datasets were employed in 23 studies, often providing institution-specific data tailored to particular clinical environments.

Among public datasets, the Lung Nodule Analysis 2016 (LUNA16) was the most frequently used, appearing in 11 studies. This was followed by the Brain Tumor Segmentation (BraTS) dataset, cited in 5 studies, and the Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI), used in 3 studies. The Gazi Brains 2020 dataset and Brain Tumor (BR35H) appeared in 2 studies.

Other publicly available datasets each used in a single study include The Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD), Tumor-Infiltrating Clonal Hematopoiesis (TIANCHI), Pulmonary Nodule (PN9), The Liver Tumor Segmentation Benchmark (LiTS), Decathlon, and PROSTATEx. The inclusion of such a diverse range of datasets highlights the richness of available resources for model development and evaluation. Public datasets often support large-scale training and benchmarking, while local datasets provide valuable, context-specific imaging data that contribute to model generalizability across different cancer types and imaging modalities.

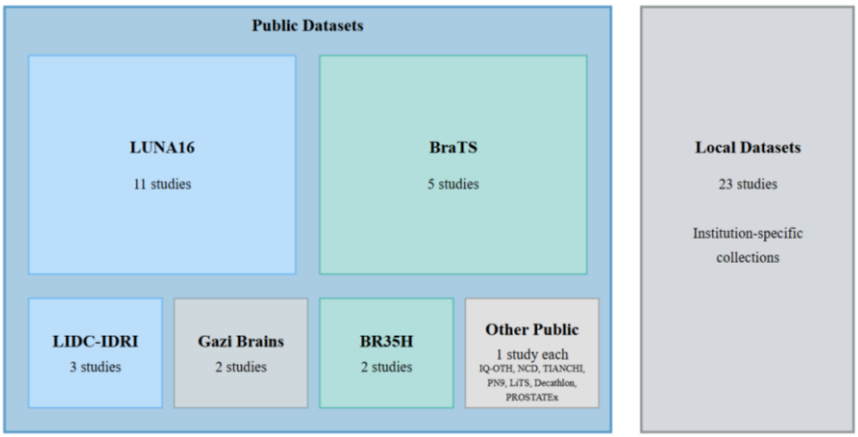

Figure 3: Frequency of Public and Local Dataset Usage in Cancer Imaging Object Detection Studies

Deep Learning Models and Object Detection Approaches

OD is a transformative approach in cancer imaging, utilizing convolutional neural networks (CNNs) to automatically detect and classify lesions, tumors, and abnormalities in modalities such as CT, MRI, and PET/CT. OD involves two primary tasks: (1) object localization, where regions of interest are identified with bounding boxes, and (2) object classification, which assigns labels to those regions. By learning hierarchical feature representations from large datasets, these models excel at recognizing subtle patterns, reducing human variability, and enhancing diagnostic accuracy and operational efficiency. In oncology, OD is instrumental for early detection, lesion characterization, and monitoring treatment response—offering performance comparable to expert radiologists while improving clinical productivity (4, 10).

OD techniques are commonly categorized into one-stage and two-stage detectors, each offering distinct computational characteristics and trade-offs. One-stage detectors, such as YOLO and SSD, carry out object classification and localization in a single pass through the network. This architecture emphasizes speed and computational efficiency, making it suitable for real-time or high-throughput clinical applications. However, performance may decline in complex imaging scenarios involving small, overlapping, or low-contrast lesions. In contrast, two-stage detectors, including Faster R-CNN and Mask R-CNN, follow a sequential pipeline: they first generate region proposals using a Region Proposal Network (RPN), then refine these candidates through additional classification and bounding box regression. While more computationally intensive, two-stage models typically offer higher accuracy, especially when detecting small or irregular lesions (19-21).

According to this scoping review, among the 46 included studies, 27 used one-stage detectors, 11 applied two-stage detectors, and 5 implemented both approaches. This distribution reflects a growing preference for one-stage detectors in cancer imaging tasks, largely due to their efficiency and ease of deployment, while two-stage architectures remain important for precision-demanding diagnostic applications.

The review identified a total of 46 studies, with a diverse set of algorithms applied across these studies. The most prevalent algorithm was YOLO and its variants, used in 25 studies. Faster R-CNN appeared in 7 studies, Mask R-CNN in 5 studies, and SSD in 3 studies. Other algorithms included CNN (1 study), KansNet (1 study), SPC-UNet (1 study), Mamba YOLOv10 (1 study), CCS-Net (1 study), M3N (1 study), Cascade R-CNN (1 study), R-CNN (1 study), and novel or ensemble models (Proposed Model) in 5 studies. This distribution highlights the dominance of YOLO-based algorithms, attributed to their balance of speed and accuracy, while two-stage detectors like Faster R-CNN and Mask R-CNN remain significant for tasks requiring high precision.

Object Detection Algorithms and Imaging Modality

CT, MRI, and PET/CT are cornerstone imaging modalities in oncology, each offering unique diagnostic advantages. CT provides rapid, high-resolution anatomical detail, making it essential for tumor localization and staging; MRI excels in soft tissue contrast, aiding in brain, prostate, and musculoskeletal cancer assessment; while PET/CT combines metabolic and structural information, enabling precise evaluation of tumor activity and treatment response.

Deep learning-based object detection effectively addresses the inherent complexity of CT, MRI, and PET/CT imaging by automatically localizing and classifying lesions across modalities with varying spatial resolutions, contrast levels, and anatomical variability. By extracting modality-specific features and learning from large annotated datasets, these algorithms enhance interpretative consistency, reduce observer variability, and support accurate and efficient cancer detection in even the most challenging diagnostic scenarios.

The distribution of OD algorithms varied across imaging modalities, reflecting different technical requirements and diagnostic goals specific to each modality. Among the 46 studies reviewed, CT was the most commonly used imaging modality (25 studies), followed by MRI (11 studies) and PET/CT (10 studies). The choice of OD algorithm often correlated with the imaging characteristics of each modality.

CT-based studies (22 of 46) most frequently adopted YOLO and its variants, which were used in 9 of the 22 CT-focused papers. YOLO's speed and ability to process high-resolution volumetric images make it well-suited for applications like lung nodule detection and liver lesion localization, where efficiency and anatomical accuracy are critical.

MRI-focused studies (22 of 46) showed a strong inclination toward both YOLO-based models (12 studies) and two-stage detectors such as Mask R-CNN and Faster R-CNN (3 studies). YOLO's efficiency benefits routine diagnostic pipelines, while two-stage models are better suited for detecting small and well-contrasted lesions such as brain tumors, owing to their refined region proposal mechanisms that align with MRI's high-resolution, soft-tissue imaging.

