The use of deep learning in interventional radiotherapy (brachytherapy): A review with a focus on open source and open data

Tobias Fechter*, Ilias Sachpazidis, Dimos Baltas

Division of Medical Physics, Department of Radiation Oncology, Medical Center University of Freiburg, Germany
Faculty of Medicine, University of Freiburg, Germany
German Cancer Consortium (DKTK), Partner Site Freiburg, Germany

Received 13 May 2022; accepted 10 October 2022

Abstract

Deep learning advanced to one of the most important technologies in almost all medical fields. Especially in areas related to medical imaging it plays a big role. However, in interventional radiotherapy (brachytherapy) deep learning is still in an early phase. In this review, first, we investigated and scrutinised the role of deep learning in all processes of interventional radiotherapy and directly related fields. Additionally, we summarised the most recent developments. For better understanding, we provide explanations of key terms and approaches to solving common deep learning problems. To reproduce results of deep learning algorithms both source code and training data must be available. Therefore, a second focus of this work is on the analysis of the availability of open source, open data and open models. In our analysis, we were able to show that deep learning plays already a major role in some areas of interventional radiotherapy, but is still hardly present in others. Nevertheless, its impact is increasing with the years, partly self-propelled but also influenced by closely related fields. Open source, data and models are growing in number but are still scarce and unevenly distributed among different research groups. The reluctance in publishing code, data and models limits reproducibility and restricts evaluation to mono-institutional datasets. The conclusion of our analysis is that deep learning can positively change the workflow of interventional radiotherapy but there is still room for improvements when it comes to reproducible results and standardised evaluation methods.

Keywords: Interventional radiotherapy; Brachytherapy; Deep learning; Open source; Artificial neural network

1 Introduction

In the treatment and diagnosis of cancer, medical images play an essential role. With the introduction of convolutional neural networks (CNNs) [1], the widespread availability of powerful graphical processing units (GPUs) and the development of easy to use open-source libraries, deep learning (DL) rose to an important tool, assisting clinical decision making in several image driven fields [2]. Also in radiation oncology DL managed to gain foothold [3]. Applications can be found in almost all processes of external beam radiotherapy, ranging from tumour staging, image segmentation and registration to treatment planning, treatment delivery and aftercare [3–6]. One might assume a similar advance-
ment in interventional radiotherapy (IRT). However, the application of DL in IRT is still in an early phase [7,8]. Among other reasons, this can be attributed to the low IRT patient volume. The fact that DL algorithms require a large amount of data and technical knowledge can be an obstacle, especially for small institutions, to conduct DL studies. Consequently, current studies are limited to small mono-institutional datasets [7]. Learning only from site-specific information can lower robustness and general applicability of an algorithm. Additionally, mono-institutional data, not publicly available, makes it impossible for third parties to reproduce results, as a trained model consists of the code and the information from the training data. Beside the datasets, the fine-tuning of the meta-parameters is crucial for a successful DL model. However, the huge amount of meta-parameters cannot be recorded in a typical journal publication. To increase reproducibility, a solution would be the publication of code and data as open-source and open-data, allowing others to replicate results and compare algorithms on the same datasets [9]. In addition, the entry barrier for developing new algorithms can be lowered with public data [10], which would increase the scientific competition and method diversity. Due to privacy issues, a publication of patient related data is often not possible. In such a case, the publication of the trained models would be an option. The positive impact of open-source and open-data can be seen from the great success of open-source libraries (e.g. Tensorflow [11], PyTorch [12], ModelHub.AI [13]), initiatives like The Cancer Imaging Archive [14], as well as from the increasing number of challenges targeting important medical problems. In this review article, our aim is twofold. First, we outline and summarise the most recent developments of DL in the field of IRT and directly connected fields. Our second aim is to highlight publications and projects closely related to IRT that publish code, data or models. Through the manuscript, the reader will get a sense of the potential of DL in IRT, the usage of open-source and open-data in the field and its implications for the scientific community. To enhance readability, also for non-experts, we included explanations of key terms and possible solutions to common DL problems in the field.

2 Material and methods

In this section, we first describe how our literature search was conducted, then give a short overview of the reported figures of merit and close the section by describing how the open source policy of research groups was investigated. An explanation of the most important terms mentioned in this manuscript can be found in the appendix.

As a basis for our review, we conducted a PubMed search in April 2022 for publications in English language using the search terms in Table 1. In addition, we scanned the references of each found paper and looked for other articles citing papers in our search results, to include publications not covered by our search terms and relevant articles from related fields. In a next step, we screened the abstracts of all articles found. If the content of an abstract indicated a fulfilment of our inclusion criteria (see 2.1), the full text article was further inspected.

During the last years, a number of reviews dealing with IRT and artificial intelligence (AI) were published [3,7,8,15–19]. Most of these publications have a wide scope, with only a small section dedicated to deep learning [7,8,15,16,19] or are specific to one organ site [17,18,20]. We discuss the reviews in the course of this work and extend them by the latest publications. Articles already covered by another review have been mentioned only when their content was of peculiar interest or they contributed publicly available source code, data or models.

It should be mentioned, that we do not claim that the list of articles considered for this review is exhaustive. Nevertheless, we can state that this review depicts the current state-of-the-art and lists all relevant deep learning related enhancements in the field.

2.1 Inclusion criteria

In order for a manuscript to be included, it had to fulfil at least the criteria regarding the topic and the algorithm. Only for imaging data related papers, the image modality played a role.

1. **Topic**: In this article the following fields of the IRT workflow are covered: image segmentation, image registration, dose prediction, treatment planning, outcome prediction or clinical parameter estimation. For an article to be considered it had to be related to an organ site treated with IRT and the presented method had to be applicable to at least one of the covered IRT fields. This criteria definition allowed us to include also general deep learning algorithms (e.g. for image segmentation or registration) that can be used in IRT without modifications.

2. **Algorithm**: Only articles facilitating deep neural networks with multiple hidden layers were considered.

3. **Image modality**: As IRT is imaging driven, most articles in this review focus on biomedical image processing. Here we focused on the common modalities: ultrasound (US), positron emission tomography (PET), magnetic resonance (MR) imaging (MRI), computed tomography (CT), cone beam CT (CBCT).

2.2 Reported figures of merit

The quality of generated contours is usually measured by the overlap with a corresponding reference contour. Almost all articles dealing with image segmentation report the
overlap in terms of the Sørensen-Dice index (DSC) [21], which is a volume based (pseudo-)metric. As the DSC has a lower sensitivity to errors with small volume, some groups report surface based metrics in addition. Common are Hausdorff distance (HD) [21] and average surface distance (ASD) [21]. For the localisation of needles and catheters, the average displacement of the shaft and the tip error are reported. Defining a specific value for DSC/HD/ASD that indicates clinical usable contours is difficult as the required quality depends on multiple factors such as the structure to be delineated or the treatment type. However, our experience indicates that the inter-observer variability represents an appropriate surrogate. DSC/HD/ASD values equal to or better than the average inter-observer variability can be assumed of a very good quality. As an example, the inter-observer DSC variability for contouring pelvic organs on CT is around 0.80 [22].

The target registration error (TRE) is a common metric in medical image registration. The TRE gives the average distance between corresponding fiducials or anatomical landmarks in the datasets to be registered. In addition, DSC, HD and ASD can be used to assess to registration quality in the region of a contoured volume.

In the case of classification, typically used figures of merit are accuracy, sensitivity, specificity and the area under a receiver operating curve (AUC). For dose prediction algorithms, dosimetric indices are used: $D_x$ gives the dose received by volume $x$, in relative or absolute volume units, e.g. $D_{2\%}$, $D_{98\%}$, $D_{0.1cc}$.

### 2.3 Open source and open data policy

The following procedure was used to identify research groups with a special open-source policy that publish code, data or models constantly with their manuscripts. In a first step, we clustered the articles by research group. Articles were assumed to belong to the same group when they have at least three authors in common or at least 50% of the authors of one article are contained by the author list of another article. We used the authors as a surrogate for the affiliations to define research groups because they are easier to process. This has the drawback that the created research groups do not necessarily reflect real institutions but our experience showed that the mapping resembles real institutions very well and is able to depict cross-institutional collaborations. After all manuscripts were clustered, we investigated the amount of published code, models or data in the clusters.

### 3 Segmentation

In this chapter we focus on tumour segmentation, like gross tumour volume (GTV) or clinical target volume (CTV), and organs at risk (OAR) segmentation on CT, MR, PET and US image datasets as well as the digitisation of needles, catheters and applicators. A review covering the segmentation of pelvic cancers (bladder, rectum, cervix, prostate) using deep learning was recently published by Kalantar et al. [23].

#### 3.1 CT

The articles identified for CT image segmentation focus on the segmentation of CTV and OARs in the pelvic region. In addition, only few manuscripts could be found addressing the localisation (reconstruction) of catheters and applicators. At the end of this subsection, two publications dealing with image quality are listed.

