Narrative review of open source, proprietary, and experimental artificial intelligence algorithms in radiology

Alex R. Ghorishi[1], Feyikemi O. Ogunfuwa[1], Tarek M. Ghaddar[1], Maya N. Kandah[1], Blake W. Smith[2], Quan Ta[1], Amaris Alayon[1], Per K. Amundson[3]

[1]Florida Atlantic University, Charles E. Schmidt College of Medicine, Boca Raton, FL, USA; [2]Nova Southeastern University, Kiran C. Patel College of Osteopathic Medicine, Davie, FL, USA; [3]School of Medicine, Indiana University, Indianapolis, IN, USA

Contributions: (I) Conception and design: AR Ghorishi; (II) Administrative support: PK Amundson; (III) Provision of study material or patients: AR Ghorishi; (IV) Collection and assembly of data: AR Ghorishi, FO Ogunfuwa; (V) Data analysis and interpretation: All authors; (VI) Manuscript writing: All authors; (VII) Final approval of manuscript: All authors.

Correspondence to: Dr. Alex R. Ghorishi. Florida Atlantic University, Charles E. Schmidt College of Medicine, 777 Glades Road BC-71, Boca Raton, FL 33431, USA. Email: alexghorishi@gmail.com.

Background and Objective: The aim of this study is to educate the reader on the applications of artificial intelligence (AI)-based algorithms, their basic functioning mechanism, and the efficacy of various algorithms which may be encountered in clinical practice. From image reconstruction and interpretation to image segmentation and clinical decision making, AI has demonstrated wide applicability in the field of radiology. The following systematic review yielded a comprehensive, but not exhaustive, summary of AI algorithms pertaining to diagnostic radiology.

Methods: Five databases, including MEDLINE, Google Scholar, Association for Computing Machinery (ACM) Digital Library, Institute of Electrical and Electronics Engineers (IEEE) Xplore, and PubMed, were queried for recent research articles pertaining to various aspects of AI in Radiology. Specific criteria narrowed the yield of research articles as those pertaining to AI as applied to image reconstruction, image interpretation, and clinical decision making.

Key Content and Findings: A broad overview of AI-driven algorithms encompassing all aspects of radiology from image reconstruction to image interpretation to decisions on next steps are included in this review article.

Conclusions: Although AI demonstrates excellent efficiency and efficacy when applied to image reconstruction, current technological limitations hinder the widespread adoption of AI in image interpretation and clinical decision making. Since many algorithms have had recurrent false positive results, integration of AI into the radiologists' workflow at this precise moment in time does not improve efficiency and accuracy when compared to traditional approaches which do not rely on computer vision and image feature extraction. As AI drives further advancement in the field of radiomics, AI system will become more accurate. In the meantime, false-positive results can be alleviated by confirming the algorithm decision with expert opinion based off the clinical history and physical exam findings given. In that sense, it could act as a safety net for potentially overlooked diagnoses, but not as the final arbiter of diagnosis itself.

Keywords: Computed tomography (CT) image reconstruction; machine learning (ML); deep learning (DL); artificial intelligence (AI); convolutional neural networks (CNNs)

Received: 09 October 2022; Accepted: 02 May 2023; Published online: 20 May 2023.

doi: 10.21037/jmai-22-89

View this article at: https://dx.doi.org/10.21037/jmai-22-89

Introduction

Artificial intelligence (AI) encompasses the technological simulation of intelligence. As a highly technology reliant field, radiology has consistently been on the forefront of scientific and computational advancements. A core component of AI is its role in image recognition. From facial and object recognition to self-driving vehicles, AI has developed into a meaningful tool for streamlining otherwise tedious workflows. As a subset of AI, machine learning (ML) represents the specific algorithms which give rise to computational intelligence. ML has been used in precision medicine to predict patient success on various treatment protocols given specific characteristics of the treatment and the patient's disease (1). ML works by fitting models to data and subsequently improving the model through iterative training with larger data sets. Neural networks refer to a specific type of ML which takes on a form reminiscent of neural interaction in the human brain. Complex artificial neural networks (ANNs) with multiple levels of computation and hierarchical nodal structure give rise to deep learning (DL). DL has revolutionized the field of radiomics by detecting clinically relevant imaging features which are imperceptible to the human eye (2). In other words, machine learning uses data to improve performance at an intended task without explicit coding but requires human intervention to adjust errors. Implementation facilitates prediction, modeling, and other related relatively simple tasks.

Deep learning takes this further, allowing the AI to adjust errors on its own, without direct human intervention, allowing for complex behavior-like performances. The most prevalent DL technique in imaging uses convolutional neural networks (CNNs) (3). CNNs comprise collections of neurons that are organized in a series of integrated layers. CNNs are dynamic learning systems which can emulate simpler patterns with lower layer depths, graduating to higher complexity with further layers (4). An input layer extracts information from the input array by multiplying with a filter. An array of smaller dimensions is produced, simplifying the input sequence. By simplifying a complex input into a smaller array, distinct feature maps of the original data are produced. The detected features are compared to the desired outputs, and the filter can be adjusted accordingly (5,6).

The aim of this paper is to delineate the current state of AI in radiology. The uses of AI in radiology are highly diverse: DL-based radiomics tools have proven useful in the diagnosis and risk stratification of various cancers (7). Multiple studies in lung cancer have demonstrated accurate prediction of distant metastasis, disease recurrence, and overall survival based on radiomics data derived from ANN models (8-10). As the influx of imaging data overwhelms radiologists' capacity to interpret, the need for a more efficient system has become paramount. McDonald *et al.* suggests that an average radiologist must interpret one image every 3 s in an 8-h workday to fulfill their duties (11). AI-based pre-screening of radiological images may not only improve efficiency, but also catch errors inevitably made in such high-pressure, high-volume settings.

As image acquisition hardware technology advances, the potential for increased image detail increases. However, limitations in image reconstruction software remain a bottleneck (12). Further, in multimodal fusion imaging applications, AI-based techniques may aid image registration. Currently, image registration is typically guided by landmark and edge-based measures which are sensitive to initializations, predefined similarity features and the reference image (13). These fixed, predefined criteria are less capable than more advanced DL methods which have greater capacity for registering images featuring complex tissue deformation while compensating for motion artifacts (14).

Owing to the endless potential application of AI in radiology, the number of AI-based proprietary, open source and experimental software and products in radiology has rapidly increased. From 2017 to 2021, the number of AI exhibitors at the yearly meeting of the Radiological Society of North America (RSNA) and European Congress of Radiology (ECR) has nearly quadrupled (15,16). The extent to which these algorithms have been validated varies widely, with highly limited evidence available for commercially available AI software. Thus, the aim of this study is to educate the reader on the applications of AI-based algorithms, their basic functioning mechanism, and the efficacy of various algorithms which may be encountered in clinical practice. We present this article in accordance with the Narrative Review reporting checklist (available at https://jmai.amegroups.com/article/view/10.21037/jmai-22-89/rc).

Methods

A literature search for peer-reviewed publications in five databases including MEDLINE, Google Scholar, ACM Digital Library, IEEE Xplore, and PubMed was

Table 1 The search strategy summary

Items	Specification
Date of search	July 2022
Databases and other sources searched	MEDLINE, Google Scholar, ACM Digital Library, and IEEE Xplore, PubMed
Search terms used	"Artificial intelligence", "machine learning", "deep learning", "convolutional neural networks", "radiology", "CT image reconstruction", "AI image interpretation", "AI in radiology", "automated segmentation", and "AI-assisted radiology"
Timeframe	2017 to present
Inclusion and exclusion criteria	Non-English and non-peer-reviewed articles were excluded
Selection process	Reviewer AG conducted the selection independently and reviewed the yielding results with the remainder of the author team for complete consensus

performed (*Table 1*). These databases were chosen to yield a comprehensive selection of peer-reviewed articles covering all aspects of the topic including various subspecialties in medicine and surgery as well as computer science and engineering. All articles older than 5 years were filtered out from the search. The article lists were generated by querying for the following relevant keywords, "artificial intelligence", "machine learning", "deep learning", "convolutional neural networks", "radiology", "CT image reconstruction", "AI image interpretation", "AI in radiology", "automated segmentation", and "AI-assisted radiology". One reviewer, AG, evaluated the resulting 205 articles for inclusion in this study. Non-English and non-peer-reviewed articles were excluded from this analysis. Further, papers concerning applications in radiation oncology were excluded.

Results

All the results included below are tabulated in *Table 2*.

Image reconstruction and optimization

There exists a schism in radiological technology between the hardware that captures the raw data and the software employed to process these data into the images which are examined by the radiologist. Furthermore, the advent of new low dose computed tomography (CT) protocols and low-field magnetic resonance imaging (MRI) has led to lower-quality studies compared to conventional imaging methods. In the last 30 years, CT reconstruction algorithms have remained relatively unchanged (84). New reconstruction algorithms employing deep learning techniques have shown promise in improving overall image quality, reducing artifactual distortion, reducing patient dose, and reducing runtime.

CT image reconstruction and denoising

Many of the articles included in this systematic review focus on the role of ML in reducing image noise with the end goal of improving diagnostic accuracy in various radiological modalities. Due to the recent increasing concern over the stochastic risks of CT scans, there has been a push for employing low dose techniques in CT imaging. AI-driven techniques have demonstrated value in enhancing imaging quality from low dose CT studies.

Liu and Tang demonstrated the efficacy of an expectation-maximization denoising algorithm (EM algorithm) in the detection and diagnosis of renal dysplasia. The underlying pathogenesis of renal dysplasia is related to defects in the formation of kidneys during their embryonic development. Although seemingly rare, the incidence of neonatal congenital renal dysplasia can be up to 0.2% of the population. Since renal dysplasia carries a high likelihood of progression to chronic kidney disease, the early diagnosis and treatment of this condition is paramount. Ultrasound is less sensitive than CT in the diagnosis of renal pathology. To minimize CT doses, denoising reconstructive techniques are employed. Liu and Tang's work showed superior denoising effect of the EM algorithm compared to conventional denoising techniques. The peak signal to noise ratio (PSNR) of the EM algorithm was higher than the conventional techniques with a shorter runtime (22).