PET/CT studies (2 of 46) demonstrated balanced use of YOLO (1 study) and Mask R-CNN (1 study). Given PET/CT's need to merge anatomical and metabolic data, these selections reflect a trade-off between real-time localization and detailed interpretation of lesion uptake characteristics in cancers such as head and neck and prostate. This modality-specific use of OD algorithms is summarized in Table 2, which includes frequency per modality and cancer type.

Table 2: Distribution of Object Detection Algorithms Across Imaging Modalities and Cancer Types

Imaging Modality	Total Studies	Cancer Types (Studies)	YOLO1 (all versions)	Faster R-CNN[2]	Mask R-CNN	SSD[3]	Other Algorithms
CT	22	Lung (15), Liver (2), Pancreas (1), Thyroid (1), Adrenal (1), Small Intestine (1), Brain (1)	9	5	1	1	Kans Net[4] (1), Mamba YOLOv10 (1), M3N[5] (1), Retina Net (1), Proposed Model (1), SPC- U-Net[6] (1)
MRI	22	Brain (15), Prostate (1), Breast (2), Renal (1), Hypo pharyngeal (1), Spinal Schwannoma (1), Meningioma (1)	12	2	1	1	CNN (1), CCS-Net[7] (1), R-CNN (1), Retina Net (2), Cascaded Deep Learning (1)
PET/CT	2	Head/.Neck (1), Prostate (1)	1		1		
	46		23	7	4	2	**12**

[1]YOLO: You Only Live Once; [2]CNN: Convolutional Neural Network; [3]SSD: Single Shot Detector; [4]KansNet: Kolmogorov–Arnold Networks;[5]M3N: Multiscale 3D Anchor-Free Deep Learning Network; [6]SPC-UNet: Spatial Pyramid Convolution with U-Net; [7]CCS-Net: CCS-Net: Cascaded Contextual Segmentation.

This table categorizes the use of object detection models based on imaging modality (CT, MRI, and PET,et al.CT) and cancer type. It reports the frequency of each algorithm—such as YOLO, Faster R-CNN, Mask R-CNN, SSD, and other specialized models—highlighting trends in model selection across different clinical and anatomical contexts.

Object Detection Algorithms and Best Performance

The review identified a broad spectrum of deep learning-based object detection (OD) algorithms, each exhibiting varied performance levels depending on model architecture, imaging modality, and clinical application. Performance evaluation metrics such as mean Average Precision (mAP), accuracy, sensitivity, Area under the Curve (AUC), and Dice Similarity Coefficient (DSC) were reported across studies to benchmark model efficacy. Table 3 summarizes the highest-performing studies per algorithm, offering comparative insight into which models yield optimal results under different imaging and cancer type conditions.

Table 3: The best Performance Metrics of Object Detection Algorithms in Cancer Imaging Studies

#	Algorithm	mAP/AP[7]	Accuracy	Sensitivity	AUC[8]	Other Metrics
(23)	YOLO[1]v5	89.5%	-	-	-	-
(28)	Mask R-CNN[2]	91.5%	-	90.1%	-	-
(41)	CNN	-	98.86%	98.80%		
(37)	Mamba YOLOv10	96%	93%	98%		
(47)	YOLOv9	71.3%				F1 Score: 0.700
(31)	KansNet[3]	89.2%				
(30)	YOLOv5m	92.4%	93.1%		0.96	
(29)	YOLOv4			89%		F-Score: 0.84
(48)	YOLOv11	68%				
(22)	YOLOv6	97.9%	97.5%	96.9%		
(36)	Faster R-CNN			94.89%		CPM[9]: 0.892
(24)	SPC-UNet[4]		96.18%			CPM: 0.924
(11)	YOLOv5	87%		83%		
(49)	YOLOv5		98.4%		0.989	
(25)	YOLOv7	95%		98%		
(43)	YOLOv8	77.5%				
[35]	SSD[5]			98%		DSC[10]:93%
(26)	YOLOv7	95.39%		95.4%		
(50)	YOLO			93%		
(51)	YOLOv5	97.2%				
(52)	YOLOv5	98.8%				
(53)	YOLOv5	98.32%				
(54)	YOLOv8					DSC: 80.55%
(45)	M3N					CPM: 90.6%
(55)	Graph Convolution Network		57.4%			
(39)	YOLOv4		84.1%			
(56)	Mask R-CNN	70%				
(40)	Ensemble of Detectors	83.8%				
(57)	Cascade R-CNN	61.4%		68.7%		
(32)	Mask R-CNN			83.35%	90.03%	
(33)	CCS-Net[6]	78.9%				
(57)	Cascaded deep learning			97.8%		
(58)	YOLOv2			87.95%		F1: 19.35%
(59)	YOLOv5	91.2%				
(38)	YOLO	91.67%				
(46)	Mask R-CNN				0.937	F1: 0.954
(44)	YOLO,	50%				
(60)	Faster R-CNN					Precision: 90.7%
(61)	YOLOv5				0.89	
(62)	R-CNN		94.57%			
(63)	YOLOv3		93.5%			
(64)	Proposed model	47.6%				
(65)	SSD			88.7%		
(66)	Faster R-CNN				0.925	
(67)	Faster R-CNN	83.6				
(68)	CNN-Fs	72%		88%		

[1]YOLO: You Only Live Once; [2]CNN: Convolutional Neural Network; [3]Kans: Net: Kolmogorov–Arnold Networks; [4]SPC-UNet: Spatial Pyramid Convolution with U-Net; [5]SSD: Single Shot Detector; [6]CCS-Net: Cascaded Contextual Segmentation-Net; [7]mAP: mean Average Precision (mAP), [8]AUC: Area Under the Curve, [9]CPM:Confidence Probability Metric; [10]DSC: Dice Similarity Coefficient.

This table summarizes the diagnostic performance of various deep learning-based object detection models across the reviewed studies. Reported metrics include mean Average Precision (mAP), accuracy, sensitivity, area under the curve (AUC), and additional indicators such

as Dice Similarity Coefficient (DSC), F1-score, and Confidence Probability Metric (CPM), providing a comparative assessment of algorithm effectiveness in different clinical applications.

Results of Quality assessment of included studies

The QUADAS-2 tool was applied to assess the risk of bias and applicability of the 46 included studies. In the patient selection domain, 25 studies (54.3%) were rated as low risk and 21 studies (45.7%) as high risk. For the index test, 30 studies (65.2%) had low risk, 11 (23.9%) were unclear, and 5 (10.9%) were rated high. The reference standard showed 20 studies (43.5%) with low risk, 4 (8.7%) unclear, and 22 (47.8%) with high risk. In the flow and timing domain, 38 studies (82.6%) were rated low risk, and 8 (17.4%) were unclear. Overall, 24 studies (52.2%) were judged to have low risk of bias, 21 (45.7%) high risk, and 1 study (2.2%) unclear. Regarding applicability, all 46 studies (100%) were rated as having low concern across all three domains: patient selection, index test, and reference standard. The overall applicability concern was rated low in all studies.