Liu et al. [24] presented an adversarial network for segmenting the CTV for cervical cancer. Their algorithm

### Table 1

| Process                        | Search term                                                                 |
|--------------------------------|-----------------------------------------------------------------------------|
| Segmentation                   | (brachytherapy OR (“interventional radiotherapy”)) AND (segmentation OR (delineation)) AND (deep learning OR (neural network) OR (CNN) OR (artificial intelligence) OR (machine learning)) |
| Registration                   | (brachytherapy OR (“interventional radiotherapy”)) AND ((“image registration”) OR ("deformable registration") OR ("rigid registration") OR ("image alignment")) AND (deep learning OR (neural network) OR (CNN) OR (artificial intelligence) OR (machine learning)) |
| Catheter reconstruction        | (brachytherapy OR (“interventional radiotherapy”)) AND ("catheter reconstruction") AND (deep learning OR (neural network) OR (CNN) OR (artificial intelligence) OR (machine learning)) |
| Dose prediction and treatment  | (brachytherapy OR (“interventional radiotherapy”)) AND ("dose estimation") OR ("dose prediction") OR ("treatment planning") OR ("planning") AND (deep learning OR (neural network) OR (CNN) OR (artificial intelligence) OR (machine learning)) |
| planning                       | (brachytherapy OR (“interventional radiotherapy”)) AND (staging OR (radiomics) OR ("classification") OR ("gleason") OR ("toxicity") OR ("toxicity prediction") OR ("outcome prediction") OR ("prediction") AND (deep learning OR (neural network) OR (CNN) OR (artificial intelligence) OR (machine learning)) |
achieved a mean DSC of 0.88, when it was evaluated with a contour dataset generated by experts. Slightly lower DSC values were reported by Chang et al. [25] investigating the fine-tuning of pre-trained networks for cervical cancer CTV delineation.

Mean DSC values of 0.81, 0.86, 0.86, 0.66 and 0.56 could be reached with a network trained for CTV, bladder, rectum, sigmoid colon, small intestine segmentation in cervical cancer patients [26]. For segmenting the CTV on post-implant CTs for tandem and ovoid’s IRT a mean DSC of 0.76 was recently reported [27].

Beside the delineation of the tumour region, several papers facilitating deep learning for OAR segmentation on CT could be identified. A mean DSC of over 0.92 could be achieved by Mohammadi et al. [28] when contouring bladder, rectum and sigmoid of cervical cancer patients. Seven cervical cancer OARs (bladder, bone marrow, left femoral head, right femoral head, rectum, small intestine, spinal cord) were delineated with a deep network by Liu et al. [29] resulting in mean DSC values of 0.92, 0.85, 0.91, 0.90, 0.79, 0.83 and 0.83, respectively. Another work [30] investigated the performance of two networks in delineating cervix-uterus, vagina, parametrium, bladder, rectum, sigmoid, femoral heads, kidneys, spinal cord and bowel bag. The models could achieve a DSC, averaged over all organs, of 0.88 on an internal test cohort and of 0.79 on an external test cohort. A similar work, contouring prostate, bladder, rectum, left femur, and right femur in the male pelvic region achieved mean DSC values of: 0.88, 0.97, 0.86, 0.97, 0.97 [31].

A multi task network for joint segmentation and registration was able to reach an ASD of 1.88 mm, 2.41 mm, 2.78 mm, 1.66 mm for prostate, seminal vesicles, rectum and bladder segmentation [32]. A semi-automatic method dedicated to bowel segmentation by Luximon et al. [33] showed an average DSC of 0.90 with the reference contours.

Some papers address the segmentation of the prostate alone, either to introduce technical novelties [34,35] or having an outstanding number of patients (more than 1000) in the training cohort [36]. All of them reported DSC values around 0.90. Xu et al. [37] presented a method to delineate bladder, rectum and prostate bed after prostatectomy. A semi-automatic method for prostate delineation on CT and transrectal US (TRUS) images was shown by Girum et al. [38].

A dedicated method for segmenting OARs (prostate, bladder, rectum, femoral heads) on CBCT was presented by Fu et al. [39]. They designed a network utilizing CBCT as well as synthetic MRI information for contouring. The group achieved average DSC values above 0.91 for the segmented OARs. Other publications [40–42] used CT and CBCT data to train their models for bladder, rectum and prostate segmentation with mean DSC values up to 0.87, 0.81 and 0.76.

A U-net based model was presented by Hu et al. [43] to reconstruct tandem and ovoid applicators in CT-based cervix IRT. The presented model achieved on average a DSC of 0.89 and a tip error of 0.80 mm for ten test cases. Jung et al. [44,45] showed in two publications how to segment interstitial needles and tandem and ovoid, Y-tandem as well as cylinder applicators for gynecological cancer IRT. The evaluation yielded mean DSC values of 0.93 and HDs around 0.70 mm. Similar results (DSC: 0.92, HD < 1 mm) were presented by Zhang et al. [46] and Deufel et al. [47] for tandem and ovoid applicators. Weishaupt et al. [48] proposed a 2D U-net based approach for the segmentation of titanium needles implanted in the prostate, with a mean tip and shaft error of 0.1 mm and 0.13 mm, respectively.

A convolutional neural network to reduce the metal artefacts caused by IRT applicators was presented by Huang et al. [49]. Another work segmented bones in the pelvic region to improve beam hardening correction [50].

### 3.2 MR

Compared to CT, MRI offers a higher soft tissue contrast which allows for a more detailed segmentation. Like for the CT a big part of the methods reviewed deals with the segmentation of tumour and OARs in the pelvic region. A few IRT specific publications focus on catheter, implants or IRT specific anatomy delineation.

Cuocolo et al. [51] provide a general overview of the use of machine learning in prostate cancer MR images. A various amount of algorithms exist for the segmentation of the prostatic gland on MR datasets. The main reason for this are three segmentation challenges [52–54], which provide public datasets and a common leader board for evaluation (Table 2). The objectives of the challenges were to segment the prostatic gland [53] as well as peripheral zone and central region of the prostate [52,54]. The highest reported average DSC values were 0.89 for the prostatic gland, 0.79 for the peripheral zone and 0.93 for the central gland [55], respectively. Other public datasets with multiple MRI sequences from different scanners for segmenting the prostatic gland and its substructures are provided by the Initiative for Collaborative Computer Vison Benchmarking [56,57] and the Prostate MR Image Database (https://prostatemridatabase.com/, accessed January 2022). In the challenges, deep convolutional neural networks could achieve the best segmentation results. A good overview can be found in the review by Gillespie et al. [58]. Since the publication of the review, additional methods came up: Tian et al. [59] showed a graph CNN, achieving a mean DSC of 0.94 on the Promise12 datasets [53]. Also U-net and V-net variants were
able to show a good performance on public datasets [60–62]. Liu et al. [63] achieved an average DSC of 0.93 on internal data. The segmentation of the prostate on heterogeneous public MRI data was the topic of two other publications [64,65]. The authors reported an average DSC of 0.92 and a symmetric surface distance of 0.77 mm. A U-net version with low computational costs was developed by Comelli et al. [66]. Attention [67] was used by Lu et al. [68] yielding a mean DSC of 0.93. Another two articles describe deep learning algorithms for segmenting subparts of the prostate [69,70]. Reproducibility, robustness of prostate zone segmentation and how to overcome limited data were the topic of three articles [71–73]. All algorithms for delineating the prostate zones were able to achieve good agreement with expert contours (DSC > 0.80) for all zones, except the peripheral one. For the peripheral zone the average DSC value varies in the range between 0.75 and 0.80.

A deep learning model for bladder wall segmentation is given by Hammouda et al. [74]. An overview of bladder segmentation on CT and MR images can be gained from the work by Bandt et al. [75].

Sanders et al. [76] evaluated multiple machine learning models for delineating prostate, seminal vesicles, external urinary sphincter, rectum and bladder on MRI for prostate cancer IRT. In a follow up study, Sanders et al. [77] assessed a network in a prospective clinical trial, showing that the network produces contours of clinical quality. A comparison of two networks for bladder, rectum and femur segmentation can be found in the paper by Savenije et al. [78]. Except for the urinary sphincter with an average DSC of 0.70, the investigated networks could achieve very good results with mean DSC values equal or above 0.80. Zabihollahy et al. [79] reported mean DSC values of 0.94, 0.88 and 0.80 for bladder, rectum, and sigmoid delineation in the female pelvic with a two-stage CNN approach.

Yoganathan et al. [80] segmented GTV, CTV and OARs (bladder, rectum, sigmoid, small intestine) of cervical cancer patients with an overall average DSC of 0.72.

A comparison of 295 deep learning algorithms to human observers when contouring prostate, external urinary sphincter, seminal vesicles, rectum, and bladder revealed that deep learning based automatic segmentation algorithms can be more consistent than human observers [81].