The advent of AI-driven CT reconstructive algorithms has spurred the clinical use of commercially available algorithms such as the iDose4 reconstruction algorithm (Philips Healthcare, Cleveland, OH). Zhang *et al.*'s work

Table 2 Summary of the studies, including their appropriate categories, objective, methods, results, dataset, and associated medical fields

Category	Study	Objective	Results	Method (specific AI algorithm)	Dataset	Relevant medical field
Image interpretation, classification of disease, assessment of disease extent, and quantification of disease	Park *et al.* (17)	To develop and apply a neural network segmentation model (HeadXNet model) for aiding diagnosis of intracranial aneurysms on head CTA	Augmenting clinicians with AI-produced segmentation predictions improved sensitivity, accuracy, and interrater agreement compared to no augmentation	CNN	Training set included 611 head CTA examinations, test set of 115 examinations from August 13, 2018 to October 4, 2018	Neurology
Clinical decision making, prognostication, and surgery or treatment planning	Yu *et al.* (18)	To use ML techniques to develop an efficient preoperative MRI radiomics evaluation approach of ALN status in breast cancer	ALN-tumor radiomic signature for ALN status prediction showed high prediction quality with AUC of 0.88 in training cohort, 0.87 in external validation cohort, and 0.87 in prospective-retrospective validation cohort	Random forest algorithm, support vector machine algorithm	Three independent cohorts of patients with breast cancer (n=1,088)	Oncology
Clinical decision making, prognostication, and surgery or treatment planning	Jonas *et al.* (19)	To evaluate the relationship of coronary stenosis, APCs and age using AI-QCT	Older patients had more plaque volume and calcified plaque. Younger patients had more plaque volume and LD-NCP in obstructive compared to non-obstructive lesions. AI-QCT identified APC signature providing foundation for AI-guided approaches to prevention, identification, and treatment of atherosclerosis	Series of validated CNNs including VGG 19 network, 3D U-Net and VGG Network Variant for image quality assessment, segmentation, lumen wall evaluation, etc.	Post-hoc analysis of data from 303 subjects enrolled in CREDENCE	Cardiology
Image reconstruction and optimization	Liang *et al.* (20)	To construct 3D representations of mandibles affected by tumors and post-surgical changes	DCGAN called CTGAN constructs mandibles with expected patient characteristics and is suitable for mandibular morphological completion	DCGAN	14,278 images of mandibular tomography (7,392 from males, 6,886 from females)	Otolaryngology
Image interpretation, classification of disease, assessment of disease extent, and quantification of disease	Knott *et al.* (21)	To explore the prognostic significance of stress MBF and MPR (the ratio of stress to rest MBF)	Decline in stress MBF resulted in higher risk of death and MACE	CNN used to delineate left ventricle cavity and myocardium, excluding myocardial fat and papillary muscles	1,049 patients ages 18 years and older referred to Barts Heart Centre and Royal Free Hospital, London, UK	Cardiology
Image reconstruction and optimization	Liu and Tang (22)	To explore the accuracy of low-dosage CT images based on the expectation-maximization algorithm denoising algorithm (EM algorithm) in the diagnosis of renal dysplasia	EM algorithm denoised CT images enhanced diagnostic accuracy of dysplasia of single kidney, absence of single kidney, horseshoe kidney, and duplex kidney	Expectation maximization algorithm	120 patients with renal dysplasia	Nephrology
Image reconstruction and optimization	Zhang *et al.* (23)	To analyze the influence of AI reconstruction algorithms on CT images in the setting of ACL injury recovery	Higher signal to noise ratio in iDose4 reconstruction algorithm groups	Philips iDose4 iterative reconstruction technique	90 patients with ACL motor injuries recruited from September 2019 to October 2020	Orthopedics
Image interpretation, classification of disease, assessment of disease extent, and quantification of disease	Chauvie *et al.* (24)	To enhance the PPV of chest DTS in lung cancer detection	Neural network approach was the best predictor with high PPV of 0.95 and sensitivity of 0.90	CNN and random forest algorithm	1,594 subjects in SOS: Studio OS servazionale clinical trial—eligible participants included smokers and former smokers aged 45 to 75 years with 20+ pack-year history	Oncology, pulmonology
Image reconstruction and optimization	Fan *et al.* (25)	To explore the application of CT image based on active contour segmentation algorithm in treatment of LDH with scalpel	Scalpel treatment was more effective than lateral crypt block treatment. AI algorithm effectively analyzed the effect of treatments	LBF algorithm (a type of CNN) and PreWork algorithm, active contour segmentation algorithm	42 males and 36 females aged 35–70 with LDH admitted to hospital and underwent CT examination	orthopedics
Image interpretation, classification of disease, assessment of disease extent, and quantification of disease	Kundisch *et al.* (26)	To determine the number of additional ICH detected by an AI algorithm	The AI algorithm detected additional 29 instances of ICH, missed 12.4% of ICH and overcalled 1.9%. Radiology reports missed 10.9% of ICH and overcalled 0.2%. Many ICH missed by AI located in subarachnoid space (42.4%)	AIDOC (Tel Aviv, Israel), commercially available ICH detection software—proprietary two-stage algorithm using CNNs	4,946 head CT from 18 hospitals included in analysis	Neurology, trauma
Image interpretation, classification of disease, assessment of disease extent, and quantification of disease	Jiang *et al.* (27)	To study the application value of MRI diagnosis under AI algorithms on patients with gynecological ovarian endometriosis	Compared to traditional HCM algorithm, AI-based FCM algorithm had higher partition coefficient with lower running time and resultant greater sensitivity and specificity	FCM clustering algorithm	116 patients with ovarian endometriosis	Gynecology
Image reconstruction and optimization	Jiang *et al.* (28)	Investigate modified GIF algorithm as applied to low-dose CTE, to study its effect on the differential diagnosis of UC and CD, by reducing noise	The peak signal-to-noise ratio and structural similarity of the modified GIF algorithm were higher than those of the control. The diagnostic sensitivity (91.5%), specificity (92.3%), accuracy (91.7%), positive predictive value (97.7%), and negative predictive value (75%) were higher. There were significant differences in symmetrical intestinal wall thickening and smooth serosal surface between UC and CD ($P<0.05$)	The GIF algorithm is modified such that the ratio of each pixel variance to the pixel variance in the filter window is standardized, reducing the whole image to a local window	120 subjects with suspected inflammatory bowel disease that presented in the hospital between June 2018 to May 2021. They were split into two 60-person groups randomly	Gastroenterology

Table 2 (*continued*)

Table 2 (*continued*)

Category	Study	Objective	Results	Method (specific AI algorithm)	Dataset	Relevant medical field
Image reconstruction and optimization	Deding *et al.* (29)	Compare relative sensitivity of CCE to CTC following an incomplete OC, investigate completion rate when combining incomplete OC and CCE, and develop a forward tracking algorithm to facilitate this	The ground truth for capsule location, as determined by expert physicians, and the AI-determined capsule location agreed a mean 77% of the time and a median 85%	The algorithm was composed by finding feature points between consecutive frames, translating the features to movement. A point-wise classifier predicted the end of the investigation	237 individuals with CTC indication– of these 105 were included. Of the included subset, 97 underwent both a CCE and CTC. 66 completed a CCE successfully.	Gastroenterology
Image reconstruction and optimization	Harper *et al.* (30)	CT images of post-infectious infant hydrocephalus were degraded in terms of spatial resolution, noise, and contrast between brain and CSF, and enhanced using deep learning algorithms—particularly in the context of low-field MRI.	Deep learning enhancement increases contrast-to-noise ratio such that the low-field image is more likely to be clinically useful. This enhancement generates structural errors, which unfortunately can lead to a misleading clinical appearance	A single encoder dual decoder architecture enhanced the reduced-quality images. Deep learning networks were trained using library images	From the 1,600 parameter combinations applied to the 10 test images, 420 cases were randomly presented to the panel of experts along with all 140 deep learning enhanced images.	Neurology, Pediatrics
Clinical decision making, prognostication, and surgery or treatment planning	Zhang *et al.* (31)	Deep learning-based electronic segmentation model was implemented to facilitate rehabilitation analysis of children with cerebral palsy and comorbid epilepsy	SPECT examination showed hypoperfusion of cerebral blood flow and decreased functional activity of neurons in the AI group before treatment. After treatment, 27 cases returned to normal (96.4%). There were 29 cases of hypoperfusion of cerebral blood flow and decreased functional activity of neurons in the control group. After treatment, 6 cases returned to normal (20.7%)	Hybrid Segmentation Network; CNN model with Python deep learning framework to write code. Adam optimizer implemented, and LeakyReLu implemented for activation function	CT brain imaging data of 73 children with cerebral palsy (both inpatient and outpatient at the hospital)	Neurology, pediatrics
Image interpretation, classification of disease, assessment of disease extent, and quantification of disease	Huang *et al.* (32)	A deep learning model was developed to aid preoperative diagnosis of peritoneal metastasis in gastric cancer, using retrospective enrollment	Results not published yet	A high generalizability, deep convolutional neural network was developed through 5-fold cross-validation and model ensemble	Retrospective enrollment of all patients with gastric cancer treated at the institution	Gastroenterology, oncology
Clinical decision making, prognostication, and surgery or treatment planning	Liu *et al.* (33)	AI-based radiomics model was retrospectively applied to investigate the positive predictive value of microvascular invasion in solitary hepatocellular carcinoma	The radiomics model exhibited a better correction and identification ability in the training and validation groups [AUC: 0.72 (95% CI: 0.58–0.83) and 0.74 (95% CI: 0.66–0.83), respectively]. Prediction performance was significantly higher than that of the image features ($P<0.05$)	Plug-in radiologics in the 3D-Slice software	The archived data of 185 patients who underwent partial hepatectomy for histopathologically confirmed hepatocellular carcinoma with microvascular invasion, between January 1st, 2014, and November 15th, 2018	Hepatology, oncology
Clinical decision making, prognostication, and surgery or treatment planning	Deng *et al.* (34)	The value of radiomics in blood oxygen level dependent MRI to differentiate benign renal tumors from malignant tumors	AUC of the model developed by multivariable logistic regression for differentiating malignant from benign renal tumors in the training and test groups were 0.881 and 0.706, with the accuracy at 82.93% and 79.00%, the sensitivity at 82.86% and 77.11%, and the specificities at 83.33% and 88.24%, respectively	Artificial Intelligence Kit software	Retrospective data of 141 patients with renal tumors confirmed histopathologically	Nephrology, oncology
Clinical decision making, prognostication, and surgery or treatment planning	Sharrock *et al.* (35)	To train a 3D deep neural network to perform intracranial hemorrhage (ICH) segmentation and estimate hemorrhage	Deep neural networks trained with an appropriate anatomic context in the network receptive field can effectively perform ICH segmentation, but those without enough context will overestimate hemorrhage along the skull and around calcifications in the ventricular system. 3D networks with appropriate anatomic context outperformed both 2D and random forest models	3D deep learning neural network, which has been made open-source	Gold standard, human labeled data directly from the phase II and phase III multi-center minimally invasive surgery with thrombolysis in intracerebral hemorrhage evacuation (MISTIE) clinical trials	Neurology
Image interpretation, classification of disease, assessment of disease extent, and quantification of disease	Gates *et al.* (36)	To estimate the local glioma grade using a machine learning model trained on preoperative image data and spatially specific tumor samples	The random forest method was the best algorithm tested. Tumor grade was predicted at 96% accuracy (κ=0.93) using Type-2 weighted imaging, ADC, CBV, and transfer constant from dynamic contrast-enhanced imaging. In the conventional imaging group, accuracy decreased (89% overall, κ=0.79) and 43% of high-grade samples were misclassified as lower-grade	Random forest, support vector machine, and neural network classifiers	Glioma patients enrolled in a prospective clinical imaging trial between 2013 and 2016	Neurology, Oncology
Image interpretation, classification of disease, assessment of disease extent, and quantification of disease	Gerendas *et al.* (37)	To evaluate the potential of machine learning and computational image analysis of optical coherence tomography to determine the prognosis of patients with DME	At baseline, intraretinal cystoid fluid in the outer nuclear layer in the 3-mm zone around the fovea bore the greatest predictive value for best-corrected visual acuity. At weeks 12 and 24, both intraretinal cystoid fluid and total retinal thickness bore the greatest predictive value for best-corrected visual after one year. The overall model accuracy was Rsq =0.21/0.23 ($P<0.001$)	Random forest model	In a randomized prospective clinical trial, 629 patients with DME underwent spectral-domain OCT scans with automated retinal layer segmentation, as well as segmentation of subretinal fluid and IRC	Ophthalmology, endocrinology