Figure 4 and Supplementary Table S2 provides a detailed breakdown of these assessments, underscoring the reliability and clinical significance of the reviewed studies. The Cohen's kappa for interrater agreement was 0.87.

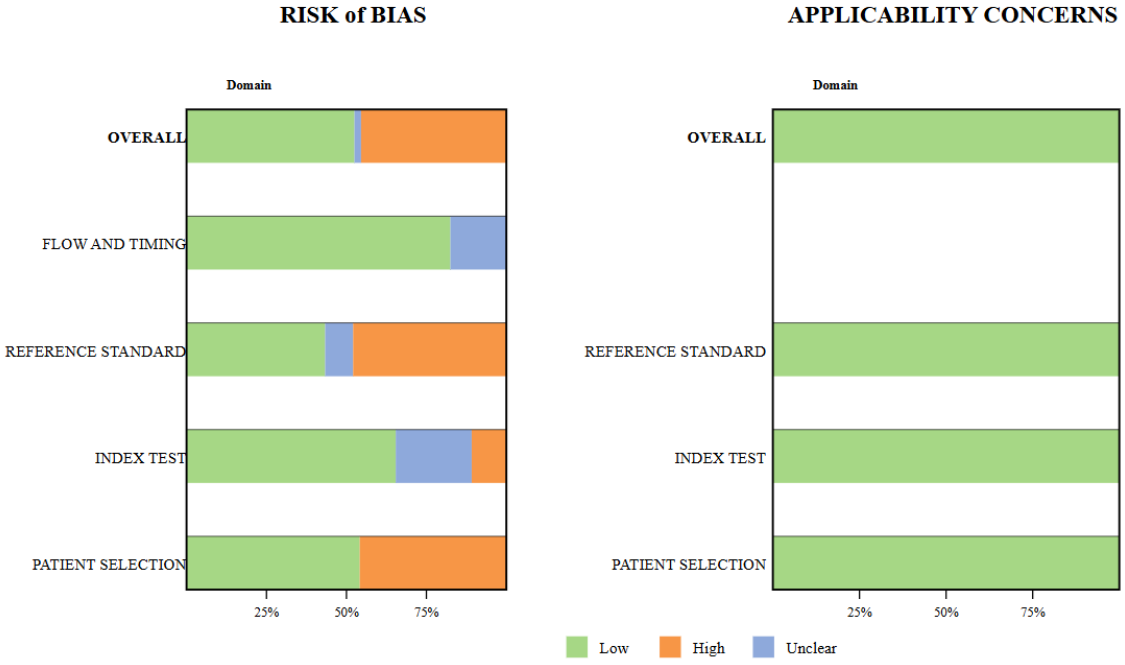

Figure 4: Summary of QUADAS-2 assessment for risk of bias and applicability concerns across 46 included studies on deep learning-based object detection in cancer imaging. (The left panel illustrates the distribution of studies rated as low (green), high (orange), or unclear (blue) risk of bias across four domains and overall. The right panel shows that all studies demonstrated low concern regarding applicability across all domains, indicating good alignment with the review's research questions and clinical context.)

Discussion

OD has emerged as a key innovation in cancer imaging, providing automated, scalable, and highly accurate solutions across multiple stages of oncologic care—from early detection and lesion classification to treatment monitoring and disease surveillance. This study emphasizes the growing clinical relevance of OD by mapping its key applications, comparing the performance and suitability of one-stage versus two-stage detection algorithms, and critically examining current challenges and limitations that may impact its broader clinical adoption.

Clinical Applications of Object Detection in Cancer Imaging

OD significantly enhances key stages of cancer care, including early detection, lesion

classification, treatment monitoring, and post-therapeutic surveillance. Its consistent performance and adaptability across various imaging modalities facilitate its growing integration into clinical workflows, supporting precision medicine and evidence-based practice (5-7).

Early Detection and Screening

Early detection is a significant contribution of OD in clinical oncology. OD algorithms automatically analyze complex imaging data to identify obscure, small, or irregular lesions, potentially overcoming limitations of manual review. This ability is especially beneficial in high-throughput screening environments such as lung cancer detection with CT or brain tumor identification with MRI.

Multiple studies demonstrated the strong performance of YOLO-based models in early diagnosis. For example, YOLOv6 achieved 97.9% mAP and 97.5% accuracy for lung nodule detection, highlighting its potential to support timely clinical interventions (22). Likewise, YOLOv5 achieved 89.5% mAP in brain tumor detection, showing robust performance across MRI datasets (23). These findings support the feasibility of integrating OD into routine screening programs to enhance diagnostic yield and expedite diagnosis.

Lesion Classification and Tumor Staging

OD algorithms do not merely locate lesions—they also play a crucial role in classifying lesions into malignant or benign categories, assisting in accurate tumor staging and personalized treatment planning. This classification capability supports clinicians in making critical decisions about treatment intensity and modality selection.

OD models such as YOLOv7, YOLOv8, and SPC-UNet achieved classification accuracies exceeding 95% across diverse cancer types, including renal, lung, and prostate cancers (24-27). These results highlight OD's potential to improve diagnostic pathways, reduce interpretation variability, and aid in immediate clinical decision-making.

Treatment Monitoring and Response Evaluation

Object detection models enable objective assessment of treatment response by analyzing sequential imaging data to track tumor changes and metabolic activity. In follow-up imaging, models like Mask R-CNN demonstrated high sensitivity, achieving 90.1% in pulmonary nodule detection (28). OD has also been applied in PET/CT for head and neck cancer to monitor therapy effectiveness (29), supporting timely clinical decisions and reducing the risk of missed disease progression.

Reducing Observer Variability and Streamlining Workflows

Manual image interpretation is time-intensive and variable among radiologists. OD automates repetitive tasks, improving diagnostic consistency and reducing workload. One-stage detectors like YOLOv5m and YOLOv7 offer real-time performance and high accuracy, making them suitable for fast-paced clinical settings such as emergency departments and screening clinics (25, 30). Their efficiency also supports deployment in resource-limited environments with limited radiologist availability.

Detecting Complex, Heterogeneous, or Postoperative Lesions

OD is particularly useful in challenging diagnostic scenarios like detecting metastases, postoperative recurrence, and lesions in anatomically complex regions. These often involve small, low-contrast, or irregular abnormalities difficult to identify manually. Two-stage models like Faster R-CNN and Mask R-CNN, along with newer models such as KansNet and CCS-Net, have shown high sensitivity and precision in such contexts, including pelvic lymph node metastases and multifocal brain tumors (29, 31-33). Their consistency over time supports longitudinal tracking and improves prognostic evaluation in cancer care.