A 2D U-net for the detection of low dose rate (LDR) IRT seeds was presented by Nosrati et al. [83,84], achieving a maximum difference of 7 mm compared to standard CT-based seed detection.

Beside organ segmentation, also catheter delineation and reconstruction on MR images for prostate [85] and gynecological [86,87] IRT has been tackled by some groups with deep neural networks. A direct comparison is difficult as authors used different figures of merit in their publications. Zaffino et al. [86] reported a mean DSC of 0.60 and an average distance of 2 mm, Dai et al. [85] showed a catheter tip error of 0.37 mm and a catheter shaft error of 0.93 mm and Shaar et al. [87] stated a mean DSC of 0.59 and an average variation of 0.97 mm.

### 3.3 US

A challenging task is the segmentation of structures on ultrasound images. Due to the high noise level and the low contrast, an accurate delineation can be very difficult. To improve the image quality of TRUS acquisitions, He et al. [88] presented a generative adversarial network (GAN) to enhance the image resolution. Several groups tried to tackle the problem of delineating the prostatic gland with deep neural networks. The techniques used to create high quality contours comprise residual neural networks [89], attention modules [90], CNNs alone [62,91–93] or in combination with statistical shape models [94–96], learned shape priors [97], a recurrent network for real-time 2D segmentation [98], a regression network with uncertainty estimation [99] or semi-automatic approaches with manual seed points [38,100]. All of them could produce contours very similar to those drawn by medical experts (DSC >= 0.90). Orlando et al. [101] investigated the effect of TRUS image quality and the number of training images on the performance of neural networks for prostate segmentation. They showed that even with a small number of datasets good results can be achieved and that the image quality of side-fire probes can significantly affect contour accuracy.

### Table 2

| Name                       | Modality | Structure | URL                      |
|----------------------------|----------|-----------|--------------------------|
| Medical Image Segmentation Decathlon [52] | MR       | Prostate  | medicaldecathlon.com     |
| Promise12 [53]             | MR       | Prostate  | promise12.grand-challenge.org |
| NCI-ISBI 2013 [54]         | MR       | Prostate  | doi.org/10.7937/K9/TCIA.2015.zF0viOPv   |
| Collaborative Computer Vison Benchmarking [56,57] | MR       | Prostate  | i2cvb.github.io          |
| Prostate MR Image Database | MR       | Prostate  | prostatemrimagedatabase.com |
| ProstateX [82]             | MR       | Prostate  | doi.org/10.7937/K9/TCIA.2017.MURS5CL  |
The methods so far focused on the segmentation of the prostatic gland as a whole. Segmenting substructures of the prostate on US is very challenging due to the low contrast. However, promising results for segmenting the prostate zones were published recently. With a U-net architecture van Sloun et al. [102,103] achieved a mean DSC above 0.90 for the whole gland and the central zone and a mean DSC of 0.86 for the peripheral zone.

Lei et al. [104,105] propose a method to segment multiple OARs on TRUS images. Their experiments yielded average DSC values of 0.93, 0.75, 0.90 and 0.86 for prostate, bladder, rectum and urethra, respectively. The deep network presented by Behboodi et al. [106] for uterus segmentation showed promising results for the central part of the organ (DSC >0.70) but poor ones for the border regions. The methods mentioned in the previous paragraphs, were developed to segment structures on US images without implanted IRT needles. The needles usually cause severe artefacts in the images, making the detection of the organ boundaries even more difficult. Girum et al. [107] presented a method incorporating learned shape prior knowledge to outline the prostatic gland with inserted needles with a mean DSC of 0.88.

Deep learning methods have been also used for the identification of IRT needles on US images. In the reviewed papers [108–111], the tip error for prostate IRT needles ranged from 0.44 mm to 2.04 mm and the shaft error was between 0.29 mm and 0.74 mm. Liu et al. [112] presented a U-net for catheter segmentation in prostate IRT and analysed factors that might influence the model performance. Additionally, to the segmentation their algorithm provides a confidence metric to support clinicians. A generic method for the localisation of applicators and needles used in prostate and gynaecologic IRT, liver and kidney ablation as well as biopsy was presented by Gillies et al. [113]. Their network was able to detect needles and applicators with an average error in tip localisation of 3.50 mm and a DSC of 0.73.

3.4 PET/CT

Kostyszyn et al. [114] presented a network to segment the prostatic tumour on PSMA PET images. The network was evaluated on internal and external cohorts and achieved median DSCs above 0.81. Matkovic et al. [115] presented a CNN for prostate and tumour delineation on PET/CT with mean DSCs of 0.93 and 0.80, respectively. For cervical cancer an average DSC of 0.84 could be achieved by Chen et al. [116].

4 Registration

Modern imaging techniques can provide detailed morphological and functional information about the tumour and OARs. The information improves diagnosis and facilitates a precise, personalised treatment. However, as each imaging modality has its own strengths, an accurate fusion of the information provided by the different modalities is necessary. Due to distinct image characteristics, the time between imaging (change of organ fillings), changes in patient positions and deformations due to external forces (ultrasound probe), the fusion of images, which is also called image registration, can be challenging. Deep learning based algorithms have succeeded also in the field of image registration, convincing with high accuracy and low running time at inference [6,117]. For the fusion of information in IRT, the registration of multimodal image data is of great importance. In the following, an overview of DL based registration of the most common image modalities used in IRT is given.

4.1 MR – US

One task that is especially important in IRT of prostatic lesions is the registration of MR images, taken before treatment, to TRUS acquisitions acquired during IRT.

Due to the large appearance differences, a huge problem in multimodal image registration is the measurement of the image alignment quality. Haskins et al. [118] optimised a network to learn a similarity metric for MR – TRUS registration. Networks for image based rigid registration were introduced by Guo et al. [119] and Song et al. [120] with an average surface error around 3.60 mm.

Hu et al. [121] designed a network for affine and deformable registration of MR and TRUS datasets. For training, their method needs labelled data, but inference works with plain images. The network achieves an average TRE of 4.2 mm and a DSC of 0.88. A label-driven approach for deformable registration of MR and TRUS prostate images was presented by Zeng et al. [122]. Their method consists of multiple networks. Two for generating TRUS and MR segmentations of the prostate, one for the affine registration matrix and one for the deformation vector field. The mean TRE was 2.53 mm. A similar approach was chosen by Chen et al. [123]. Their method for deformable registration generates vector fields that map the prostate on MR to TRUS images with an average DSC of 0.87. A network that needs only one contour beside the images was presented by Bashkanov et al. [124], showing a TRE of 4.7 mm. Fu et al. [125] incorporated the finite element method into their network and reached a TRE of 1.57 mm.

Ghavami et al. [126] investigated whether the architecture of the segmentation network in a label driven MR-TRUS registration has an impact on the results and found no statistical differences.
4.2 PET/CT – US

Sultana et al. [127] used a U-net model to generate prostate contours for driving the registration of PET/CT and TRUS images, whereas the registration process itself was not deep learning based. Their method showed a TRE of 1.96 mm.

4.3 MR – CBCT

Fu et al. [128] presented a finite element based method for training MR and CBCT registration with a TRE of 2.68 mm. The approach is similar to the one they used for registering MR and TRUS images [125].

4.4 Miscellaneous

Lei et al. [129] used a registration network to predict catheter positions for high dose rate (HDR) IRT. First, the case at hand was registered to an atlas, in a second step a regression algorithm predicted the final catheter positions. The evaluation showed that all plans calculated with predicted catheter positions met the common dose constraints. The contour based registration network achieved mean DSC values of 0.95 for prostate, 0.86 for urethra, 0.93 for bladder and 0.86 for rectum. Guo et al. [130] introduced a network for aligning a 2D TRUS frame with a 3D TRUS volume without hardware tracking. Their rigid registration method showed an average distance error of 2.73 mm between the reference TRUS slices and the registered ones. Saeed et al. [131] trained a network to predict prostate motion due to external forces (e.g. ultrasound probe) with an expected error of 0.02 mm.

5 Dose Prediction and Treatment Planning

Recently a review about treatment planning optimization in HDR IRT has been published [132]. Only a short chapter in this work deals with machine learning algorithms in the field. That AI methods are still scarce in the field of IRT treatment planning was also confirmed by a recent debate [133]. Nonetheless, the results in the small number of publications were able to show the potential value of AI to IRT. Shen et al. [134] applied reinforcement learning to adjust organ weights for the HDR treatment planning optimization and showed that their network was able to improve a plan quality score, that considers sparing of OARs, by 10.7 % compared to human generated plans. Deep reinforcement learning was also used by Pu et al. [135] to determine the source dwell time for HDR IRT of cervical cancer and could generate higher quality plans than conventional methods. Fan et al. [136] used automated source positions and dwell time estimation to establish a verification tool for QA. Nicolae et al. [137,138] compared the quality of LDR IRT plans for the prostate created by a machine-learning algorithm to the ones created by human observers and did not detect a significant difference. Aleef et al. [139,140] utilised a GAN to LDR prostate IRT treatment planning. Their plans had a similar quality compared to manually generated plans. Jaberi et al. [141] trained models to compensate for intra-fractional organ deformations in gynaecological IRT.