Table 2 (*continued*)

Table 2 (*continued*)

Category	Study	Objective	Results	Method (specific AI algorithm)	Dataset	Relevant medical field
Clinical decision making, prognostication, and surgery or treatment planning	Bhattarai *et al.* (38)	To develop a model predicting rate of *in vivo* tumor growth using a study cohort of breast cancer patients who had two serial mammograms, in which a tumor visible in the diagnostic mammogram was missed in the first screen	Serial mammography-derived *in vivo* growth rate (SM-INVIGOR) stratified discovery cohort patients into fast-growing versus slow-growing tumor subgroups. In the validation cohort, Surr-INVIGOR uncovered significant survival differences between patients with fast-growing and slow-growing tumors	(SM-INVIGOR) index was developed, along with a machine learning-based surrogate model called Surr-INVIGOR	114 breast cancer patients aged between 50 and 70 years who were presented at the Nottingham City Hospital from 1988 to 2008 with BC, and for whom review of the previous screening mammogram showed a previously undetected tumor at the same affected site	Oncology
Image interpretation, classification of disease, assessment of disease extent, and quantification of disease	Zhang *et al.* (39)	To assess the complementary prognostic information of predefined radiomic features and transfer learning features for overall survival in CT scans of PDAC patients	The weak linear relationship between PyRadiomics and LungTrans features suggest that the LungTrans features may harbor new information that PyRadiomics doesn't capture. Several color bands in the PyRadiomics *vs.* LungTrans region also suggest that some LungTrans features may have strong linear relationships with PyRadiomics features	Using retrospective CT images from PDAC patients, researchers mapped the association between PyRadiomics and a set of transfer learning features and applied four existing feature fusion and reduction methods	Patients who had undergone preoperative contrast-enhanced CT available for analysis were retrospectively enrolled in the study. The two cohorts came from two independent hospitals and consisted of a 68-person training cohort and 30-person test cohort	
Image interpretation	Joo *et al.* (40)	To investigate if a deep learning model for automated detection of unruptured intracranial aneurysms on TOF MRA is comparable to human radiologists	The sensitivity and specificity of the model were 91.11% (95% CI: 84.99–95.32%) and 93.91% (95% CI: 89.60–96.81%), respectively. Lesion-wise sensitivity was 92.26%. False-positive detection rate per case was 0.123. Of the 168 aneurysms, 13 aneurysms were missed by the model	3D skeletonization algorithm and deep learning algorithm of 3D ResNet and 3D Unet	135 aneurysm-containing exams with 168 intracranial aneurysms and 197 aneurysm-free exams	Neurology
Clinical decision making	Chen *et al.* (41)	To evaluate the application of "Internet+ hospital-to-home" nutritional care model using the improved wavelet transform algorithm based on CT images in the nutritional care management of chronic kidney disease stages 3–5	IWT algorithm showed better effects (mean square error and signal noise ratio) in the processing of 320-slice volume CT low-dose perfusion imaging compared to orthogonal wavelet denoising and mean filter denoising algorithm. Renal cortex blood flow before and after nursing was significantly different between the two groups	IWT denoising algorithm on CT images	120 patients with CKD were divided into two groups, a control group (n=60) and observation (hospital to home) group (n=60)	Nephrology
Clinical decision making	Wang *et al.* (42)	Use of radiomic nomogram to preoperatively differentiate Lauren classification of gastric cancer diffuse type from intestinal type	Radiomic nomogram demonstrated the highest predictive accuracy other predictive models. Significantly improved sensitivity of radiomic nomogram indicated better identification of diffuse type gastric cancer	B-spline interpolation algorithm, radiomic nomogram	539 patients were allocated into training cohort (n=377) and validation cohort (n=162)	Gastroenterology, oncology
Image interpretation	Song *et al.* (43)	To explore the diagnostic value of radiomic signatures based on magnetic resonance imaging for PPA and PA	Quantitative type 1 to type 2 weighted imaging radiomics model distinguished PPA and PA better (sensitivity =0.88, specificity =0.80) compared to FNAC or MRI (specificity range, 0.85–0.97) (sensitivity range, 0.70–0.86)	Least absolute shrinkage and selection operator (LASSO) method, radiomics models	252 cases were separated into a training cohort (n=176) and a validation cohort (n=76)	Otolaryngology
Clinical decision making	Kim *et al.* (44)	To determine if computer-based quantitative HRCT can be used as an efficacy endpoint in assessing disease severity in idiopathic pulmonary fibrosis	Statistically significant inverse relationship between quantitative HRCT lung fibrosis and radiological scores for QLF, QILD, and pulmonary function measurements (percent predicted forced vital capacity and carbon monoxide diffusion capacity)	Machine learning technique for QLF scoring	HRCT scans from 137 out of 142 randomized patients were used in the QLF analysis	Pulmonology
Prognostication	Min *et al.* (45)	To develop pre-procedural IVUS-based models for predicting the occurrence of stent underexpansion	Stent areas predicted by pre-procedural IVUS-based regression model significantly correlated with areas measured on post-procedural IVUS (r=0.802)	Deep-learning algorithm based on IVUS-based algorithms	618 coronary lesions in 618 patients undergoing percutaneous coronary intervention were randomized into training and test sets (5:1 ratio)	Cardiology
Classification of disease	Papp *et al.* (46)	To investigate diagnostic performance of PET/MRI for predicting lesion risk, biochemical recurrence, and overall patient risk of primary prostate cancer	Low vs high lesion risk, biochemical recurrence, and overall patient risk prediction model had cross validation AUC of 0.86, 0.90, and 0.94, respectively. PET/MRI radiomics may enhance risk classification of primary prostate cancer without biopsy sampling	Mixed ensemble learning schemes built on random forest classifiers	121 delineated lesions in 52 patients who underwent radical prostatectomy and dual-tracer, fully integrated PET/MRI scan	Oncology, urology
Clinical decision making	Zhu *et al.* (47)	To determine if deep learning models can distinguish molecular subtypes of breast cancer based on DCE-MRI	The highest AUC for distinguishing molecular subtypes was 0.65 done by off-the-shelf deep features approach, followed by transfer learning (AUC =0.60) and training from scratch (0.58)	Deep learning approaches included training from scratch, transfer learning, and off-the-shelf deep features	270 patients diagnosed with breast cancer, of which 90 were of the luminal A subtype	Oncology, gynecology
Image reconstruction	Jayachandran Preetha *et al.* (48)	To assess the diagnostic value of synthetic post-contrast T1-weighted MRI generated from pre-contrast MRI sequences for tumor response assessment in neuro-oncology	Deep convolutional neural network models yielded a median SSIM score of 0.818 and 0.809 when using CGAN and UNet, respectively, for predicting contrast enhancement of synthetic post-contrast T1-weighted MRI (P<0.0001). Volumetric tumor response assessment was comparable between synthetic and true post-contrast T1-weighted MRI (P=0.33)	2 deep learning approaches for synthetic post-contrast imaging: 3D CNN based on UNet and CGAN-based method	2,061 patients with glioblastoma from 4 cohorts were allocated into training and validation of dCNN models	Neurology, oncology

Table 2 (*continued*)

Table 2 (*continued*)