Comparison of One-Stage and Two-Stage Detectors in Clinical Applications

In cancer imaging, the selection between one-stage and two-stage OD detectors depends on clinical requirements, necessitating a balance among speed, accuracy, and computational resources.

One-stage detectors, including YOLO and SSD, execute object localization and classification within a single network pass, emphasizing speed and efficiency (19, 20, 34). Despite their strengths in high-throughput environments such as routine CT screening and

real-time MRI analysis, with YOLOv5 achieving 89.5% mAP in brain tumor detection (22) and YOLOv6 reaching 97.9% mAP for lung nodules (21), one-stage detectors' efficiency suits emergency settings and large-scale screening programs. However, they may still encounter difficulties with small, low-contrast, or overlapping lesions (30,35).

Two-stage detectors, like Faster R-CNN and Mask R-CNN, employ a sequential process of region proposal and refinement, providing superior accuracy and precision. This is particularly valuable for detecting small, complex, or low-contrast lesions where diagnostic specificity is critical (19, 20, 34). This architecture provides higher accuracy, especially for detecting small or irregular lesions, making it well-suited for precision-demanding applications such as brain tumor detection or metastatic lesion localization. To illustrate, Mask R-CNN achieved 91.5% mAP and 90.1% sensitivity in pulmonary nodule detection, and Faster R-CNN reached 94.89% accuracy in lung nodule detection with a CPM of 0.892 (28, 36). These models are particularly effective in MRI and PET/CT studies, where high-resolution imaging and soft-tissue contrast necessitate refined region proposals to delineate subtle abnormalities [32, 33]. However, their computational intensity slows down processing times, which may limit their use in real-time or resource-constrained settings (19, 34).

This review of 46 studies found that 27 utilized one-stage detectors, highlighting their dominance due to speed and ease of integration. In contrast, 11 studies employed two-stage detectors for tasks requiring high precision. Furthermore, five studies combined both approaches to balance the speed of one-stage models with the accuracy of two-stage models, aiming for optimal performance in complex scenarios.

In clinical practice, one-stage detectors are preferred for applications prioritizing speed, such as CT-based lung cancer screening, where YOLO variants efficiently process high-resolution images. In contrast, two-stage detectors are advantageous in scenarios that demand high sensitivity, including detecting small brain tumors on MRI or metastatic pelvic lymph nodes on PET/CT. Moreover, the emergence of models like Mamba YOLOv10 (96% mAP, 98% sensitivity) (37) and SPC-UNet (96.18% accuracy) (24) underscores the potential of hybrid or specialized architectures to bridge the performance gap between one-stage and two-stage models, paving the way for promising future clinical implementations.

Challenges and Limitations of Using Object Detection in Clinical Applications

Deep learning-based OD has demonstrated substantial potential in cancer imaging; however, various challenges hinder its widespread application in clinical practice. These involve aspects such as data quality, model generalizability, annotation requirements, detection limitations, workflow integration, interpretability, and regulatory compliance. This section summarizes the key barriers identified in the reviewed literature.

Data Availability and Generalizability

A core limitation of current OD models is their dependence on datasets that lack broad representation. Public datasets such as LUNA16 and BraTS are extensively used; they may not adequately reflect the range of imaging conditions, scanner types, and patient populations present in real-world scenarios (22, 23, 38). In contrast, while local datasets offer greater specificity, their limited size and institution-dependent nature often restrict their external validity (11,39). As a consequence, many OD models that exhibit high accuracy during development may fail to generalize effectively when applied to external clinical settings (7,10).

Annotation Burden and Labeling Inconsistency

The training of supervised OD models demands extensive, high-quality annotations, typically generated by expert radiologists. This requirement presents significant challenges due to the labor-intensive nature of the annotation process and its susceptibility to inter-observer variability, particularly in cases with unclear tumor boundaries or overlapping anatomy (5, 6, 8). Several studies have highlighted the high cost and time associated with annotation, as well as its influence on model performance due to inconsistent labeling (40. 41). Even with expert consensus, variations in

delineating tumor margins can impact the precision and reproducibility of model outputs.

Detection of Subtle, Small, or Low-Contrast Lesions

Many OD models, especially one-stage detectors, show reduced sensitivity for small or low-contrast lesions like early pulmonary nodules, micro-metastases, or infiltrative brain tumors (11, 28, 42, 43). This limitation is clinically important because small lesions can indicate early disease or recurrence. While two-stage detectors such as Faster R-CNN and Mask R-CNN offer higher precision in these cases, their computational demands and slower inference speeds may restrict their use in real-time applications (28, 36, 43).

Lack of Prospective Clinical Validation

Despite the high accuracy demonstrated by numerous studies using retrospective datasets, prospective validation in real-world clinical settings remains limited. The majority of models were evaluated on public datasets, lacking real-time clinical integration (22.23,45).

Workflow Integration

Effective clinical use of OD models necessitates integration with existing clinical systems and hospital infrastructures. However, the reviewed literature rarely addressed system-level integration, clinician interface design, or user experience considerations (3,4,6).

Interpretability and Clinical Trust

Limited interpretability remains a key concern for OD models. As "black boxes," most deep learning architectures offer predictions without clear explanations or visual justification (7, 10). This lack of transparency can undermine clinician trust, especially in high-stakes decisions. Despite some exploration of visual explanation tools (e.g., attention mechanisms, saliency maps), standardization and clinical validation are lacking (8, 30, 46). The absence of uncertainty quantification and prediction rationale forms a major obstacle to clinical adoption.

Regulatory, Ethical, and Legal Considerations

Deploying OD systems in healthcare settings involves navigating regulatory frameworks and addressing ethical concerns. Current regulatory models are not fully adapted to AI systems that may evolve post-deployment through continuous learning (6,7). Additionally, ethical challenges—such as bias in training data, accountability for false negatives, and equitable access—must be addressed to ensure fairness and transparency (3,4).

Limitations

This scoping review, while comprehensive, is subject to certain limitations. Its inclusion criteria—restricted to English-language, peer-reviewed articles on specific cancer types via CT, MRI, or PET/CT—may have excluded relevant non-English studies, conference papers, or research using emerging modalities. Limiting the search to only PubMed and Scopus databases may have led to missing studies indexed elsewhere, such as IEEE Xplore, thereby excluding additional technical insights. Moreover, the heterogeneity of performance metrics (e.g., mAP, sensitivity, accuracy) across studies makes direct comparisons difficult. Finally, the review's scope did not encompass clinical implementation or cost-effectiveness, focusing only on technical and diagnostic outcomes. These constraints underscore the need for broader reviews to fully capture the evolving landscape of OD in cancer imaging.