Another application of deep learning is to predict the dose calculated in the planning process. The predicted dose can be used for QA or to assist physicists in tuning the treatment plan parameters. Mao et al. [142] developed RapidBrachyDL, a network to predict the dose for Ir-192-based HDR IRT. Compared to Monte Carlo ground truth, the predicted dose deviated for prostate cases by 0.73% for CTV D90, 1.1% for rectum D2cc, 1.45% for urethra D0.1cc and 1.05% for bladder D2cc. Similar, the work by Villa et al. [143] achieved a mean percentage error of -1.19% inside the prostate. As ground truth, they also used Monte Carlo simulations. For cervical cancer HDR IRT PBrDoseSim was introduced by Akhavanallaf et al. [144]. The network showed a mean relative absolute error of 1.16%. Lei et al. [145] used a registration network to transfer dose maps from an atlas to the case at hand. The examined DVH-parameters of their predicted dose maps showed no significant difference to the clinically used dose distribution.

6 Outcome prediction and estimation of other clinical parameters

Using deep neural networks for predicting clinical parameters can be attributed to the field of Radiomics [146]. Either in a way to predict clinical parameters directly with a neural network or to use feature-maps of pre-trained networks in combination with other machine learning algorithms. Currently the latter approach is more common as it requires less training data than the first one. Reviews of Radiomics in prostate cancer were recently published [147,148]. As an application related to IRT, the reviews show deep learning methods successfully predicting the Gleason-score. One of the best performing methods was presented by Chaddad et al. [149], who made use of properties extracted from feature maps and were able to predict the Gleason-score with an AUC > 0.80. Apart from Gleason-score prediction many publication deal with tumour grading (e.g. PI-RADS or ISUP) and tissue classification [150–155]. In 2017, Wang et al. [156] showed the potential of deep learning in differentiating benign and malignant prostate cancer tissue. Castillo et al. [157] compared a deep learning [158] and a Radiomics model for prostate cancer classification, interest-
ingly the classical Radiomics approach outperformed the deep learning method on independent test datasets. A multi-stage computer-aided detection and diagnosis model for prostate cancer detection was presented by Saha et al. [159]. The model achieved an AUC of 0.88. Datasets for estimating the clinical significance of prostate lesions are provided by the ProstateX [82] challenge.

Deep networks have also been used to detect vessel invasion in patients with cervical cancer. Jiang et al. [160] and Hua et al. [161] reached AUCs of 0.91 and 0.78 on an internal dataset. To determine the myometrial invasion on endometrial cancer MR images, Chen et al. [162] and Dong et al. [163] used deep networks and achieved an accuracy of 0.85 and 0.79, respectively. Wang et al. [164] differentiated malignant and benign ovarian lesions with an accuracy of 0.87. Urushibara et al. [165] showed that a deep network can classify uterine cervical cancer on a radiologist’s level. All methods mentioned so far use MRI for their calculations. CT, histology and grade information was used by Dong et al. [166] to predict the lymph node status in operable cervical cancer patients with an AUC above 0.90. Shen et al. [167] facilitated PET/CT image information to predict local recurrence and the occurrence of distant metastasis after chemoradiotherapy treated cervical cancer patients with an accuracy of 0.89 and 0.87, respectively. The general application of AI in gynaecological malignancies was the topic of multiple reviews in the past two years [15,18,20,168].

The dose distribution in the rectum after combined external beam radiotherapy and IRT was used by Zhen et al. [169] for toxicity prediction. Their network achieved an AUC of 0.89, a sensitivity of 0.75 and a specificity of 0.83.

7 Open source and open data

While analysing the collected data we noticed that 16 publications made use of publicly available datasets. One should note that all of the 6 public datasets (Table 2) contain solely MR images and are intended for segmentation and/or classification of prostate tissue. Twenty manuscripts come with publicly available code and 6 published the trained models. An overview of papers with available code or models is given in Table 3. In total 25 manuscripts were published with code, data or models (Table 2 and Table 3). One can see from the tables that IRT specific code or models are scarce [86,139,140], most of the articles deal with topics also relevant for radiology or external beam radiotherapy.

The clustering of the articles by research group to identify groups with a special open-source policy yielded 108 groups in total. What attracts attention when investigating the distribution of reviewed articles per group is that on the one hand, 83 (~77%) groups are represented by only one manuscript, on the other hand, one single institution composed 16 (~10%) of the articles at hand. The group with 16 publications is dominant in the segmentation and registration of prostate datasets and did not publish code, models or data. An overview of the articles per group is given in Table 4. Out of the 26 open source or open data contributions, eight came from institutions with only one article in this review. No institution is represented with more than three open source or data articles. The group in Table 4 with four open source/data publications represents the initiatives around ModelHub.AI [13] and three challenges [52–54]. From the four institutions with more than four articles, only two published open source or data.

8 Discussion

Most articles concerning the application of DL in IRT were identified in the field of image segmentation, especially in the delineation of organs. As the delineation of organs in IRT is similar to the delineation in related fields like radiology or external beam radiotherapy, the IRT community profited from activities in those fields. A confounding factor that complicates the segmentation of structures in IRT are artefacts caused by implanted catheters or applicators. We could identify only a few algorithms that could segment images with implants [27,107]. For other IRT specific applications like localisation of catheters and applicators, several DL based algorithms could be included in this review. For automated treatment planning it was shown that deep learning algorithms have the potential to generate plans of the same quality as human observers. The big advantage of such algorithms would be that they are able to compute a plan within a few seconds [139], whereas a manual plan needs several minutes. However, that the inverse plan optimization in IRT based on AI has not been fully explored, might be due to the increasing computational power which enables a very fast multi-criterial optimization (MCO) and searching for the best optimization solution on Pareto space. If the Pareto space can be properly scanned in a fast and consistent way, the produced results will be always more accurate [133].

The research currently focuses on the pelvic region, which is a main application of IRT and therefore offers more data for the training process. The ratio between articles focusing on the male pelvic area and papers about the female pelvis is approximately 2.5:1. A possible reason for this imbalance are the public challenge datasets for the segmentation or classification of prostate tissue.

A key factor in the evaluation of deep learning methods is the composition of the cohorts used for training and testing the network. Beside the nominal number of the samples required the quality of the samples play a crucial role. The chosen samples should cover all possible cases. A validation with external independent datasets is important, as it is the only way to detect an overfitting to institutional specific
cohort characteristics [172]. The number of patients in studies ranged from 10 [134] to 2317 [159]. It is noticeable that most studies applied computational methods, such as k-fold cross validation, to tackle the issue of low patient number and to prevent overfitting. Saunders et al. [73] examined the effects of the training cohort size for prostate segmentation on MR images. They were able to show that, with a proper learning strategy and well selected samples a number of 20 patients can be already enough to generate contours on a human expert level. Cohorts of this size can be easily obtained from online databases such as The Cancer Imaging Archive [14]. However, in the same work, the authors showed that changing the learning strategy can double the amount of data needed to achieve the same contour quality. Most of the reviewed studies limited their research to data coming from a single institution. The restriction to single site data can have severe impact on the generalizability of a model [58,72,73]. All three studies showed that performance can significantly drop when a model is applied to images from a different scanner or patients with other characteristics. Another point that hampers a direct comparison of methods is that many groups reported results only for internal data. The allegedly better performance of an algorithm could be caused by the properties of the used dataset like region of interest or imaging protocols. If it is not possible to present results for public datasets, we would strongly rec-