Category	Study	Objective	Results	Method (specific AI algorithm)	Dataset	Relevant medical field
Assessing disease extent	Pekmezci *et al.* (49)	To determine if fiber-laser based SRH can identify microscopic residual disease from glioma margins	SRH identified residual tumor in 49% of the samples. Postoperative MRI overlaid with navigation coordinates showed that 94.4% of samples were at the tumor margins	Segmentation algorithm using custom software developed in C++2017	31 patients diagnosed with a glioma	Neurology, pathology
Prognostication	Xu *et al.* (50)	To establish long-term outcome prediction model for HICH using CT radiomics and machine learning	Accuracies of all machine learning algorithms in validation set exceeded 80%. RF and XGBoost models in the validation set had sensitivity, specificity, and accuracy of 93.3%, 92.5%, and 92.7% and 92.3%, 88.1%, and 89.1%, respectively. RF and XGBoost models were the best two among all models	6 machine learning algorithms: support vector machine, k-nearest neighbor, logistic regression, decision tree, random forest, and XGBoost algorithms	270 patients with HICH were randomly allocated into training (n=215) and validation (n=55) sets	Neurology
Image interpretation	Lenchik *et al.* (51)	To determine if automated chest CT measurement of paraspinous SMA and SMD can be used to predict survival of older adults	Men with higher SMA and SMD were associated with lower risk of all-cause mortality ($P<0.05$). Women had no significant associations	Automated pipeline for skeletal muscle measurement based on open-source machine learning methods	16,803 men and 4,558 women at age 60–69 years at time of enrollment were randomly assigned to a chest CT scan arm or chest X-ray arm	Gerontology
Classification of disease	Long *et al.* (52)	To develop and validate a mathematical model for predicting ICP noninvasively using PC-MRI	A novel ICP-predicting model was developed based on the nonlinear relationships between CSF parameters, using the Levenberg-Marquardt and general global optimisation methods with an accuracy of the model for predicting ICP of 0.8999 in the training cohort and 0.861 in the independent validation cohort	Levenberg-Marquardt and general global optimisation methods	138 patients with hydrocephalus, divided into a training group (n=97) and a validation group (n=41)	Neurology
Prognostication	Mokhtari *et al.* (53)	Use dynamic brain networks and fMRI data to prospectively identify individuals most likely to succeed in an 18-month behavioral weight loss intervention	The prediction accuracy exceeded 95%, suggesting there exists a consistent pattern of connectivity which correctly predicts success with weight loss at the individual level	Machine learning using SPM12 and ANTS preprocessed fMRI images	52 overweight or obese individuals (BMI ≥28 kg/m^2 but <42 kg/m^2) with history of CAD or metabolic syndrome	Neurology
Prognostication	He *et al.* (54)	Develop a multi-task, multi-stage deep transfer learning framework using the fusion of brain outcome and clinical data for early joint prediction of multiple abnormal neurodevelopmental outcomes at 2 years corrected age in very preterm infants	The model identified very preterm infants at high-risk for cognitive, language, and motor deficits at 2 years corrected age with an area under the ROC curve of 0.86, 0.66, and 0.84, respectively	Multi-task multi-stage deep transfer learning model	3 cohorts: source cohort (n=884), intermediate cohort (n=291), and a target cohort (n=51)	Neurology, pediatrics
Classification of disease	Rastegar *et al.* (55)	Develop a predictive model to classify osteoporosis, osteopenia and normal patients using radiomics and machine learning approaches	AUC values ranged from 0.50 to 0.78 in discriminating osteopenia *vs.* normal, osteoporosis *vs.* normal, osteopenia *vs.* osteoporosis and osteoporosis + osteopenia *vs.* osteoporosis	Machine learning methods: random forest, random committee, logit boost, K-nearest neighbors. Feature selection methods: classifies attribute evaluation, one rule attribute evaluation, gain ratio attribute evaluation and principal components analysis	147 patients underwent bone mineral densitometry images in 7 regions and 54 texture features were extracted from the regions	Rheumatology
Prognostication, clinical decision making	Zhang *et al.* (56)	Develop and validate a deep learning model that could preoperatively predict the microsatellite instability status of rectal cancer based on MRI	The clinical model correctly classified 37.5% of MSI status in the testing cohort, with an AUC value of 0.573. The pure imaging-based model and the combined model correctly classified 75% and 85.4% of MSI status in the testing cohort, with AUC values of 0.820 and 0.868.	Multivariate binary logistic regression classifies for clinical model. For deep learning model, a pure image model and a combined model that incorporated both MRI images and clinical variables.	491 rectal cancer patients: training/validation cohort (n=395) and testing cohort (n=96)	Oncology, gastroenterology
Clinical decision making, Prognostication	Afshar *et al.* (57)	Develop a deep learning-based radiomics model for the time-to-event outcome prediction that takes raw PET/CT images as inputs, and calculates the image-based risk of death or recurrence	Deep learning-based radiomics model is as accurate or better in predicting predefined clinical outcomes compared to hand-crafted radiomics	CNN	132 lung cancer patients	Oncology, pulmonology
Prognostication	Nielson *et al.* (58)	Apply topology-based data-driven discovery to identify natural subgroups of patients, based on the TBI and CDEs collected	TDA identified a subset of mild TBI patients with specific multivariate phenotype associated with unfavorable outcome at 3 and 6 months after injury.	TDA	586 acute TBI patients	Neurology
Classification of disease	Stuckey *et al.* (59)	To determine the diagnostic performance of cPSTA in assessing CAD in patients presenting with chest pain.	The machine-learned algorithm had a sensitivity of 92% and specificity of 62% on blind testing in the verification cohort. The negative predictive value was 96%	cPSTA	606 subjects consisting of a development of 512 subjects and a verification set of 94 subjects	Cardiology

Table 2 (*continued*)

Table 2 (*continued*)

Category	Study	Objective	Results	Method (specific AI algorithm)	Dataset	Relevant medical field
Treatment planning	Bielak *et al.* (60)	Investigate the difference in segmentation performance of geometrically distorted and corrected diffusion-weighted data using data of patients with head and neck tumors	The CNN segmentation performance scored an average Dice coefficient of 0.40±0.18 for data including distortion-corrected ADC and 0.37±0.21 for uncorrected data. Paired t test revealed that the performance was not significantly different	CNNs	18 patients with head and neck tumors	Oncology, neurology
Treatment planning, assessing disease extent	Eresen *et al.* (61)	Develop and validate machine learning models that utilize either patient-characteristics or quantitative CT texture features for preoperative accurate diagnosis of metastasis in regional lymph nodes and to compare their performance with clinical diagnosis criteria for lymph nodes in colon cancer patients	The clinical model had a diagnostic accuracy of 65.38% and 62.82% for training and test cohorts. The patient-demographic model obtained an accuracy of 67.31% and 73.08% for training and test cohorts. The radiomic-derived model resulted in an accuracy of 81.09% and 79.49% for training and test cohorts	Kernel-based support vector machine classifiers (patient-characteristic model and radiomic-derived model)	390 colon cancer patients randomly separated into training (312 patients) and test cohorts (78 patients)	Oncology, hastroenterology
Clinical decision making, Treatment planning	Advanced Analytics Group of Pediatric Urology and ORC Personalized Medicine Group (62)	Develop a model to predict the probability of recurrent urinary tract infection associated vesicoureteral reflux in children after an initial urinary tract infection	The model predicted recurrent urinary tract infection associated vesicoureteral reflux with an AUC of 0.761 in the testing set	Optimal classification trees	500 subjects split into training, validation, and testing sets	Pediatric Urology
Clinical decision making, prognostication	Schmidt-Erfurth *et al.* (63)	Evaluate the potential of machine learning to predict BCVA outcomes from structural and functional assessments during the initiation phase in patients receiving standardized ranibizumab therapy for neovascular AMD	Computational image analysis enabled fully automated quantitative characterization of neovascular lesions in a large-scale clinical SD-OCT data set	Random forest regression model	614 patients receiving intravitreal ranibizumab monthly or pro re nata	Ophthalmology
Image reconstruction	Chen *et al.* (64)	To investigate the clinical feasibility of data-driven self-calibration and reconstruction of wave-encoded SSFSE imaging for computation time reduction and quality improvement	The proposed data-driven calibration and reconstruction achieved twice faster computation with reduced perceived noise, providing a fast and robust self-calibration and reconstruction for clinical abdominal SSFSE imaging	Data acquisition with a wave-encoded SSFSE Sequence	Clinical abdominal scanning was performed on 29 consecutive adult patients (18 males, 11 females, ranging from 24 to 77 years) on a 3T MRI scanner using a 32-channel torso coil and a 2D multi-slice wave-encoded SSFSE imaging sequence	N/a
Clinical decision making	Tomaszewski *et al.* (65)	Computational analysis of pre-accrual imaging data can be used for patient enrichment to better identify patients who can potentially benefit from investigational agents	Had an appropriate model been used for selective patient inclusion, SARC021 trial could have met its primary survival objective for patients with metastatic STS	Radiomic biomarker-driven inclusion/exclusion criterion	164 radiomics features were extracted from 296 SARC021 patients with lung metastases, divided into training and test sets	Oncology
Image interpretation	Cho *et al.* (66)	An angiography-based supervised ML algorithm was developed to classify lesions as having fractional flow reserve ≤0.80 versus >0.80	The angiography-based ML model shows good diagnostic performance for Identifying ischemia-producing lesions and may reduce future need for pressure wires and risk of procedural complications	XGBoost library	1,501 patients with 1,501 lesions were enrolled. They were randomly assigned into a training or test sample group at a 4:1 ratio. Thus, 1,204 patients were used for model training (training sample), and a nonoverlapping group of 297 patients was used for evaluating the diagnostic performance of the model	Cardiology
Image interpretation	van Gastel *et al.* (67)	Automatic measurement of kidney and liver volumes from MR images of patients affected by ADPKD	Developed fully automated segmentation method that measures TKV and TLV	DL model	80% of a set of 440 abdominal MR images from patients with ADPKD to train the network, remaining 20% used for validation	Nephrology
Image interpretation	Togo *et al.* (68)	dCNN-based features can represent the difference between CS and non-CS using polar maps	The dCNN-based high-level features may be more effective than low-level features used in conventional quantitative analysis methods for CS classification	ReliefF algorithm	85 patients (33 CS patients and 52 non-CS patients) were analyzed as our study subjects using PET/CT images	Cardiology
Clinical decision making	Shan *et al.* (69)	To construct a prediction model based on peritumoral radiomics signatures from CT images and investage its efficiency in predicting ER of hepatocellular carcinoma (HCC) after curative treatment	Peritumoral area for PT-RO signature is a powerful preoperative predictor for the ER of HCC	Radiomics features were automatically extracted from the RIOs by A.K. software through computing algorithms	156 patients with primary HCC were randomly divided into the training cohort (109 patients) and the validation cohort (47 patients)	Oncology

Table 2 (*continued*)

Table 2 (*continued*)