In addition, a substantial proportion of studies demonstrated high risk of bias in patient selection and reference standard domains, which may impact the robustness of the synthesized findings. While all studies showed low concern regarding applicability, inconsistencies in methodological reporting and validation procedures warrant cautious interpretation. Addressing these limitations through standardized design and reporting frameworks will be essential for enhancing future evidence synthesis.

Conclusion

This scoping review highlights the substantial potential of deep learning-based object detection in cancer imaging, particularly for tasks including early detection, lesion classification, treatment monitoring, and longitudinal assessment. One-stage detectors, such as YOLO variants, demonstrate strong performance in time-sensitive applications, while two-stage detectors like Faster R-CNN remain valuable for tasks demanding high precision. These findings collectively reinforce that deep learning object detection models are

becoming crucial tools for enhancing clinical decision-making in oncology.

Despite progress, challenges generalizability, annotation burden, interpretability, and workflow integration limit clinical adoption. A lack of standardized evaluation and external validation limits translational potential across diverse settings. Future research should prioritize prospective validation, standardized evaluation, and the creation of explainable, interoperable, and efficient models for real-time clinical integration. Addressing these gaps will allow object detection systems to improve precision oncology and patient outcomes globally.

Acknowledgements

Not Applicable

Authors' Contribution

P. Geramifar and S. Eslami supervised the study. M. Jajroudi and M.R. Afrash conceptualized the study and defined the review framework. M. Jajroudi, M.R. Afrash, and S.A. Najafi Fadafen conducted the literature search, screening, and data extraction. M. Jajroudi and S.A. Najafi Fadafen performed the quality assessment and methodological verification. M. Jajroudi and S.A. Najafi Fadafen synthesized the results. M. Enferadi, A. Movassagh, and A. Alnattah prepared the figures, tables and contributed to writing and revising the manuscript. M. Jajroudi interpreted the findings. All authors reviewed and approved the final manuscript.

Data Availability Statement

The Data supporting this article is available from the corresponding authors upon reasonable request.

Funding Statement

Not Applicable

Conflict of Interest Disclosure

The authors declare no competing interests or conflicts of interest.

Ethics Approval Statement

The Research Ethics Committee of Mashhad University of Medical Sciences, Mashhad, Iran, approved this study (Ethics Code: IR.MUMS.REC.1401.347). As the study design did not involve direct participant intervention, consent to participate was not applicable

Patient Consent Statement

Not Applicable

Permission to Reproduce Material from Other Sources

Not Applicable

Clinical Trial Registration

Not Applicable

Table S4: Search strategy in two databases (PubMed and Scopus) and its results

Database	#N	Keyword	Strings	Field	
PubMed	#1	Object Detection and synonyms	"Object Detection" OR "Detection algorithm*"	Title/Abstract	
	#2	3D Medical Imaging	"computed tomography" OR "CT" OR "magnetic resonance imaging " OR "MRI" OR "positron emission tomography" OR "PET" OR "nuclear medicine"	Title/Abstract	
	#3	Cancer and synonyms	carcinoma* OR neoplasms* OR "Carcinoma" OR "Cancer" OR "Neoplasms" OR cancer* OR tumor* OR oncolog*	MeSH Terms/Title/Abstract	
	#1 AND #2 AND #3 AND ((y_10[Filter]) AND (english[Filter])				**170 results**
Scopus	#1	Object Detection and synonyms	"Object Detection" OR "Detection algorithm*"	Title/Abstract/Keyword	
	#2	3D Medical Imaging	"computed tomography" OR "CT" OR "magnetic resonance imaging " OR "MRI" OR "positron emission tomography" OR "PET" OR "nuclear medicine"	e/Abstract/Keyword	
	#3	Cancer and synonyms	carcinoma* OR neoplasms* OR "Carcinoma" OR "Cancer" OR "Neoplasms" OR cancer* OR tumor* OR oncolog*	Title/Abstract/Keyword	
	#1 AND #2 AND #3 AND (PUBYEAR > 2013)) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (DOCTYPE , "ar"))				**642 results**
Total Articles					**46**

Table S5: The Check list of QUADAS-2 assessment for risk of bias and applicability for each included study

First Author (Year)	Patient Selection	Index Test	Reference Standard	Flow & Timing	Overall Risk	Patient Selection Applicability	Index Test Applicability	Reference Standard Applicability	Over All Applicability
Ahsan,R, 2025 (22)	Low	Low	Unclear	Low	Low	Low	Low	Low	Low
Aishwarya,K.V 2025 (27)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Chaudhary,A.2025 (40)	Low	Low	Unclear	Low	Low	Low	Low	Low	Low
Dai, J.2025 (36)	High	Low	Unclear	Unclear	High	Low	Low	Low	Low
Gui, H.2025 (46)	High	Low	Unclear	Low	High	Low	Low	Low	Low
Jiang, C.2025 (30)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Muksimova, S.2025 (29)	High	Unclear	High	Low	High	Low	Low	Low	Low
Qasem, A,.2025 (28)	High	Low	Low	Low	High	Low	Low	Low	Low
Saidani, T.2025 (47)	High	High	Unclear	Unclear	High	Low	Low	Low	Low
Tang, C, 2025 (21)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Zamanidoost, Y, 2025 (35)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Zhang, M, 2025 (23)	Low	Low	Unclear	Low	Low	Low	Low	Low	Low
Abdusalomov A, 2024 (11)	High	Unclear	Unclear	Low	High	Low	Low	Low	Low
Ahmadyar, Yashar. 2024 (48)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Anari, Pouria Yazdian, 2024 (24)	High	Unclear	Unclear	Low	High	Low	Low	Low	Low
Chai, Y.F.2024 (42)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Hikmah, N.F. 2024 (34)	High	Unclear	Unclear	Unclear	High	Low	Low	Low	Low
Liu, Y. 2024 (24)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Manokaran, Jenita, 2024 (49)	High	Unclear	Unclear	Unclear	High	Low	Low	Low	Low
Pandey, S.K. 2024 (50)	Low	Low	Unclear	Low	Low	Low	Low	Low	Low
Piao, Z.2024 (51)	High	High	Unclear	Low	High	Low	Low	Low	Low
Suryawanshi, 2024 (52)	Low	Low	Unclear	Low	Low	Low	Low	Low	Low
Randar, S, 2024 (53)	Low	Unclear	Low	Low	Unclear	Low	Low	Low	Low
Song, Wen, 2024 (44)	Low	Low	Unclear	Low	Low	Low	Low	Low	Low
Gao, Z,2024 (54)	Low	Low	Unclear	Low	Low	Low	Low	Low	Low
Ito, Sadayuki, 2023 (38)	High	High	Unclear	Unclear	High	Low	Low	Low	Low
Terzi, Duygu Sinanc, 2023 (55)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Terzi, Ramazan, 2023 (39)	Low	Unclear	Low	Low	Low	Low	Low	Low	Low
Xie, Fei. 2023 (56)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Xu, Di, 2023 (31)	High	Low	Low	Low	High	Low	Low	Low	Low
Zhang, S, 2023 (32)	High	Low	Low	Low	High	Low	Low	Low	Low
Mehralivand, Shabnam, 2022 (26)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Oh, Jin Huh, 2022 (57)	High	Unclear	Unclear	Low	High	Low	Low	Low	Low