| Name                | Scope          | Code | Model         | URL                                           |
|---------------------|----------------|------|---------------|-----------------------------------------------|
| **Segmentation**    |                |      |               |                                               |
| MR                  |                |      |               |                                               |
| Gillespie et al. [58]| prostate       | ✔    |               | github.com/AIEMMU/MRI_Prostate               |
| Tian et al. [59]    | prostate       | ✔    |               | github.com/AlanMorningLight/GCN-Based-Interactive-Prostate-Segmentationon-MR-Images |
| Liu et al. [64]     | prostate       | ✔    |               | github.com/liuquande/MS-Net                  |
| Liu et al. [65]     | prostate       | ✔    |               | github.com/liuquande/SAML                    |
| Savenije et al. [78]| bladder, rectum, femur | ✔ | in supplementary of [78] |                                               |
| Zaffino et al. [86] | catheter       | ✔    |               | available in 3D Slicer [170] DeepInfer [171] |
| Saha et al. [159]   | prostate cancer| ✔    |               | github.com/DIAGNijmegen/prostateMR_3D-CAD-csPCa |
| CT/CBCT             |                |      |               |                                               |
| Xu et al. [37]      | bladder, rectum, prostate bed | ✔ |               | github.com/superxuangan/amtata-net             |
| Brion et al. [40]   | bladder, rectum, prostate | ✔ |               | github.com/eliottbrion/unsupervised-domain-adaptation-unet-keras |
| Léger et al. [41]   | bladder, rectum, prostate | ✔ |               | github.com/eliottbrion/pelvis_segmentation    |
| **TRUS**            |                |      |               |                                               |
| Wang et al. [90]    | prostate       | ✔    |               | github.com/wulalago/DAF3D                      |
| Xu et al. [99]      | prostate       | ✔    |               | github.com/DIAL-RPI/PTN                       |
| **PET**             |                |      |               |                                               |
| Kostyszyn et al. [114]| prostate cancer| ✔ |               | gitlab.com/dejankostyszyn/prostate-gtv-segmentation |
| **Registration**    |                |      |               |                                               |
| MR ↔ TRUS           |                |      |               |                                               |
| Song et al. [120]   | prostate       | ✔    |               | github.com/DIAL-RPI/Attention-Reg             |
| TRUS ↔ TRUS         |                |      |               |                                               |
| Guo et al. [130]    | prostate       | ✔    |               | github.com/DIAL-RPI/FVR-Net                   |
| **Planning**        |                |      |               |                                               |
| Aleef et al. [139]  | LDR plan       | ✔    |               | github.com/tajwarabraraleef/TP-GAN             |
| Aleef et al. [140]  | LDR plan       | ✔    |               | github.com/tajwarabraraleef/3Dpix2pix-for-prostate-brachytherapy |
| **Predicting clinical parameters** | | | | |
| Chaddad et al. [149]| Gleason score  | ✔    |               | github.com/fchollet/deep-learning-models      |
| Schelb et al. [152] | PI-RADS        | ✔    |               | github.com/MIC-DKFZ/PROUNET                   |
| Duran et al. [153]  | Gleason score  | ✔    |               | github.com/AudreyDuran/ProstAttention-Net     |
ommend publishing the source code or models. This would allow comparisons of algorithms also with internal data [9].

The restriction of many articles to internal data and the fact that deep learning models are only fully reproducible with source code and data available, are the reasons, why we focused in this work on manuscripts with published code, data, or models. The analysis showed that the release of code, data and models is still rare in the field of IRT but increasing over time. The clustering of publications into research groups could not identify any group that publishes code, data or models on a regular basis. However, the clustering revealed that people from one institution authored a big part of the deep learning publications. To the best of our knowledge, neither code, data nor models were released with these manuscripts, which limits validation and reproduction of their results significantly. The dominance of one institution bares the risk that developed algorithms do not reflect the whole spectrum of methodologies. Especially in a field like IRT that relies heavily on human experience, which causes variable techniques across institutions this should be seen critically. In our eyes, public datasets are the foundation to enable a fair comparison of methods and to keep diversity in the scientific field. We are aware that privacy regulations render the publication of patient related data very effortful and time-consuming. Joint initiatives from professional associations like the American Association of Physicians in Medicine or the European Federation of Organisations for Medical Physics could reduce the amount of work for single institutions. Another approach could be to generate artificial patient data for training or testing [173]. In addition to the datasets a common assessment framework with a predefined data processing pipeline is needed (e.g. the significance of a high DSC value is a different one whether only a centre cropped region of interest is handled by an algorithm or a full body scan is taken as input). Beside a common dataset and assessment framework, it is desirable that author publish their code. We see three big advantages in public code. First, it enhances reproducibility. Second, quality can be increased with the input of other researchers. Third, it allows others to build upon an existing code-base, which can accelerate scientific progress. The European Union has also identified these needs. The EU-funded project ProCancer-I strives to build an open-source framework for the development, sharing and deployment of AI models for prostate cancer patients (https://www.procancer-i.eu/, accessed February 2022). Other noteworthy projects that pursue the same objectives are e.g. The Cancer Imaging Archive [14], Image Biomarker Standardization Initiative [174], ModelHub.AI [13], MONAI [175], etc.

In addition to the already established applications of DL in IRT, we see several other areas of use. The first one is automatic adaptive planning. DL algorithms could be used to adjust dwell time and source positions to organ movement or catheter displacements. Another one would be the automatic implant generation in HDR brachytherapy. Algorithms could design patient specific implants which are produced using 3D printing. Additionally, algorithms could be used for treatment selection, identifying patients, who might benefit the most from IRT.

A limitation of our current review might be that it has a big focus on image processing. However, we think that the review shows clearly the big potential of deep learning in IRT and the role of open source, models and data in the field.

| Total # publications (with open source, data or models) | # Groups |
|--------------------------------------------------------|----------|
| 16 (0)                                                 | 1        |
| 7  (2)                                                 | 1        |
| 6  (3)                                                 | 1        |
| 5  (0)                                                 | 1        |
| 4  (4)                                                 | 1        |
| 4  (2)                                                 | 1        |
| 4  (0)                                                 | 1        |
| 3  (2)                                                 | 1        |
| 3  (1)                                                 | 1        |
| 3  (0)                                                 | 3        |
| 2  (2)                                                 | 1        |
| 2  (1)                                                 | 2        |
| 2  (0)                                                 | 10       |
| 1  (1)                                                 | 8        |
| 1  (0)                                                 | 75       |

9 Conclusion

In this review the most recent articles about the application of deep learning (DL) in IRT were presented. The reviewed articles covered the whole IRT workflow and show clearly that deep learning techniques could positively affect the IRT workflow. The DL algorithms can generate results very quickly with very high quality comparable to human experts in some applications. Additionally, this work showed that the number of publications with open source, data or models is still low in the field, which hampers reproducibility, comparability and transferability of results and methods significantly.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Appendix

Glossary:

GANs (generative adversarial networks) consist of two neural networks competing with each other. They are often used for generating synthetic images. One network (generator) creates fake images, the other one (discriminator) tries to differentiate between fake and real images.

Atlas based methods project the case at hand to one or more reference datasets and transfer a-priori knowledge (e.g. organ boundaries) from the reference dataset to the case at hand.

Radiomics covers techniques that extract features from medical images for characterisation. The usage of hand-crafted features is often referred to as classical Radiomics. An alternative to hand-crafted features is to use deep neural networks for feature learning or characterisation.

GTV (gross tumour volume) is the gross palpable or visible/demonstrable extent of the malignant growth.

CTV (clinical target volume) consists of a GTV and surrounding areas that are likely to contain microscopic (subclinical) proliferations. E.g. in prostate cancer patients CTV can include the whole prostate plus seminal vesicles, in cervical cancer patients CTV encompasses the whole cervix, uterus, parametrium, parts of the vagina and pelvic lymph nodes.

Overfitting is a wide spread problem in deep learning because of the huge amount of parameters. An overfitted model learned to perfectly fit the training data but failed to learn general patterns in the data. Therefore the accuracy drops significantly for new data sets.

K-fold cross validation is a resampling method to assess models and to tackle problems like overfitting. First, the whole dataset at hand is split into K parts. In a second step, K-1 parts are used for training and 1 part is used for testing the model. This is repeated K times until each part was used once for training.