Category	Study	Objective	Results	Method (specific AI algorithm)	Dataset	Relevant medical field
Image interpretation	Weber *et al.* (70)	To develop dCNN models for efficient segmentation tasks in MFI	CNNs improve efficiency and objectivity of muscle measures allowing for the quantitative monitoring of muscle properties in disorders of and beyond the cervical spine	dCNN model	MRI datasets from 39 participants (26 female, average age ± SD = 31.7±9.3 years) were obtained from a prospective observational longitudinal study exploring recovery from whiplash	Orthopedics
Clinical decision making	Gates *et al.* (71)	To reduce glioma biopsy undersampling by estimating Ki-67 using MRI data against a stereotactic histopathology standard	Ki-67 can be predicted to clinically useful accuracies using clinical imaging data	Random forest algorithm	23 patients with 2–4 biopsies each, for a total of 52 biopsies and 52 virtual biopsies	Neurology, oncology
Quantification of disease	Eisenberg *et al.* (72)	Assess the prognostic value of deep learned EAT volume and attenuation measurements from cardiac CT in predicting MACE	ASCVD risk score, CAC, and EAT volume indicated an increased risk of MACE (hazard ratio =1.03, 1.25, and 1.35). EAT attenuation was inversely related with MACE (hazard ratio of 0.83) and measured a Harrell's C-statistic of 0.76	Automated Deep Learning algorithm incorporated into QFAT research software	2,068 asymptomatic subjects from the EISNER trial with available CT imaging data, no known CAD, and that have completed long term prognostic follow up	Cardiology
Quantification of disease	Dey *et al.* (73)	Asses if a machine learning ischemic risk score from quantitative CTA plaque measures can accurately predict lesion-specific ischemia by invasive fractional flow reserve	Machine learning had a higher AUC (0.84) than CTA in measures of stenosis (0.76), low density non-calcified plaque volume (0.77), total plaque volume (0.74) and pretest likelihood of CAD (0.63)	Boosted ensemble algorithm	254 patients from the NXT trial with suspected stable CAD, and having undergone coronary CTA less than 60 days prior to invasive coronary angiography	Cardiology
Classification of disease	Toivonen *et al.* (74)	Validate a classifier system that uses radiomics and texture features of T2w, diffusion weighted imaging, and T2-mapping to predict prostatic cancer Gleason score	Out of 100 of the prostatic lesions analyzed, 20 had Gleason scores of 3+3, and 80 had scores of >3+3. Model performance was greatest by selecting the top 1% features of T2w, apparent diffusion coefficient of the monoexponential function, and K. Resulted in AUC of 0.88	Regularized logistic regression	100 prostatic cancer lesions from the MRI data of 62 patients. 67 of these lesions were located in the peripheral zone and 33 were in the central gland	Urology/oncology
Classification of disease	Ou *et al.* (75)	Assess PET and CT radiomic capabilities in distinguishing breast carcinoma from breast lymphoma using a machine learning approach	The PETa model and the CTa model had the greatest capability in differentiating the two cancers in the training and validation groups. PETa model had AUC values of 0.867 and 0.806, while the CTa model had AUC values of 0.891 and 0.759, respectively	Linear Discriminant analysis	44 patients with either breast cancer (25) or breast lymphoma (19) who received a ^{18}F-FDG PET/CT scan in West China Hospital of Sichuan University from October 2013 to March 2018	Oncology
Classification of disease	Kurata *et al.* (76)	Evaluate the diagnostic capability of CT-FFR determinations for detecting coronary artery disease. Assessed by invasive FFR	CT-FFR and invasive FFR had a correlation coefficient of 0.786 when detecting CAD in 47 vessels of 42 patients. CT-FFR corrected standard coronary CTA classifications in 18 of the patients, and confirmed classification in 45 patients. Ultimately, the per patient accuracy of classifying CAD was increased from 66% to 85%	Prototype Machine learning algorithm	Retrospective review of 74 patients with calcium scores less than 1,500 who underwent CT-FFR and invasive FFR within 90 days of one another	Cardiology
Assessing disease extent	Dong *et al.* (77)	Evaluate the performance of an infrared thermal imaging system when detecting cervical lymph node metastasis from oral cancer	EGSVM-based Infrared analysis compared to manual qualitative analysis resulted in higher sensitivity (84.8% *vs.* 71.7%), specificity (77.3% *vs.* 72.7%), accuracy (81.1% *vs.* 72.2%), positive predictive value (79.6% *vs.* 73.3%), and negative predictive value (82.9% *vs.* 71.1%). EGSVM- based IR analysis showed a trend of higher sensitivity, whereas contrast enhanced CT showed trends of higher specificity	EGSVM	90 patients who were scheduled for neck dissection with resection of previous untreated oral cancer. 46 out of 90 of the patients were suspected of pre-surgery metastasis based on contrast enhanced CT and physical examination	Oncology/ Otolaryngology
Assessing disease extent	Jun *et al.* (78)	Evaluate deep learned 3D BB imaging with an auto labeling technique and 3D Convolutional neural networks for detecting brain metastases. This would eliminate the need for an additional BB scan	Figure of merits values were 0.9708 with deep-learned BB imaging and 0.9437 with original BB imaging when comparing diagnostic performance. Sensitivities were 100% for both models, but original BB imaging recorded false positives in two patients. Sensitivities were 90.3% for deep learned BB and 100% for original BB imaging in per-lesion analysis. Per-lesion original BB imaging had eight false positives compared to deep-learned BB imaging's single false positive	3D convolutional neural network	Records of 124 MRI studies between March and June of 2017 were retrieved from a radiology database. 29 of the 124 patients who underwent MRI evaluation for metastasis were randomly selected for the training set, and 36 for the testing set. The testing set contained 18 patients with metastases and 18 patients without metastasis	Oncology/ Neurology
Classification of disease	Ginsburg *et al.* (79)	Determine if the computer extracted texture features useful for detection of prostate cancer in multiparametric 3 Tesla MRI are similar or differ between the transition zone and peripheral zone of the prostate	The useful radiomic features identified for prostate cancer detection in the peripheral zone were different from those useful for detecting transition zone tumors. On an independent test set, a peripheral zone specific classifier detected peripheral zone tumors with greater accuracy (AUC 0.61-0.71) than a non-specific classifier trained to detect cancer spanning the entire prostate	Logistic regression classifier	Study included 80 patients from Turku University Hospital, St. Vincent's hospital, and Mt. Sinai Hospital. All patients had a multiparametric MRI performed for prostatic cancer suspicion prior to prostate biopsy or prostatectomy	Oncology/Urology

Table 2 (*continued*)

Table 2 (*continued*)

Category	Study	Objective	Results	Method (specific AI algorithm)	Dataset	Relevant medical field
Image Interpretation	Sheng *et al.* (80)	To evaluate the accuracy of diffusion weighted imaging based off of a higher order singular value decomposition denoising algorithm (GL-HOSVD) in detecting ischemic penumbra in patients with early, acute cerebral infarctions	GL-HOSVD had better peak signal-to-noise ratio and root mean square error of the FA parameter when compared to nonlocal means of deviation correction and the low rank edge algorithm. The GL-HOSVD algorithm had a higher sensitivity (87.6% *vs.* 57.8%), specificity (81.25% *vs.* 53.33%), accuracy (87.62% *vs.* 57.14%), and consistency (0.52 *vs.* 0.35) when compared to standard diffusion weighted imaging	Higher Order Singular Value Decomposition denoising algorithm	210 patients with acute cerebral infarction were selected as research subjects and randomly assorted into two groups. 105 patients selected for the conventional DWI, and 105 selected for GL-HOSVD	Neurology
Image interpretation	Aydoseli *et al.* (81)	To introduce an early warning system that utilizes a supervised machine learning algorithm to quickly detect extra axial hematomas in emergency settings	An alarm was transmitted for all CTs with an EAH, giving this imaging modality a 0% false-negative. In 16% of cases an alarm was sent that a patient might have a EAH despite normal CT findings. Respective positive and negative predictor values of 86% and 100%	Random forest algorithm	This study pulled from 150 sets of cranial CT scans composing a total of 11,025 images. 75 of the CT scans selected for the study showed an extra axial hematoma, while the other 75 scans were normal	Neurology
Prognostication	Huang *et al.* (82)	To validate a CT based nomogram that utilizes radiomic and clinical-radiological features from nodular and perinodular areas to differentiate preinvasive lesions from pulmonary invasive lesions	The AUCs for the combined radiomic signature from the nodular and perinodular areas were 0.93, 0.91, and 0.90 from three institutions. The nomogram with clinical and combined radiomic signatures predicted interstitial invasion in solitary pulmonary nodule-having patients with AUC values of 0.94, 0.90, and 0.92. Decision curve analysis and Akaike criteria concluded the radiomic nanogram outperformed any clinical or radiomic signatures	LASSO algorithm, logistic regression analysis	373 patients who underwent CT scanning that showed a solitary pulmonary nodule for the first time. Additional inclusion criteria were having a contrast enhanced CT scan within the past 3 months, pathologically confirmed precancerous lesions, and lesions less than 30 mm with no metastases	Oncology/ pulmonary
Prognostication	Yu *et al.* (83)	Design and evaluate a CT based radiomics nomogram that assists in predicting extrathyroidal extension in patients with papillary thyroid cancer	There were 4 radiomic features selected. The 6 models showed the value of radiomics by having AUC values ranging from 0.642–0.701. The nomogram that combined the Rad-score with clinical risk factors showed improved performance with AUC values of 0.750 for the internal test set and 0.797 for the external test set	Least absolute shrinkage and selection operator, K nearest neighbor, logistic regression, decision tree, linear SVM, gaussian-SVM, polynomial-SVM	Retrospective study including 153 patients from Yantai Yuhuangding Hospital were randomly assigned to either a training set or an internal testing at a 7:3 ratio, 46 additional patients from Qilu Hospital of Shandong University served as an external test set	Oncology/ endocrinology

AI, artificial intelligence; CTA, computed tomographic angiography; CNN, convolutional neural network; ML, machine learning; MRI, magnetic resonance imaging; ALN, axillary lymph node; AUC, area under the curve; APCs, atherosclerotic plaque characteristics; AI-QCT, AI enabled quantitative coronary computed tomographic angiography; LD-NCP, low-density non-calcified plaque; VGG, visual geometry group; CREDENCE, Computed TomogRaphic Evaluation of Atherosclerotic Determinants of Myocardial Is-ChEmia; DCGAN, deep convolutional generative adversarial network; MACE, major adverse cardiovascular events; MBF, myocardial blood flow; MPR, myocardial perfusion reserve; CT, computed tomography; ACL, anterior cruciate ligament; PPV, positive predictive value; DTS, digital tomosynthesis; LBF, local binary fitting; LDH, lumbar disc herniation; ICH, intracranial hemorrhages; FCM, fuzzy C-means; HCM, hard C-means; GIF, guided image filtering; CTE, CT enterography; UC, ulcerative colitis; CD, Crohn's disease; CCE, colon capsule endoscopies; CTC, computed tomography colonography; OC, optical colonoscopy; CSF, cerebrospinal fluid; SPECT, single photon emission computerized tomography; CI, confidence interval; ADC, apparent diffusion coefficient; CBV, cerebral blood volume; DME, diabetic macular edema; OCT, optical coherence tomography; IRC, intraretinal cystoid fluid; PDAC, pancreatic ductal adenocarcinoma; TOF, time-of-flight; MRA, magnetic resonance angiography; IWT, improved wavelet transform; CKD, chronic kidney disease; PPA, parotid pleomorphic adenoma; PA, parotid adenolymphoma; FNAC, fine needle aspiration cytology; QLF, qualitative lung fibrosis; HRCT, high resolution computed tomography; QLF, qualitative lung fibrosis; QILD, quantitative interstitial lung disease; IVUS, intravascular ultrasound; PET, positron emission tomography; DCE-MRI, dynamic contrast enhanced magnetic resonance imaging; SSIM, structural similarity index measure; dCNN, deep convolutional neural network; CGAN, conditional general adversarial neural networks; SRH, stimulated Raman histology; HICH, hypertensive intracerebral hemorrhage; RF, Random forest; SMA, skeletal muscle area; SMD, skeletal muscle density; ICP, intracranial pressure; PC-MRI, phase-contrast cine MRI; fMRI, functional magnetic resonance imaging; SPM12, statistical parametric mapping 12 software; ANTS, advanced normalization tools; CAD, coronary artery disease; TDA, topological data analysis; TBI, traumatic brain injury; CDEs, common data elements; sPSTA, Cardiac Phase Space Tomography Analysis; BCVA, best-corrected visual acuity; AMD, age-related macular degeneration; SSFSE, single-shot fast spin echo; STS, soft tissue sarcoma; ML, machine learning; XGBoost, eXtreme Gradient Boosting; TKV, total kidney volume; TLV, total liver volume; ADPKD, autosomal dominant polycsytic kidney disease; CS, cardiac sarcoidosis; PT-RO, peritumoral radiomics; ER, early recurrence; MFI, muscle fat infiltration; EAT, epicardial adipose tissue; ASCVD, atherosclerotic cardiovascular disease; T2w, T2-weighted imaging; FFR, fractional flow reserve; EGSVM, entropy gradient support vector machine; EAH, extra axial hematoma; LASSO, least absolute shrinkage and selection operator; SVM, support vector machine; BB, Black-Blood.

found superior signal-to-noise ratio (SNR) and carrier-to-noise ratio (CNR) using the iDose4 algorithm compared to conventional filtered back projection (FBP) techniques. The iDose4 reconstruction algorithm allowed for greater diagnostic accuracy with simultaneous reduced tube voltage. However, Zhang *et al.*'s work primarily centered around trauma patients recovering from anterior cruciate ligament injury, and may not be generalizable to all CT imaging applications (23). Further work by Fan *et al.* demonstrates the usefulness of an active contour segmentation algorithm in the evaluation of treatment response in patients with lumbar disc herniation (LDH). The authors demonstrated superior efficacy of the AI algorithm compared to traditional methods (25).