First Author (Year)	Patient Selection	Index Test	Reference Standard	Flow & Timing	Overall Risk	Patient Selection Applicability	Index Test Applicability	Reference Standard Applicability	Over All Applicability
Shelatkar, Tejas, 2022 (58)	Low	Low	Unclear	Low	Low	Low	Low	Low	Low
Son, Jeong Woo, 2022 (37)	High	Low	Low	Low	High	Low	Low	Low	Low
Swinburne, Nathaniel C, 2022 (45)	High	Low	High	Low	High	Low	Low	Low	Low
Wang, Han, 2022 (43)	High	High	Unclear	Unclear	High	Low	Low	Low	Low
Xu, Jun, 2022 (59)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Chegraoui, Hamza, 2021(60)	Low	Low	Unclear	Low	Low	Low	Low	Low	Low
Gunasekara, Shanaka Ramesh. 2021(61)	High	Unclear	High	Low	High	Low	Low	Low	Low
Ito, Sadayuki, 2021 (62)	High	Unclear	High	Unclear	High	Low	Low	Low	Low
Peng, Xian, 2021 (63)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Takao, Hiroshi, 2021 (64)	High	Low	Unclear	Unclear	High	Low	Low	Low	Low
Adachi, Mio, 2020 (65)	Low	Unclear	Low	Low	Low	Low	Low	Low	Low
Su, Ying, 2020 (66)	Low	Low	Low	Low	Low	Low	Low	Low	Low
Zhao, Z, 2019 (67)	High	High	Unclear	Low	High	Low	Low	Low	Low

References

1. Bray F, Laversanne M, Sung H, Ferlay J, Siegel RL, Soerjomataram I, et al. Global cancer statistics 2022: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA Cancer J Clin. 2024;74(3):229-63. 10.3322/caac.21834.

2. Ibrahim A, Mohamed HK, Maher A, Zhang B. A Survey on Human Cancer Categorization Based on Deep Learning. Front Artif Intell. 2022;5:884749. 10.3389/frai.2022.884749.

3. Chen MM, Terzic A, Becker AS, Johnson JM, Wu CC, Wintermark M, et al. Artificial intelligence in oncologic imaging. Eur J Radiol Open. 2022;9:100441. 10.1016/j.ejro.2022.100441.

4. Paudyal R, Shah AD, Akin O, Do RKG, Konar AS, Hatzoglou V, et al. Artificial Intelligence in CT and MR Imaging for Oncological Applications. Cancers (Basel). 2023;15(9). 10.3390/cancers15092573.

5. Ahmad I, Alqurashi F. Early cancer detection using deep learning and medical imaging: A survey. Crit Rev Oncol Hematol.2024;204:104528.10.1016/j.critrevonc.2024.104528.

6. Shamshad F, Khan S, Zamir SW, Khan MH, Hayat M, Khan FS, et al. Transformers in medical imaging: A survey. Medical image analysis. 2023;88:102802.

7. Jiang X, Hu Z, Wang S, Zhang Y. Deep Learning for Medical Image-Based Cancer Diagnosis. Cancers (Basel). 2023;15(14). 10.3390/cancers15143608.

8. Sobek J, Medina Inojosa JR, Medina Inojosa BJ, Rassoulinejad-Mousavi SM, Conte GM, Lopez-Jimenez F, et al. MedYOLO: A Medical Image Object Detection Framework. J Imaging Inform Med. 2024;37(6):3208-16. 10.1007/s10278-024-01138-2.

9. Picarra C, Winzeck S, Monteiro M, Mathieu F, Newcombe VFJ, Menon PDK, et al. Automatic localisation and per-region quantification of traumatic brain injury on head CT using atlas mapping. Eur J Radiol Open. 2023;10:100491. 10.1016/j.ejro.2023.100491.

10. Suganyadevi S, Seethalakshmi V, Balasamy K. A review on deep learning in medical image analysis. Int J Multimed Inf Retr. 2022;11(1):19-38. 10.1007/s13735-021-00218-1.

11. Abdusalomov A, Rakhimov M, Karimberdiyev J, Belalova G, Cho YI. Enhancing Automated Brain Tumor Detection Accuracy Using Artificial Intelligence Approaches for Healthcare Environments. Bioengineering (Basel). 2024;11(6). 10.3390/bioengineering11060627.

12. Kim JS, Cho Y, Lim TH. Prediction of locations in medical images using orthogonal neural networks. Eur J Radiol Open. 2021;8:100388. 10.1016/j.ejro.2021.100388.

13. Sakha MA, Ameri A. Detection and Classification of Lesions in Mammograms using One-Stage Models. Journal of Biomedical Physics and Engineering. 2025.

14. Liu Y, Li C, Li F, Lin R, Zhang D, Lian Y. Advances in computer vision and deep learning-facilitated early detection of melanoma. Briefings in Functional Genomics. 2025;24:elaf002.

15. Paudyal R, Grkovski M, Oh JH, Schöder H, Nunez DA, Hatzoglou V, et al. Application of community detection algorithm to investigate the correlation between imaging biomarkers of tumor metabolism, hypoxia, cellularity, and perfusion for precision radiotherapy in head and neck squamous cell carcinomas. Cancers. 2021;13(15). 10.3390/cancers13153908.

16. Paudyal R, Grkovski M, Oh JH, Schöder H, Nunez DA, Hatzoglou V, et al. Application of Community Detection Algorithm to Investigate the Correlation between Imaging Biomarkers of Tumor Metabolism, Hypoxia, Cellularity, and Perfusion for Precision Radiotherapy in Head and Neck Squamous Cell

Carcinomas. Cancers (Basel). 2021;13(15). 10.3390/cancers13153908.

17. Qasem A, Zhou Z. Automated tumor localization and segmentation through hybrid neural network in head and neck cancer. Medical Dosimetry. 2025;50(1):80-90. 10.1016/j.meddos.2024.09.001.

18. Yang H, Yang M, Chen J, Yao G, Zou Q, Jia L. Multimodal deep learning approaches for precision oncology: a comprehensive review. Briefings in Bioinformatics. 2025;26(1):bbae699.