References

[1] Lecun Y, Bottou L, Bengio Y, Haffner P. Gradient-based learning applied to document recognition. Proc IEEE 1998;86:2278–2324. https://doi.org/10.1109/5.726791.
[2] Levine AB, Schlosser C, Grewel J, Coope R, Jones SJM, Yip S. Rise of the Machines: Advances in Deep Learning for Cancer Diagnosis. Trends Cancer 2019;5:157–169. https://doi.org/10.1016/j.trecan.2019.02.002.
[3] Field M, Hardcastle N, Jameson M, Ahern N, Holloway L. Machine learning applications in radiation oncology. Phys Imaging Radiat Oncol 2021;19:13–24. https://doi.org/10.1016/j.phro.2021.05.007.
[4] Sahiner B, Pezeshk A, Hadjiiski LM, Wang X, Drukker K, Cha KH, et al. Deep learning in medical imaging and radiation therapy. Medical Physics 2019;46:e1–e36. https://doi.org/10.1002/mp.13264.
[5] Wang M, Zhang Q, Lam S, Cai J, Yang R. A Review on Application of Deep Learning Algorithms in External Beam Radiotherapy Automated Treatment Planning. Front Oncol 2020;10:580919. https://doi.org/10.3389/fonc.2020.580919.
[6] Fu Y, Lei Y, Wang T, Curran WJ, Liu T, Yang X. Deep learning in medical image registration: a review. Phys Med Biol 2020;65:20TR01. https://doi.org/10.1088/1361-6560/ab843e.
[7] Song WY, Robar JL, Morén B, Larson T, Carlsson Tedgren Å, Jia X. Emerging technologies in brachytherapy. Phys Med Biol 2021;66. https://doi.org/10.1088/1361-6560/ac344d.
[8] Banerjee S, Goyal S, Mishra S, Gupta D, Bishit SS, Narang K, et al. Artificial intelligence in brachytherapy: a summary of recent developments. Br J Radiol 2021;94:20200842. https://doi.org/10.1259/bjr.20200842.
[9] El Naqa I, Boone JM, Benedict SH, Goodsite MM, Chan H-P, Drukker K, et al. AI in medical physics: guidelines for publication. Med Phys 2021;48:4711–4714. https://doi.org/10.1002/mp.15170.
[10] Dalca A, Yipeng Hu, Vercauteren T, Heinrich M, Hansen L, Modat M, et al. Learn2Reg-The Challenge. Zenodo 2020. https://doi.org/10.5281/zenodo.3715652.
[11] TensorFlow Developers. TensorFlow. Zenodo 2022. https://doi.org/10.5281/zenodo.5949169.
[12] Paszke A, Gross S, Massa F, Lerer A, Bradbury J, Chanan G, et al. PyTorch: An Imperative Style, High-Performance Deep Learning Library. in. Red Hook, NY, USA: Curran Associates Inc; 2019.
[13] Hosny A, Schwier M, Berger C, Omek EP, Turan M, Tran PV, et al. ModelHub.AI: Dissemination Platform for Deep Learning Models. arXiv 2019. https://doi.org/10.48550/arXiv.1911.13218.
[14] Clark K, Vendt B, Smith K, Freymann J, Kirby J, Koppel P, Moore S, Phillips S, Maffitt D, Pringle M, Tarbox L, Prior F. The Cancer Imaging Archive (TICIA): maintaining and operating a public information repository. J Digit Imaging 2013;26:1045–1057. https://doi.org/10.1007/s10278-013-9622-7.
[15] Akazawa M, Hashimoto K. Artificial intelligence in gynecologic cancers: Current status and future challenges - A systematic review. Artif Intell Med 2021;120:102164. https://doi.org/10.1016/j.artmed.2021.102164.
[16] Fionda B, Boldrini L, D’Aviero A, Lancellotta V, Gambacorta MA, Kovács G, Patarinello S, Valentinni V, Tagliaferri L. Artificial intelligence (AI) and interventional radiotherapy (brachytherapy): state of art and future perspectives. J Contemp Brachytherapy 2020;12:497–500. https://doi.org/10.5114/jcb.2020.100384.
[17] Hu H, Shao Y, Hu S. A Review of the Application of Deep Learning in Brachytherapy. OALib 2020;07:1. https://doi.org/10.4236/oalib.1105689.
[18] Luo W. Predicting Cervical Cancer Outcomes: Statistics, Images, and Machine Learning. Front Artif Intell 2021;4:627369. https://doi.org/10.3389/frai.2021.627369.
[19] Chua JAM, Flynn R, Bélanger C, Callaghan C, Kim Y, Jia X, et al. Brachytherapy Future Directions. Semin Radiat Oncol 2018;28:106. https://doi.org/10.1016/j.semradonc.2018.06.004.
[20] Zhou J, Zeng ZY, Li L. Progress of Artificial Intelligence in Gynecological Malignant Tumors. Cancer Manag Res 2020;12:12823–12840. https://doi.org/10.2147/CMAR.S279990.
[21] Yeghiazaryan V, Voiculescu I. Family of boundary overlap metrics for the evaluation of medical image segmentation. J Med Imaging (Bellingham) 2018;5:15006. https://doi.org/10.1117/1.JMI.5.1.015006.
[22] Wong J, Fong A, McVicar N, Smith S, Giambattista J, Wells D, et al. Comparing deep learning-based auto-segmentation of organs at risk and clinical target volumes to expert inter-observer
variability in radiotherapy planning. Radiother Oncol 2020;144:152–158. https://doi.org/10.1016/j.radonc.2019.10.019.

[23] Kalantar R, Lin G, Winfield JM, Messiou C, Lalondrelle S, Blackledge MD, et al. Automatic Segmentation of Pelvic Cancers Using Deep Learning: State-of-the-Art Approaches and Challenges. Diagnostics (Basel) 2021;11. https://doi.org/10.3390/diagnostics11111964.

[24] Liu Z, Chen W, Guan H, Zhen H, Shen J, Liu X, et al. An Adversarial Deep-Learning-Based Model for Cervical Cancer CTV Segmentation With Multicenter Blinded Randomized Controlled Validation. Front Oncol 2021;11. https://doi.org/10.3389/fonc.2021.702270.

[25] Chang Y, Wang Z, Peng Z, Zhou J, Pi Y, Xu XG, Pei X. Clinical application and improvement of a CNN-based auto-segmentation model for clinical target volumes in cervical cancer radiotherapy. J Appl Clin Med Phys 2021;22:115–125. https://doi.org/10.1002/acm2.13440.

[26] Jiang X, Wang F, Chen Y, Yan S. RefineNet-based automatic delineation of the clinical target volume and organs at risk for three-dimensional brachytherapy for cervical cancer. Ann Transl Med 2021;9:1721. https://doi.org/10.21037/atm-21-4074.

[27] Cao Y, Vassantachart A, Ragab O, Bian S, Mitra P, Xu Z, Gallogly AZ, Cui J, Shen ZL, Balik S, Gribble M, Chang EL, Fan Z, Yang W. Automatic segmentation of high-risk clinical target volume for tandem-and-ovoids brachytherapy patients using an asymmetric dual-path convolutional neural network. Medical Physics 2022. https://doi.org/10.1002/mp.15490.

[28] Mohammadi R, Shokatian I, Salehi M, Arabi H, Shiri I, Zaidi H. Deep learning-based auto-segmentation of organs at risk in high-dose rate brachytherapy of cervical cancer. Radiother Oncol 2021;159:231–240. https://doi.org/10.1016/j.radonc.2021.03.030.

[29] Liu Z, Liu X, Xiao B, Wang S, Miao Z, Sun Y, Zhang F. Segmentation of organs-at-risk in cervical cancer CT images with a convolutional neural network. Phys Med 2020;69:184–191. https://doi.org/10.1016/j.ejmp.2019.12.008.

[30] Rigaud B, Anderson BM, Yu ZH, Gobeli M, Cazoulat G, Söderberg J, et al. Automatic Segmentation Using Deep Learning to Enable Online Dose Optimization During Adaptive Radiation Therapy of Cervical Cancer. Int J Radiat Oncol Biol Phys 2021;109:1096–1110. https://doi.org/10.1016/j.ijrobp.2020.10.038.

[31] Zhang Z, Zhao T, Gaiy H, Zhang W, Sun B. ARPM-net: A novel CNN-based adversarial method with Markov random field enhancement for prostate and organs at risk segmentation in pelvic CT images. Medical Physics 2021;48:227–237. https://doi.org/10.1002/mp.14580.

[32] Elmahdy MS, Beljaards L, Yousef S, Sokooti H, Verbeek F, et al. Joint Registration and Segmentation via Multi-Task Learning for Adaptive Radiotherapy of Prostate Cancer. IEEE Access 2021;9:95551–95568. https://doi.org/10.1109/ACCESS.2021.3091011.

[33] Luximon DC, Abdulkadir Y, Chow PE, Morris ED, Lamb JM. Machine-assisted interpolation algorithm for semi-automated segmentation of highly deformable organs. Medical Physics 2022;49:41–51. https://doi.org/10.1002/mp.15351.

[34] He K, Lian C, Adeli E, Hua J, Gao Y, Zhang B, et al. MetricUINet: Synergistic image- and voxel-level learning for precise prostate segmentation via online sampling. Med Image Anal 2021;71:102039. https://doi.org/10.1016/j.media.2021.102039.

[35] Lei Y, Dong X, Tian Z, Liu Y, Tian S, Wang T, et al. CT prostate segmentation based on synthetic MRI-aided deep attention fully convolutional network. Med Phys 2020;47:530–540. https://doi.org/10.1002/mp.13933.

[36] Liu C, Gardner SJ, Wen N, Elshaikh MA, Siddiqui F, Movsas B, et al. Automatic Segmentation of the Prostate on CT Images Using Deep Neural Networks (DNN). Int J Radiat Oncol Biol Phys 2019;104:924–932. https://doi.org/10.1016/j.ijrobp.2019.03.017.

[37] Xu X, Lian C, Wang S, Zhu T, Chen RC, Wang AZ, et al. Asymmetric multi-task attention network for prostate bed segmentation in computed tomography images. Med Image Anal 2021;72:102116. https://doi.org/10.1016/j.media.2021.102116.

[38] Ginum KB, Créhange G, Hussain R, Lalande A. Fast interactive medical image segmentation with weakly supervised deep learning method. Int J Comput Assist Radiol Surg 2020;15:1437–1444. https://doi.org/10.1007/s11548-020-02223-x.