Jiang *et al.*'s work with ulcerative colitis (UC) and Crohn's disease (CD) patients demonstrated significantly greater noise reduction by using edge-aware weighting factors in guided image filtering (GIF) algorithms. Compared to standard GIF, weighted GIF (WGIF), and gradient domain GIF (GGIF), the AI-modified GIF produced better results with optimized diagnostic capability in detecting abnormalities in the intestinal wall and intraluminal lesions associated with UC and CD (28).

Applications in MRI reconstruction

DL algorithms have demonstrated varying usefulness in the post processing of MRI studies. Harper *et al.* found that while DL enhancement can substantially increase the contrast-to-noise in reduced-quality images obtained from low-field MRI technology, there was an increased risk of introducing structural errors creating the risk of incorrect clinical interpretations (30). However, Jayachandran *et al.*'s work found that deep CNNs (dCNNs) are useful for applying synthetic contrast to MRIs performed without IV contrast. Studies have shown gadolinium-based contrast agents (GBCAs) accumulate in the brain from repeated contrast administration. Despite the unknown clinical significance of GBCA accumulation, avoiding contrast administration may be beneficial, especially for patients with contrast allergy or impaired renal function. Although segmentation of contrast-enhancing tumors from synthetic post-contrast T1-weighted sequences underestimated the tumor's true volume, there was no difference in patients' predicted overall survival (48).

dCNNs may also increase the accuracy and reduce computational time for single-shot fast spin echo (SSFSE) imaging reconstruction. Chen *et al.* compared the image quality of a dCNN-driven reconstruction approach compared to conventional techniques. There was an average 2.1-fold increase in computation speed with corresponding reduced perceived noise level with the data-driven self-calibration and reconstruction approach (64).

Image interpretation

Applications in MRI

ML has proven useful in interpreting magnetic resonance scans of the head. Applications in neuroradiology include non-invasive prediction of intracranial pressure (52), automated detection of unruptured intracranial aneurysms (40), DL-driven black blood (BB) imaging for brain metastasis detection (78), and diagnosis of ischemic penumbra (80).

Non-neuroradiology applications

Cardiovascular MR perfusion mapping

Other applications of DL in the MR modality include deducing risk of adverse cardiovascular outcomes from cardiovascular MR perfusion mapping. An existing commercially available software known as CV142 (Circle cardiovascular imaging, Calgary, AB, Canada) has shown to accurately predict myocardial blood flow and myocardial perfusion reserve—indicators of cardiovascular risk (21).

Endometriosis detection

In gynecology, Jiang *et al.* found greater sensitivity and specificity for the diagnosis of ovarian endometriosis with an AI-driven fuzzy C-means clustering algorithm used for pattern recognition compared to a conventional hard C-means (HCM) approach (27).

Prostate cancer

AI found further success in predicting pathological data from radiomic features in Toivonen *et al.*'s work on diffuse-weighted imaging texture feature analysis for the prediction of Gleason score in prostate cancer patients (74). Further work in prostate cancer by Ginsburg *et al.* showed the benefit of a zone-aware classifier for accurate detection of cancerous lesions in the peripheral zone. Logistic regression classifiers found distinct radiomic features associated with prostate cancer in the transitional zone versus the peripheral zone (79).

Neuroradiology applications

Glioma grading

The random forest ML algorithm can train on image data to effectively estimate local glioma grade. Gates *et al.* demonstrated accurate prediction of pathology data from imaging input using these predictive models, with up to 96% accuracy in tumor grade prediction (36).

Parotid lesion differentiation

Song *et al.* employed the support vector machine (SVM) ML algorithm, which was more capable of differentiating parotid pleomorphic adenoma from parotid adenolymphoma than traditional pathological and physical diagnostic methods (43).

Intracranial pressure prediction

Intracranial pressure (ICP) prediction through Levenberg-Marquardt and general global optimization methods demonstrated remarkable accuracy for predicting ICP—0.899 in the training cohort (n=97) and 0.861 in the independent validation cohort (n=41) (52).

Aneurysm detection

Joo *et al.*'s work employed a DL model for detection of unruptured intracranial aneurysms on MRA imaging with sensitivity of 87% and specificity of 92%. Using the open-source 3D ResNet ML framework, a DL model with diagnostic performance comparable to that of a human radiologist was trained and validated. Out of 168 aneurysms, 13 aneurysms from 12 examinations were missed in total (40).

Brain metastases detection

Jun *et al.* developed a "deep-learned" 3D BB imaging with corresponding 3D CNN for brain metastases detection without conducting an additional BB scan. The figure of merits, corresponding to the diagnostic performance of radiologists, were 0.9708 with DL-derived BB scan and 0.9437 with conventional BB imaging. There was no significant difference in diagnostic performance between the methods, suggesting that DL 3D BB imaging is effective for brain metastasis detection (78).

Applications in CT

This systematic review found several applications of ML in the interpretation of CT scans for the diagnosis and management of cancer patients. Additional uses included intracranial hemorrhage detection and cardiac evaluation.

Lung cancer

Chauvie *et al.* found greater positive predictive value in lung cancer detection with AI compared to the Lung CT Screening Reporting and Data Systems (lung-RADS) classification system (24). The transfer learning (TL) features were extracted using the widely available CNN model, LungTrans, which was pretrained on non-small cell lung cancer images. The fused DL-TL model achieving a 40% increase in area under the curve (AUC) compared to traditional feature fusion and reduction methods (39). Further work by Eresen *et al.* showed the superior performance of an ML-derived classification model compared to a clinical model in the diagnosis of lymph node metastasis (61).

Pancreatic cancer

Zhang *et al.*'s work focused on a prototype algorithm featuring radiomics combined with transfer learning feature detection for pancreatic ductal adenocarcinoma (PDAC) detection (39).

Cardiac sarcoidosis

Other benefits of a ML approach included the differentiation of cardiac sarcoidosis (CS) and non-CS using polar maps through use of the ReliefF algorithm (68).

Cardiac CTA

Dey *et al.* and Kurata *et al.* reported greater effectiveness of an ML-based approach in the evaluation of coronary computed tomographic angiography (CTA). Dey demonstrated improved prediction of lesion-specific ischemia through an ML-driven feature selection model built from quantitative CTA compared to methods using plaque measurement or clinical assessments of pre-test likelihood of coronary artery disease (CAD) (73). A commercially available prototype, cFFR version 3.0.0 (Siemens Healthcare) provided good diagnostic performance for detecting hemodynamically significant CAD (76).

Intracranial hemorrhage (ICH) detection

ML-driven algorithms found additional success in neuroradiological applications including the detection of extra-axial hematomas in cranial CT in the emergency trauma setting, detection of intracranial hemorrhage (ICH) detection, and prognostication of hypertensive ICH (26,50,81). Kundisch *et al.* found 12.2% increased ICH detection when human expertise was aided by the commercially available AIDOC (Tel Aviv, Israel) detection software (26).

Clinical decision making

The applications of AI in clinical decision making and prognostication are diverse with 15 articles covering oncology, 5 in neurology, and 2 in cardiology. Other relevant specialties in this topic included ophthalmology, urology, nephrology, and pulmonology.

In oncology, many authors focused on the use of ML algorithms in predicting tumor distribution for preoperative analysis (18,33,38,42,60,61,69,82,83). Other oncological papers used AI to predict prognosis, specifically time-to-event and mortality quantification (38,57). In the cardiology space, Jonas *et al.* found that quantitative coronary CTA identifies unique atherosclerotic plaque characteristics for personalized prevention and treatment of atherosclerotic cardiovascular disease (19). Further work by Min *et al.* showed successful use of DL algorithm to predict incomplete stent expansion to guide treatment decisions to avoid preventable stent failures (45). In ophthalmology, Schmidt-Erfurth *et al.* used validated, fully automated computational image analysis to extract biomarkers from optical coherence tomography (OCT) for accurate prediction of best-corrected visual acuity outcomes (63). ML-based prediction of recurrent urinary tract infections (UTIs) in pediatric patients to guide decision for voiding cystourethrogram (VCUG) is possible (62). Chen *et al.* built a newly improved wavelet transform algorithm for CT evaluation of chronic kidney disease (CKD) to guide nursing management (41). Lastly, Kim *et al.* developed a ML-driven quantitative CT score as a secondary efficacy endpoint for the treatment of idiopathic pulmonary fibrosis (IPF) (44). All authors employed a combination of open source, proprietary, and novel AI algorithms for data processing.

Conclusions

Our review highlights recent AI-based algorithms applied MRI and CT and their application within various medical specialties. Many of the articles in this review demonstrated preliminary success of AI-based algorithms. Many studies concluded that their findings have the potential to improve radiology by improving image quality through image reconstruction, providing accurate image interpretation, and evaluating characteristics in studies to aid in clinical decision making.

It is important to note that the use of AI in radiology for detection of pathology is not a new concept. For example, the Food and Drug Administration (FDA) approved the first computer aided detection (CAD) application for breast mammograms in 1998. Nowadays, most breast cancer screening mammograms are interpreted by radiologists who use CAD assistance (85). The majority of current AI applications primarily complete perception and reasoning tasks that include, but are not limited to, quantification of features, detecting suspicious areas, and diagnosing and classifying abnormalities (1).