19. Liu W, Anguelov D, Erhan D, Szegedy C, Reed S, Fu C-Y, et al., editors. Ssd: Single shot multibox detector. Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part I 14; 2016: Springer.

20. Redmon J, Divvala S, Girshick R, Farhadi A, editors. You only look once: Unified, real-time object detection. Proceedings of the IEEE conference on computer vision and pattern recognition; 2016.

21. Ren S, He K, Girshick R, Sun J. Faster r-cnn: Towards real-time object detection with region proposal networks. Advances in neural information processing systems. 2015;28.

22. Tang C, Zhou F, Sun J, Zhang Y. Lung-YOLO: Multiscale feature fusion attention and cross-layer aggregation for lung nodule detection. Biomedical Signal Processing and Control. 2025;99. 10.1016/j.bspc.2024.106815.

23. Ahsan R, Shahzadi I, Najeeb F, Omer H. Brain tumor detection and segmentation using deep learning. Magnetic Resonance Materials in Physics, Biology and Medicine. 2025;38(1):13-22. 10.1007/s10334-024-01203-5.

24. Zhang M, Sun L, Li X, Zhu W, Yi Y, Yan F. A multi-scale self-calibrating lung nodule detection based on SPC-UNet. Biomedical Signal Processing and Control. 2025;104. 10.1016/j.bspc.2025.107515.

25. Anari PY, Obiezu F, Lay N, Firouzabadi FD, Chaurasia A, Golagha M, et al. Using YOLO v7 to Detect Kidney in Magnetic Resonance Imaging. ArXiv. 2024.

26. Liu Y, Ao Y. Deformable attention mechanism-based YOLOv7 structure for lung nodule detection. Journal of Supercomputing. 2024;80(17):25450-69. 10.1007/s11227-024-06381-6.

27. Mehralivand S, Yang D, Harmon SA, Xu D, Xu Z, Roth H, et al. A Cascaded Deep Learning–Based Artificial Intelligence Algorithm for Automated Lesion Detection and Classification on Biparametric Prostate Magnetic Resonance Imaging. Academic Radiology. 2022;29(8):1159-68. 10.1016/j.acra.2021.08.019.

28. Aishwarya KV, Asuntha A, Murugan J. Optimizing pulmonary nodule segmentation in CT imaging: A comparative study of anchor-based and anchor-free detectors using attention mechanism. Multimedia Tools and Applications. 2025. 10.1007/s11042-025-20752-y.

29. Qasem A, Zhou Z. Automated tumor localization and segmentation through hybrid neural network in head and neck cancer. Med Dosim. 2025;50(1):80-90. 10.1016/j.meddos.2024.09.001.

30. Muksimova S, Umirzakova S, Mardieva S, Iskhakova N, Sultanov M, Cho YI. A lightweight attention-driven YOLOv5m model for improved brain tumor detection. Computers in Biology and Medicine. 2025;188. 10.1016/j.compbiomed.2025.109893.

31. Jiang C, Li Y, Luo H, Zhang C, Du H. KansNet: Kolmogorov–Arnold Networks and multi slice partition channel priority attention in convolutional neural network for lung nodule detection. Biomedical Signal Processing and Control. 2025;103. 10.1016/j.bspc.2024.107358.

32. Xu D, Ma M, Cao M, Kishan AU, Nickols NG, Scalzo F, et al. Mask R-CNN assisted 2.5D object detection pipeline of 68Ga-PSMA-11 PET/CT-positive metastatic pelvic lymph node after radical prostatectomy from solely CT imaging. Scientific Reports. 2023;13(1). 10.1038/s41598-023-28669-y.

33. Zhang S, Miao Y, Chen J, Zhang X, Han L, Huang Z, et al. CCS-Net: Cascade Detection Network With the Convolution Kernel Switch Block and Statistics Optimal Anchors Block in Hypopharyngeal Cancer MRI. IEEE Journal of Biomedical and Health Informatics. 2023;27(1):433-44. 10.1109/JBHI.2022.3217174.

34. Du L, Zhang R, Wang X, editors. Overview of two-stage object detection algorithms. Journal of Physics: Conference Series; 2020: IOP Publishing.

35. Hikmah NF, Hajjanto AD, Surbakti AFA, Prakosa NA, Asmaria T, Sardjono TA. Brain tumor detection using a MobileNetV2-SSD model with modified feature pyramid network levels. International Journal of Electrical and Computer Engineering. 2024;14(4):3995-4004. 10.11591/ijece.v14i4.pp3995-4004.

36. Zamanidoost Y, Ould-Bachir T, Martel S. OMS-CNN: Optimized Multi-Scale CNN for Lung Nodule Detection Based on Faster R-CNN. IEEE Journal of Biomedical and Health Informatics. 2025;29(3):2148-60. 10.1109/JBHI.2024.3507360.

37. Dai J, He C, Jin L, Chen C, Wu J, Bian Y. A deep learning detection method for pancreatic cystic neoplasm based on Mamba architecture. Journal of X-ray science and technology.2025;33(2):461-71. 10.1177/08953996251313719.

38. Son JW, Hong JY, Kim Y, Kim WJ, Shin DY, Choi HS, et al. How Many Private Data are Needed for Deep Learning in Lung Nodule Detection on CT Scans? A Retrospective Multicenter Study. Cancers. 2022;14(13). 10.3390/cancers14133174.

39. Ito S, Nakashima H, Segi N, Ouchida J, Oda M, Yamauchi I, et al. Automated Detection and Diagnosis of Spinal Schwannomas and Meningiomas Using Deep Learning and Magnetic Resonance Imaging. Journal of Clinical Medicine. 2023;12(15). 10.3390/jcm12155075.

40. Terzi R. An Ensemble of Deep Learning Object Detection Models for Anatomical and Pathological Regions in Brain MRI. Diagnostics (Basel). 2023;13(8). 10.3390/diagnostics13081494.

41. Chaudhary A, Mittal K, Tejpal B, Thakur K, Varughese DA, Sridevi S. ENHANCING CNN PERFORMANCE WITH RIGHT-NEIGHBOR DEVIATION (RND) POOLING: A FOCUS ON MULTI-CLASS BRAIN TUMOR CLASSIFICATION IN MRI IMAGES. Biomedical Engineering - Applications, Basis and Communications. 2025;37(2). 10.4015/S1016237224500467.

42. Abdusalomov A, Rakhimov M, Karimberdiyev J, Belalova G, Cho YI. Enhancing Automated Brain Tumor Detection Accuracy Using Artificial Intelligence Approaches for Healthcare Environments. Bioengineering. 2024;11(6). 10.3390/bioengineering11060627.