[39] Yabo Fu, Lei Y, Wang T, Tian S, Patel P, Jani AB, et al. Pelvic multi-organ segmentation on cone-beam CT for prostate adaptive radiotherapy. Med Phys 2020;47:3413–3422. https://doi.org/10.1002/mp.14196.

[40] Brion E, Jean Léger AM, Barragán-Montero NM, Lee JA, Macq B. Domain adversarial networks and intensity-based data augmentation for male pelvic organ segmentation in cone beam CT. Comput Biol Med 2021;131:104269. https://doi.org/10.1016/j.compbiomed.2021.104269.

[41] Léger J, Brion E, Desbordes P, De Vleeschouwer C, Lee JA, Macq B. Cross-Domain Data Augmentation for Deep-Learning-Based Male Pelvic Organ Segmentation in Cone Beam CT. Appl Sci 2020;10:1154. https://doi.org/10.3390/app10031154.

[42] Brion E, Léger J, Javuid A, Lee J, Vleeschouwer CD, Macq B. Using planning CTs to enhance CNN-based bladder segmentation on cone beam CT. Medical Imaging 2019: Image-Guided Procedures, Robotic Interventions, and Modeling. SPIE; 2019.

[43] Hu H, Yang Q, Li J, Wang P, Tang B, Wang X, Lang J. Deep learning applications in automatic segmentation and reconstruction in CT-based cervix brachytherapy. J Contemp Brachytherapy 2021;13:325–330. https://doi.org/10.5114/jcb.2021.106118.

[44] Jung H, Gonzalez Y, Shen C, Klages P, Albuquerque K, Jia X. Deep-learning-assisted automatic digitization of applicators in 3D CT image-based high-dose-rate brachytherapy of gynecological cancer. Brachytherapy 2019;18:841–851. https://doi.org/10.1016/j.bray.2019.06.003.

[45] Jung H, Shen C, Gonzalez Y, Albuquerque K, Jia X. Deep-learning assisted automatic digitization of interstitial needles in 3D CT image based high dose-rate brachytherapy of gynecological cancer. Phys Med Biol 2019;64:215003. https://doi.org/10.1088/1361-6560/ab3fcb.

[46] Zhang D, Yang Z, Jiang S, Zhou Z, Meng M, Wang W. Automatic segmentation and reconstruction for CT-based brachytherapy of cervical cancer using 3D convolutional neural networks. J Appl Clin Med Phys 2020;21:158–169. https://doi.org/10.1002/acm2.13024.

[47] Deufel CF, Tian S, Yan BB, Vaisnava HD, Haddock MG, Petersen IA. Automated applicator digitization for high-dose-rate cervix brachytherapy using image thresholding and density-based clustering. Brachytherapy 2020;19:111–118. https://doi.org/10.1016/j.bray.2019.09.002.

[48] Weishaupt LL, Sayer HK, Mao X, Choo R, Stish BJ, Enger SA, et al. Approaching automated applicator digitization from a new angle: Using sagittal images to improve deep learning accuracy and robustness in high-dose-rate prostate brachytherapy. Brachytherapy 2022. https://doi.org/10.1016/j.bray.2022.02.002.

[49] Huang X, Wang J, Tang F, Zhong T, Zhang Y. Metal artifact reduction on cervical CT images by deep residual learning. Biomed Eng Online 2018;17:175. https://doi.org/10.1186/s12938-018-0609-y.
[50] Jeuthé J, Sánchez JCG, Magnusson M, Sandborg M, Tedgren AC, Malusek A. Semi-automated 3d segmentation of pelvic region bones in CT volumes for the annotation of machine learning datasets. Radiat Prot Dosimetry 2021;195:172–176. https://doi.org/10.1093/rpd/ncab073.

[51] Cuocelo R, Cipullo MB, Stanzionale A, Uggia L, Romero V, Radice L, et al. Machine learning in prostate cancer magnetic resonance imaging. Eur Radiol Exp 2019;3:35. https://doi.org/10.1186/s41747-019-0109-2.

[52] Antonelli M, Reinke A, Bakas S, Farahani K, Kopp-Schneider A, Landman BA, et al. Med Segment Decathlon 2021. https://doi.org/10.48550/arxiv.2106.05735.

[53] Litjens G, Toth R, van de Ven W, Hoeks C, Kerksstra S, van Ginneken B, et al. Evaluation of prostate segmentation algorithms for MRI: the PROMISE12 challenge. Med Image Anal 2014;18:359–373. https://doi.org/10.1016/j.media.2013.12.002.

[54] Nichols Bloch AM, NICI-ISBI. Challenge: Automated Segmentation of Prostate Structures. Cancer Imag Arch 2013. https://doi.org/10.7937/K9/TICA.2015.zFv01OP.

[55] Khan Z, Yahya N, Alsaibah K, Ali SSA, Meriaudeau F. Evaluation of Deep Neural Networks for Semantic Segmentation of Prostate in T2W MRI. Sensors (Basel) 2020;20. https://doi.org/10.3390/s20113183.

[56] Lemaitre G, Marti R, Meriaudeau F. Original Multi-Parametric MRI Images Of Prostate. Zenodo 2016. https://doi.org/10.5281/zenodo.162231.

[57] Lemaitre G, Marti R, Freixenet J, Vilanova JC, Walker PM, Meriaudeau F. Computer-Aided Detection and diagnosis for prostate cancer based on mono and multi-parametric MRI: a review. Comput Biol Med 2015;60:8–31. https://doi.org/10.1016/j.compbiomed.2015.02.009.

[58] Gillespie D, Kendrick C, Boon I, Boon C, Rattay T, Yap MH. Deep learning in magnetic resonance prostate segmentation: A review and a new perspective; 2020. https://doi.org/10.48550/ARXIV.2011.07795.

[59] Tian Z, Li X, Zheng Y, Chen Z, Shi Z, Liu L, et al. Graph-convolutional-network-based interactive prostate segmentation in MR images. Med Phys 2020;47:4164–4176. https://doi.org/10.1002/mp.14327.

[60] Jin Y, Yang G, Fang Y, Li R, Xu X, Liu Y, et al. 3D PVNet-An automated prostate MRI data segmentation method. Comput Biol Med 2021;128:104160. https://doi.org/10.1016/j.compbiomed.2020.104160.

[61] Sarma KV, Raman AG, Dhinagar NJ, Priester AM, Harmon S, Sanford T, et al. Harnessing clinical annotations to improve deep learning performance in prostate segmentation. PLoS One 2021;16:e0253829.

[62] Pellicer-Valero OJ, Gonzalez-Perez V, Ramón-Borja JLC, García IM, Benito MB, Gómez PP, et al. Robust Resolution-Enhanced Prostate Segmentation in Magnetic Resonance and Ultrasound Images through Convolutional Neural Networks. Appl Sci (Basel) 2021;11:844. https://doi.org/10.3390/app11020844.

[63] Liu Y, Miao Q, Suraweche C, Zheng H, Nguyen D, Yang G, et al. Deep Learning Enables Prostate MRI Segmentation: A Large Cohort Evaluation With Inter-Rater Variability Analysis. Front Oncol 2021;11:801876. https://doi.org/10.3389/fonc.2021.801876.

[64] Liu Q, Dou Q, Yu L, Heng PA. MS-Net: Multi-Site Network for Improving Prostate Segmentation With Heterogeneous MRI Data. IEEE Trans Med Imaging 2020;39:2713–2724. https://doi.org/10.1109/TMI.2020.2974574.

[65] Liu Q, Dou Q, Heng P-A. Shape-Aware Meta-learning for Generalizing Prostate MRI Segmentation to Unseen Domains. In: Martel AL, Abolmaesumi P, Stoyanov D, Mateus D, Zuluaga MA, Zhou SK, Racoeandeau D, Joskowicz L, editors. Medical Image Computing and Computer Assisted Intervention – MICCAI 2020. Cham: Springer International Publishing; 2020. p. 475–485. https://doi.org/10.1007/978-3-030-59713-9_46.

[66] Cornelli A, Dahiya N, Stefano A, Vernuccio F, Portoghese M, Cutiaa G, et al. Deep Learning-Based Methods for Prostate Segmentation in Magnetic Resonance Imaging. Appl Sci (Basel) 2021;11. https://doi.org/10.3390/app11020782.

[67] Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, et al. In: Attention is All You Need, in. Red Hook, NY, USA: Curran Associates Inc; 2017. p. 6000–6010.

[68] Lu Z, Zhao M, Pang Y. CDA-Net for Automatic Prostate Segmentation in MR Images. Appl Sci (Basel) 2020;10:6678. https://doi.org/10.3390/app10196678.