Although AI in radiology presents itself as an avenue for improvement of patient care, there remains limitations and concerns regarding its use. One prominent limitation in the use of deep learning methods is the black box problem, in which AI applications are unable to explain their results. In comparison, radiologists are able to provide thorough explanations for their interpretations (86). Other limitations include the ability of most AI applications to target only one anatomic region while some applications have difficulty integrating into an existing workflow, which might compromise productivity (85,87). One concern is the potential use of improper data that might incorporate biases into the algorithm. For example, data with evident gender and racial biases may be used to create a biased algorithm. In addition, inadequate data pools can fail to provide enough variation to train and validate AI algorithms, which could lead to suboptimal detection and diagnosis of pathologies (88).

The advancement in the development of AI in radiology is promising in its ability to contribute to improved patient care through improved radiologist efficiency and accuracy. Future opportunities of AI in radiology include improving accuracy of classifiers to identify and flag irregularities with minimal radiologist oversight. Such irregularities may include abnormal chest radiograph, detection of intracranial hemorrhage, or low-quality images. Detection and flagging of imaging requiring urgent care would alert the radiologist and possible reduce the time from diagnosis to treatment, thereby providing faster care to patients (86). It is also predicted that deep learning may help with routine tasks, giving the radiologist more time to generate final decisions regarding imaging studies (89). Furthermore, if medical facilities around the world develop strategies to share databases that are absent of patient identifiers, then deep learning models would have a larger dataset with more variety that would provide a more robust better training, while minimizing the risk of introducing biases to the algorithm. As previously mentioned, there remains apprehension regarding the implementation of AI in radiology. Moving forward, collaboration between radiologists and developers should be encouraged to address the concerns and limitations regarding the realistic use of AI in radiology.

Acknowledgments

Funding: None.

Footnote

Reporting Checklist: The authors have completed the Narrative Review reporting checklist. Available at https://jmai.amegroups.com/article/view/10.21037/jmai-22-89/rc

Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at https://jmai.amegroups.com/article/view/10.21037/jmai-22-89/coif). The authors have no conflicts of interest to declare.

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

References

1. Lee SI, Celik S, Logsdon BA, et al. A machine learning approach to integrate big data for precision medicine in acute myeloid leukemia. Nat Commun 2018;9:42.
2. Vial A, Stirling D, Field M, et al. The role of deep learning and radiomic feature extraction in cancer-specific predictive modelling: a review. Transl Cancer Res 2018;7:803-16.
3. Litjens G, Kooi T, Bejnordi BE, et al. A survey on deep learning in medical image analysis. Med Image Anal 2017;42:60-88.
4. Mamoshina P, Vieira A, Putin E, et al. Applications of Deep Learning in Biomedicine. Mol Pharm 2016;13:1445-54.
5. Li Y, Huang C, Ding L, et al. Deep learning in bioinformatics: Introduction, application, and perspective in the big data era. Methods 2019;166:4-21.
6. Vaz JM, Balaji S. Convolutional neural networks (CNNs): concepts and applications in pharmacogenomics. Mol Divers 2021;25:1569-84.
7. Kolossváry M, Kellermayer M, Merkely B, et al. Cardiac Computed Tomography Radiomics: A Comprehensive Review on Radiomic Techniques. J Thorac Imaging 2018;33:26-34.
8. Coroller TP, Grossmann P, Hou Y, et al. CT-based radiomic signature predicts distant metastasis in lung adenocarcinoma. Radiother Oncol 2015;114:345-50.
9. Huynh E, Coroller TP, Narayan V, et al. Associations of Radiomic Data Extracted from Static and Respiratory-Gated CT Scans with Disease Recurrence in Lung Cancer Patients Treated with SBRT. PLoS One 2017;12:e0169172.
10. Parmar C, Grossmann P, Bussink J, et al. Machine Learning methods for Quantitative Radiomic Biomarkers. Sci Rep 2015;5:13087.
11. McDonald RJ, Schwartz KM, Eckel LJ, et al. The effects of changes in utilization and technological advancements of cross-sectional imaging on radiologist workload. Acad Radiol 2015;22:1191-8.
12. Gjesteby L, Cong W, Wang G. Numerical study on simultaneous emission and transmission tomography in the MRI framework. In: Müller B, Wang G, editors. Developments in X-Ray Tomography XI. SPIE; 2017:14. doi: 10.1117/12.2272505.
13. El-Gamal FEZA, Elmogy M, Atwan A. Current trends in medical image registration and fusion. Egypt Inform J 2016;17:99-124.
14. Yang X, Kwitt R, Styner M, et al. Quicksilver: Fast predictive image registration - A deep learning approach. Neuroimage 2017;158:378-96.
15. RSNA 2017 Celebrates Innovation in Radiology. Accessed August 11, 2022. Available online: https://press.rsna.org/timssnet/media/pressreleases/14_pr_target.cfm?ID=1997
16. Exhibitors and sponsors. Accessed August 11, 2022. Available online: https://www.rsna.org/annual-meeting/exhibitors-and-sponsors
17. Park A, Chute C, Rajpurkar P, et al. Deep Learning-Assisted Diagnosis of Cerebral Aneurysms Using the HeadXNet Model. JAMA Netw Open 2019;2:e195600.
18. Yu Y, He Z, Ouyang J, et al. Magnetic resonance imaging radiomics predicts preoperative axillary lymph node metastasis to support surgical decisions and is associated with tumor microenvironment in invasive breast cancer: A machine learning, multicenter study. EBioMedicine 2021;69:103460.
19. Jonas R, Earls J, Marques H, et al. Relationship of age, atherosclerosis and angiographic stenosis using artificial intelligence. Open Heart 2021;8:e001832.
20. Liang Y, Huan J, Li JD, et al. Use of artificial intelligence to recover mandibular morphology after disease. Sci Rep 2020;10:16431.

21. Knott KD, Seraphim A, Augusto JB, et al. The Prognostic Significance of Quantitative Myocardial Perfusion: An Artificial Intelligence-Based Approach Using Perfusion Mapping. Circulation 2020;141:1282-91.
22. Liu Y, Tang S. Artificial Intelligence Algorithm-Based Computed Tomography Image of Both Kidneys in Diagnosis of Renal Dysplasia. Comput Math Methods Med 2022;2022:5823720.
23. Zhang H, Zheng H, Deng R, et al. Computed Tomography Imaging under Artificial Intelligence Reconstruction Algorithm Used in Recovery of Sports Injury of the Knee Anterior Cruciate Ligament. Contrast Media Mol Imaging 2022;2022:1199841.
24. Chauvie S, De Maggi A, Baralis I, et al. Artificial intelligence and radiomics enhance the positive predictive value of digital chest tomosynthesis for lung cancer detection within SOS clinical trial. Eur Radiol 2020;30:4134-40.
25. Fan X, Qiao X, Wang Z, et al. Artificial Intelligence-Based CT Imaging on Diagnosis of Patients with Lumbar Disc Herniation by Scalpel Treatment. Comput Intell Neurosci 2022;2022:3688630.
26. Kundisch A, Hönning A, Mutze S, et al. Deep learning algorithm in detecting intracranial hemorrhages on emergency computed tomographies. PLoS One 2021;16:e0260560.
27. Jiang N, Xie H, Lin J, et al. Diagnosis and Nursing Intervention of Gynecological Ovarian Endometriosis with Magnetic Resonance Imaging under Artificial Intelligence Algorithm. Comput Intell Neurosci 2022;2022:3123310.
28. Jiang F, Fu X, Kuang K, et al. Artificial Intelligence Algorithm-Based Differential Diagnosis of Crohn's Disease and Ulcerative Colitis by CT Image. Comput Math Methods Med 2022;2022:3871994.
29. Deding U, Kaalby L, Bøggild H, et al. Colon Capsule Endoscopy vs. CT Colonography Following Incomplete Colonoscopy: A Systematic Review with Meta-Analysis. Cancers (Basel) 2020;12:3367.
30. Harper JR, Cherukuri V, O'Reilly T, et al. Assessing the utility of low resolution brain imaging: treatment of infant hydrocephalus. Neuroimage Clin 2021;32:102896.
31. Zhang X, Wang Z, Liu J, et al. Value of Rehabilitation Training for Children with Cerebral Palsy Diagnosed and Analyzed by Computed Tomography Imaging Information Features under Deep Learning. J Healthc Eng 2021;2021:6472440.
32. Huang Z, Liu D, Chen X, et al. Retrospective imaging studies of gastric cancer: Study protocol clinical trial (SPIRIT Compliant). Medicine (Baltimore) 2020;99:e19157.
33. Liu P, Tan XZ, Zhang T, et al. Prediction of microvascular invasion in solitary hepatocellular carcinoma ≤ 5 cm based on computed tomography radiomics. World J Gastroenterol 2021;27:2015-24.
34. Deng Y, Pan L, Xing W, et al. Application of BOLD-MRI-based radiomics in differentiating malignant from benign renal tumors. Zhong Nan Da Xue Xue Bao Yi Xue Ban 2021;46:1010-7.
35. Sharrock MF, Mould WA, Ali H, et al. 3D Deep Neural Network Segmentation of Intracerebral Hemorrhage: Development and Validation for Clinical Trials. Neuroinformatics 2021;19:403-15.
36. Gates EDH, Lin JS, Weinberg JS, et al. Imaging-Based Algorithm for the Local Grading of Glioma. AJNR Am J Neuroradiol 2020;41:400-7.
37. Gerendas BS, Bogunovic H, Sadeghipour A, et al. Computational image analysis for prognosis determination in DME. Vision Res 2017;139:204-10.
38. Bhattarai S, Klimov S, Aleskandarany MA, et al. Machine learning-based prediction of breast cancer growth rate in vivo. Br J Cancer 2019;121:497-504.
39. Zhang Y, Lobo-Mueller EM, Karanicolas P, et al. Improving prognostic performance in resectable pancreatic ductal adenocarcinoma using radiomics and deep learning features fusion in CT images. Sci Rep 2021;11:1378.
40. Joo B, Choi HS, Ahn SS, et al. A Deep Learning Model with High Standalone Performance for Diagnosis of Unruptured Intracranial Aneurysm. Yonsei Med J 2021;62:1052-61.
41. Chen X, Huang X, Yin M. Implementation of Hospital-to-Home Model for Nutritional Nursing Management of Patients with Chronic Kidney Disease Using Artificial Intelligence Algorithm Combined with CT Internet. Contrast Media Mol Imaging 2022;2022:1183988.
42. Wang XX, Ding Y, Wang SW, et al. Intratumoral and peritumoral radiomics analysis for preoperative Lauren classification in gastric cancer. Cancer Imaging 2020;20:83.
43. Song LL, Chen SJ, Chen W, et al. Radiomic model for differentiating parotid pleomorphic adenoma from parotid adenolymphoma based on MRI images. BMC Med Imaging 2021;21:54.
44. Kim GHJ, Goldin JG, Hayes W, et al. The value of imaging and clinical outcomes in a phase II clinical trial of a lysophosphatidic acid receptor antagonist in idiopathic pulmonary fibrosis. Ther Adv Respir Dis 2021;15:17534666211004238.