43. Chai YF, Zhang XX. Enhanced Chest CT Detection of Pulmonary Nodules Based on YOLOv8. Engineering Letters. 2024;32(12):2221-31.

44. Wang H, Tang N, Zhang C, Hao Y, Meng X, Li J. Practice toward standardized performance testing of computer-aided detection algorithms for pulmonary nodule.

Frontiers in Public Health. 2022;10. 10.3389/fpubh.2022.1071673.

45. Song W, Tang F, Marshall H, Fong KM, Liu F. A multiscale 3D network for lung nodule detection using flexible nodule modeling. Medical Physics. 2024;51(10):7356-68. 10.1002/mp.17283.

46. Swinburne NC, Yadav V, Kim J, Choi YR, Gutman DC, Yang JT, et al. Semisupervised Training of a Brain MRI Tumor Detection Model Using Mined Annotations. Radiology. 2022;303(1):80-9. 10.1148/RADIOL.210817.

47. Gui H, Su T, Jiang X, Li L, Xiong L, Zhou J, et al. FS-YOLOv9: A Frequency and Spatial Feature-Based YOLOv9 for Real-time Breast Cancer Detection. Academic Radiology. 2025;32(3):1228-40. 10.1016/j.acra.2024.09.048.

48. Saidani T. Efficient Tumor Detection in Medical Imaging Using Advanced Object Detection Model: A Deep Learning Approach. International Journal of Advanced Computer Science and Applications. 2025;16(1):1139-45. 10.14569/IJACSA.2025.01601109.

49. Ahmadyar Y, Kamali-Asl A, Arabi H, Samimi R, Zaidi H. Hierarchical approach for pulmonary-nodule identification from CT images using YOLO model and a 3D neural network classifier. Radiological Physics and Technology. 2024;17(1):124-34. 10.1007/s12194-023-00756-9.

50. Manokaran J, Mittal R, Ukwatta E. Pulmonary nodule detection in low dose computed tomography using a medical-to-medical transfer learning approach. Journal of Medical Imaging. 2024;11(4):44502. 10.1117/1.JMI.11.4.044502.

51. Pandey SK, Bhandari AK. YOLOv7 for brain tumour detection using morphological transfer learning model. Neural Computing and Applications. 2024;36(32):20321-40. 10.1007/s00521-024-10246-7.

52. Piao Z, Meng M, Yang H, Xue T, Jia Z, Liu W. Distinguishing between aldosterone-producing adenomas and non-functional adrenocortical adenomas using the YOLOv5 network. Acta Radiologica. 2024;65(8):1007-14. 10.1177/02841851241251446.

53. Suryawanshi S, Patil SB. Brain Tumor Detection Using YoloV5 and Faster RCNN. International Journal of Intelligent Systems and Applications in Engineering. 2024;12(4s):335-42.

54. Randar S, Shah V, Kulkarni H, Suryawanshi Y, Joshi A, Sawant S. YOLOv8-Based Frameworks for Liver and Tumor Segmentation Task on LiTS. SN Computer Science. 2024;5(6). 10.1007/s42979-024-03097-5.

55. Gao Z, Guo Y, Wang G, Chen X, Cao X, Zhang C, et al. Robust deep learning from incomplete annotation for accurate lung nodule detection. Comput Biol Med. 2024;173:108361. 10.1016/j.compbiomed.2024.108361.

56. Terzi DS, Azginoglu N. In-Domain Transfer Learning Strategy for Tumor Detection on Brain MRI. Diagnostics. 2023;13(12). 10.3390/diagnostics13122110.

57. Xie F, Ju J, Zhang T, Wang H, Liu J, Wang J, et al. A Small Intestinal Stromal Tumor Detection Method Based on an Attention Balance Feature Pyramid. Sensors. 2023;23(24). 10.3390/s23249723.

58. Oh JH, Lee KM, Kim HG, Yoon JT, Kim EJ. Deep learning-based detection algorithm for brain metastases on black blood imaging. Scientific Reports. 2022;12(1). 10.1038/s41598-022-23687-8.

59. Shelatkar T, Urvashi D, Shorfuzzaman M, Alsufyani A, Lakshmanna K. Diagnosis of Brain Tumor Using Light Weight Deep Learning Model with Fine-Tuning Approach. Computational and Mathematical Methods in Medicine. 2022;2022. 10.1155/2022/2858845.

60. Xu J, Ren H, Cai S, Zhang X. An improved faster R-CNN algorithm for assisted detection of lung nodules. Computers in Biology and Medicine. 2023;153. 10.1016/j.compbiomed.2022.106470.

61. Chegraoui H, Philippe C, Dangouloff-Ros V, Grigis A, Calmon R, Boddaert N, et al. Object detection improves tumour segmentation in mr images of rare brain tumours. Cancers. 2021;13(23). 10.3390/cancers13236113.

62. Gunasekara SR, Kaldera HNTK, Dissanayake MB. A Systematic Approach for MRI Brain Tumor Localization and Segmentation Using Deep Learning and Active Contouring. Journal of Healthcare Engineering. 2021;2021. 10.1155/2021/6695108.

63. Ito S, Ando K, Kobayashi K, Nakashima H, Oda M, MacHino M, et al. Automated Detection of Spinal Schwannomas Utilizing Deep Learning Based on Object Detection From Magnetic Resonance Imaging. Spine. 2021;46(2):95-100. 10.1097/BRS.0000000000003749.

64. Peng X, Yang X. Liver tumor detection based on objects as points. Physics in Medicine and Biology. 2021;66(23). 10.1088/1361-6560/ac35c7.

65. Takao H, Amemiya S, Kato S, Yamashita H, Sakamoto N, Abe O. Deep-learning single-shot detector for automatic detection of brain metastases with the combined use of contrast-enhanced and non-enhanced computed tomography images. European Journal of Radiology. 2021;144. 10.1016/j.ejrad.2021.110015.

66. Adachi M, Fujioka T, Mori M, Kubota K, Kikuchi Y, Xiaotong W, et al. Detection and diagnosis of breast cancer using artificial intelligence based assessment of maximum intensity projection dynamic contrast-enhanced magnetic resonance images. Diagnostics. 2020;10(5). 10.3390/diagnostics10050330.

67. Su Y, Li D, Chen X. Lung Nodule Detection based on Faster R-CNN Framework. Computer Methods and Programs in Biomedicine. 2021;200. 10.1016/j.cmpb.2020.105866.

68. Zhao Z, Ye C, Hu Y, Li C, Li X. Cascade and Fusion of Multitask Convolutional Neural Networks for Detection of Thyroid Nodules in Contrast-Enhanced CT. Comput Intell Neurosci. 2019;2019:7401235. 10.1155/2019/7401235.