45. Min HS, Ryu D, Kang SJ, et al. Prediction of Coronary Stent Underexpansion by Pre-Procedural Intravascular Ultrasound-Based Deep Learning. JACC Cardiovasc Interv 2021;14:1021-9.
46. Papp L, Spielvogel CP, Grubmüller B, et al. Supervised machine learning enables non-invasive lesion characterization in primary prostate cancer with [68Ga] Ga-PSMA-11 PET/MRI. Eur J Nucl Med Mol Imaging 2021;48:1795-805.
47. Zhu Z, Albadawy E, Saha A, et al. Deep learning for identifying radiogenomic associations in breast cancer. Comput Biol Med 2019;109:85-90.
48. Jayachandran Preetha C, Meredig H, Brugnara G, et al. Deep-learning-based synthesis of post-contrast T1-weighted MRI for tumour response assessment in neuro-oncology: a multicentre, retrospective cohort study. Lancet Digit Health 2021;3:e784-94.
49. Pekmezci M, Morshed RA, Chunduru P, et al. Detection of glioma infiltration at the tumor margin using quantitative stimulated Raman scattering histology. Sci Rep 2021;11:12162.
50. Xu X, Zhang J, Yang K, et al. Prognostic prediction of hypertensive intracerebral hemorrhage using CT radiomics and machine learning. Brain Behav 2021;11:e02085.
51. Lenchik L, Barnard R, Boutin RD, et al. Automated Muscle Measurement on Chest CT Predicts All-Cause Mortality in Older Adults From the National Lung Screening Trial. J Gerontol A Biol Sci Med Sci 2021;76:277-85.
52. Long J, Sun D, Zhou X, et al. A mathematical model for predicting intracranial pressure based on noninvasively acquired PC-MRI parameters in communicating hydrocephalus. J Clin Monit Comput 2021;35:1325-32.
53. Mokhtari F, Rejeski WJ, Zhu Y, et al. Dynamic fMRI networks predict success in a behavioral weight loss program among older adults. Neuroimage 2018;173:421-33.
54. He L, Li H, Wang J, et al. A multi-task, multi-stage deep transfer learning model for early prediction of neurodevelopment in very preterm infants. Sci Rep 2020;10:15072.
55. Rastegar S, Vaziri M, Qasempour Y, et al. Radiomics for classification of bone mineral loss: A machine learning study. Diagn Interv Imaging 2020;101:599-610.
56. Zhang W, Yin H, Huang Z, et al. Development and validation of MRI-based deep learning models for prediction of microsatellite instability in rectal cancer. Cancer Med 2021;10:4164-73.
57. Afshar P, Mohammadi A, Tyrrell PN, et al. [Formula: see text]: deep learning-based radiomics for the time-to-event outcome prediction in lung cancer. Sci Rep 2020;10:12366.
58. Nielson JL, Cooper SR, Yue JK, et al. Uncovering precision phenotype-biomarker associations in traumatic brain injury using topological data analysis. PLoS One 2017;12:e0169490.
59. Stuckey TD, Gammon RS, Goswami R, et al. Cardiac Phase Space Tomography: A novel method of assessing coronary artery disease utilizing machine learning. PLoS One 2018;13:e0198603.
60. Bielak L, Wiedenmann N, Nicolay NH, et al. Automatic Tumor Segmentation With a Convolutional Neural Network in Multiparametric MRI: Influence of Distortion Correction. Tomography 2019;5:292-9.
61. Eresen A, Li Y, Yang J, et al. Preoperative assessment of lymph node metastasis in Colon Cancer patients using machine learning: a pilot study. Cancer Imaging 2020;20:30.
62. Advanced Analytics Group of Pediatric Urology and ORC Personalized Medicine Group. Targeted Workup after Initial Febrile Urinary Tract Infection: Using a Novel Machine Learning Model to Identify Children Most Likely to Benefit from Voiding Cystourethrogram. J Urol 2019;202:144-52.
63. Schmidt-Erfurth U, Bogunovic H, Sadeghipour A, et al. Machine Learning to Analyze the Prognostic Value of Current Imaging Biomarkers in Neovascular Age-Related Macular Degeneration. Ophthalmol Retina 2018;2:24-30.
64. Chen F, Cheng JY, Taviani V, et al. Data-driven self-calibration and reconstruction for non-cartesian wave-encoded single-shot fast spin echo using deep learning. J Magn Reson Imaging 2020;51:841-53.
65. Tomaszewski MR, Fan S, Garcia A, et al. AI-Radiomics Can Improve Inclusion Criteria and Clinical Trial Performance. Tomography 2022;8:341-55.
66. Cho H, Lee JG, Kang SJ, et al. Angiography-Based Machine Learning for Predicting Fractional Flow Reserve in Intermediate Coronary Artery Lesions. J Am Heart Assoc 2019;8:e011685.
67. van Gastel MDA, Edwards ME, Torres VE, et al. Automatic Measurement of Kidney and Liver Volumes from MR Images of Patients Affected by Autosomal Dominant Polycystic Kidney Disease. J Am Soc Nephrol 2019;30:1514-22.
68. Togo R, Hirata K, Manabe O, et al. Cardiac sarcoidosis classification with deep convolutional neural network-based features using polar maps. Comput Biol Med 2019;104:81-6.

69. Shan QY, Hu HT, Feng ST, et al. CT-based peritumoral radiomics signatures to predict early recurrence in hepatocellular carcinoma after curative tumor resection or ablation. Cancer Imaging 2019;19:11.
70. Weber KA, Smith AC, Wasielewski M, et al. Deep Learning Convolutional Neural Networks for the Automatic Quantification of Muscle Fat Infiltration Following Whiplash Injury. Sci Rep 2019;9:7973.
71. Gates EDH, Lin JS, Weinberg JS, et al. Guiding the first biopsy in glioma patients using estimated Ki-67 maps derived from MRI: conventional versus advanced imaging. Neuro Oncol 2019;21:527-36.
72. Eisenberg E, McElhinney PA, Commandeur F, et al. Deep Learning-Based Quantification of Epicardial Adipose Tissue Volume and Attenuation Predicts Major Adverse Cardiovascular Events in Asymptomatic Subjects. Circ Cardiovasc Imaging 2020;13:e009829.
73. Dey D, Gaur S, Ovrehus KA, et al. Integrated prediction of lesion-specific ischaemia from quantitative coronary CT angiography using machine learning: a multicentre study. Eur Radiol 2018;28:2655-64.
74. Toivonen J, Montoya Perez I, Movahedi P, et al. Radiomics and machine learning of multisequence multiparametric prostate MRI: Towards improved non-invasive prostate cancer characterization. PLoS One 2019;14:e0217702.
75. Ou X, Zhang J, Wang J, et al. Radiomics based on 18 F-FDG PET/CT could differentiate breast carcinoma from breast lymphoma using machine-learning approach: A preliminary study. Cancer Med 2020;9:496-506.
76. Kurata A, Fukuyama N, Hirai K, et al. On-Site Computed Tomography-Derived Fractional Flow Reserve Using a Machine-Learning Algorithm- Clinical Effectiveness in a Retrospective Multicenter Cohort. Circ J 2019;83:1563-71.
77. Dong F, Tao C, Wu J, et al. Detection of cervical lymph node metastasis from oral cavity cancer using a non-radiating, noninvasive digital infrared thermal imaging system. Sci Rep 2018;8:7219. Erratum in: Sci Rep 2018;8:10624.
78. Jun Y, Eo T, Kim T, et al. Deep-learned 3D black-blood imaging using automatic labelling technique and 3D convolutional neural networks for detecting metastatic brain tumors. Sci Rep 2018;8:9450.
79. Ginsburg SB, Algohary A, Pahwa S, et al. Radiomic features for prostate cancer detection on MRI differ between the transition and peripheral zones: Preliminary findings from a multi-institutional study. J Magn Reson Imaging 2017;46:184-93.
80. Sheng H, Wang X, Jiang M, et al. Deep Learning-Based Diffusion-Weighted Magnetic Resonance Imaging in the Diagnosis of Ischemic Penumbra in Early Cerebral Infarction. Contrast Media Mol Imaging 2022;2022:6270700.
81. Aydoseli A, Unal TC, Kardes O, et al. An Early Warning System Using Machine Learning for the Detection of Intracranial Hematomas in the Emergency Trauma Setting. Turk Neurosurg 2022;32:459-65.
82. Huang L, Lin W, Xie D, et al. Development and validation of a preoperative CT-based radiomic nomogram to predict pathology invasiveness in patients with a solitary pulmonary nodule: a machine learning approach, multicenter, diagnostic study. Eur Radiol 2022;32:1983-96.
83. Yu P, Wu X, Li J, et al. Extrathyroidal Extension Prediction of Papillary Thyroid Cancer With Computed Tomography Based Radiomics Nomogram: A Multicenter Study. Front Endocrinol (Lausanne) 2022;13:874396.
84. Pan X, Sidky EY, Vannier M. Why do commercial CT scanners still employ traditional, filtered back-projection for image reconstruction? Inverse Probl 2009;25:1230009.
85. Mun SK, Wong KH, Lo SB, et al. Artificial Intelligence for the Future Radiology Diagnostic Service. Front Mol Biosci 2021;7:614258.
86. Syed AB, Zoga AC. Artificial Intelligence in Radiology: Current Technology and Future Directions. Semin Musculoskelet Radiol 2018;22:540-5.
87. Rezazade Mehrizi MH, van Ooijen P, Homan M. Applications of artificial intelligence (AI) in diagnostic radiology: a technography study. Eur Radiol 2021;31:1805-11.
88. Kim B, Koopmanschap I, Mehrizi MHR, et al. How does the radiology community discuss the benefits and limitations of artificial intelligence for their work? A systematic discourse analysis. Eur J Radiol 2021;136:109566.
89. Saba L, Biswas M, Kuppili V, et al. The present and future of deep learning in radiology. Eur J Radiol 2019;114:14-24.

doi: 10.21037/jmai-22-89
Cite this article as: Ghorishi AR, Ogunfuwa FO, Ghaddar TM, Kandah MN, Smith BW, Ta Q, Alayon A, Amundson PK. Narrative review of open source, proprietary, and experimental artificial intelligence algorithms in radiology. J Med Artif Intell 2023;6:5.