[69] Aldoj N, Biavati F, Michalek F, Stober S, Dewey M. Automatic prostate and prostate zones segmentation of magnetic resonance images using DenseNet-like U-net. Sci Rep 2020;10:14315. https://doi.org/10.1038/s41598-020-71080-6.

[70] Rouvière O, Moldovan PC, Vlachomitrou A, Gouttard S, Riche B, Groth A, et al. Combined model-based and deep learning-based automated 3D zonal segmentation of the prostate on T2-weighted MR images: clinical evaluation. Eur Radiol 2022. https://doi.org/10.1007/s00330-021-08408-5.

[71] Sunoqrot MRS, Selañas KM, Sandmark E, Langorgen S, Bertilsson H, Bathein TF, et al. The Reproducibility of Deep Learning-Based Segmentation of the Prostate Gland and Zones on T2-Weighted MR Images. Diagnostics (Basel) 2021;11. https://doi.org/10.3390/diagnostics11091690.

[72] Zavala-Romero O, Breto AL, Xu IR, Chang Y-C-C, Gautney N, Dal Pra A, et al. Segmentation of prostate and prostate zones using deep learning A multi-MRI vendor analysis. Strahlenther Onkol 2020;196:932–942. https://doi.org/10.1007/s00330-020-01607-x.

[73] Saunders SL, Leng E, Spilseet B, Wasserman N, Metzger GJ, Bolan PJ. Training Convolutional Networks for Prostate Segmentation With Limited Data. IEEE Access 2021;9:109214–109223. https://doi.org/10.1109/access.2021.3100585.

[74] Hammouda K, Khalifa F, Soliman A, Ghazel M, El-Ghar MA, Haddad A, et al. A Deep Learning-Based Approach for Accurate Segmentation of Bladder Wall using MR Images. In: in: 2019 IEEE International Conference on Imaging Systems and Techniques (IST), Abu Dhabi. United Arab Emirates: IEEE; 2019. p. 1–6. https://doi.org/10.1109/IST48021.2019.9010233.

[75] Bandyk MG, Gopireddy DR, Lall C, Balaji KC, Dolz J. MRI and CT bladder segmentation from classical to deep learning based approaches: Current limitations and lessons. Computers in Biology and Medicine 2021;134:104472. https://doi.org/10.1016/j.compbiomed.2021.104472.

[76] Sanders JW, Lewis GD, Thames HD, Kudchadker RJ, Venkatesan AM, Bruno TL, et al. Machine Segmentation of Pelvic Anatomy in MRI-Assisted Radiosurgery (MARS) for Prostate Cancer Brachytherapy. Int J Radiat Oncol Biol Phys 2020;108:1292–1303. https://doi.org/10.1016/j.ijrobp.2020.06.076.

[77] Sanders JW, Kudchadker RJ, Tang C, Mok H, Venkatesan AM, Thames HD, et al. Prospective Evaluation of Prostate and Organs at Risk Segmentation Software for MRI-based Prostate Radiation Therapy. Radiol Artif Intell 2022;4:e210151.

[78] Savenije MHF, Maspero M, Sikkes GG, van Voort Zyp JRN, Kotte Z, et al. The Reproducibility of Deep Learning-Based Prostate Segmentation in Bladder Wall Using Magnetic Resonance Imaging. Eur Radiol Exp 2019;3:35. https://doi.org/10.1007/s41598-020-0724-x.

[79] van Oort Z, van der Meijden IM, Landman BA, et al. Med Segment Decathlon 2021. https://doi.org/10.48550/arxiv.2106.05735.

[80] van Oort Z, van der Meijden IM, Landman BA, et al. Med Segment Decathlon 2021. https://doi.org/10.48550/arxiv.2106.05735.
[79] Zabihollahy F, Viswanathan AN, Schmidt EJ, Morcos M, Lee J. Fully automated multiorgan segmentation of female pelvic magnetic resonance images with coarse-to-fine convolutional neural networks. Med Phys 2021;48:7028–7042. https://doi.org/10.1002/mp.15268.

[80] Yoganathan SA, Paul SN, Paloor S, Torfeh T, Chandramouli SH, Hammond R, et al. Automatic segmentation of magnetic resonance images for high-dose-rate cervical cancer brachytherapy using deep learning. Med Phys 2022. https://doi.org/10.1002/mp.15506.

[81] Sanders JW, Mok H, Hanania AN, Venkatesan AM, Tang C, Bruno TL, et al. Computer-aided segmentation on MRI for prostate radiotherapy, part II: Comparing human and computer observer populations and the influence of annotator variability on algorithm variability. Radiother Oncol 2021. https://doi.org/10.1016/j.radonc.2021.12.033.

[82] Lijens G, Debats O, Barentsz J, Karssmeijer N, Huisman H. SPIE- AAPM PROSTATEx Challenge Data. Cancer Imaging Arch 2017. https://doi.org/10.7937/K9CTIA.2017.MURSSC1.

[83] Nosrati R, Soliman A, Safigholi H, Hashemi M, Wronski M, Morton G, et al. MRI-based automated detection of implanted low dose rate (LDR) brachytherapy seeds using quantitative susceptibility mapping (QSM) and unsupervised machine learning (ML). Radiat Oncol 2018;12:540–547. https://doi.org/10.1016/j.radonc.2018.09.003.

[84] Nosrati R, Wronski M, Tseng C-L, Chung H, Pejović A, Saad Zaf, Milić T. Attentive Features for Prostate Segmentation in 3D Transrectal Ultrasound. In: Medical Image Computing and Computer Assisted Intervention - MICCAI Brachytherapy Using Residual Neural Networks. In: Medical Image Computing and Computer Assisted Intervention - MICCAI. Springer; 2021. https://doi.org/10.1007/978-3-030-85915-0_10.

[85] Dai X, Lei Y, Zhang Y, Qiu RJ, Wang T, Dresser SA, et al. Automatic multi-catheter detection using deeply supervised convolutional neural network in MRI-guided HDR prostate brachytherapy. Med Phys 2020;47:4115–4124. https://doi.org/10.1002/mp.14307.

[86] Zaffino P, Pernelle G, Mastmeyer A, Mehrtash A, Zhang H, Kikinis R, et al. Fully automatic catheter segmentation in MRI with 3D convolutional neural networks: application to MRI-guided gynecologic brachytherapy. Phys Med Biol 2019;64:165008. https://doi.org/10.1088/1361-6560/ab247f.

[87] Shaer A, Paudel M, Smith M, Tonolete F, Ravi A. Deep-learning-assisted algorithm for catheter reconstruction during MR-only gynecological interstitial brachytherapy. J Appl Clin Med Phys 2021. https://doi.org/10.1016/acm.2021.13494.

[88] He X, Lei Y, Liu Y, Tian Z, Wang T, Curran W, et al. Deep attentional GAN-based high-resolution ultrasound imaging. In: Medical Imaging 2020: Ultrasonic Imaging and Tomography. Houston, United States: SPIE; 2020. p. 10. https://doi.org/10.1117/12.2549556.

[89] Anas EMA, Nouranian S, Mahdavi SS, Spadinger I, Morris WJ, Salcudean SE, et al. Clinical Target-Volume Delineation in Prostate Brachytherapy Using Residual Neural Networks. In: Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence. AAAI Press; 2017. p. 1633–1639.

[90] Orlando N, Gyacskov I, Guo F, Romagnoli C, D’Souza D, et al. Effect of dataset size, image quality, and image type on deep learning-based automatic prostate segmentation in 3D ultrasound. Phys Med Biol 2022;67. https://doi.org/10.1088/1361-6560/ac5a93.

[91] van Sloun R, Wildeboer RR, Mannaerts CK, Postema AW, Gayer M, Wijksstra H, et al. Zonal Segmentation in Transrectal Ultrasound Images of the Prostate Through Deep Learning. In: 2018 IEEE International Ultrasonics Symposium (IUS), Kobe. IEEE; 2018. p. 1–4.

[92] Orlando N, Gillies DJ, Gyacskov I, Romagnoli C, D’Souza D, Fenster A. Automatic prostate segmentation using deep learning on clinically diverse 3D transrectal ultrasound images. Med Phys 2020;47:2413–2426. https://doi.org/10.1002/mp.14134.

[93] Lei Y, Tian S, He X, Wang T, Wang B, Patel P, et al. Ultrasound prostate segmentation based on multidirectional deeply supervised V-Net. Med Phys 2019;46:3194–3206. https://doi.org/10.1002/mp.13577.

[94] Zeng Q, Samei G, Karimi D, Kesch C, Mahdavi SS, Abolmaesumi P, et al. Prostate segmentation in transrectal ultrasound using magnetic resonance imaging priors. Int J Comput Assist Radiol Surg 2018;13:749–757. https://doi.org/10.1007/s11548-018-1742-6.

[95] Karimi D, Zeng Q, Mathur P, Avinash A, Mahdavi S, Spadinger I, et al. Accurate and robust deep learning-based segmentation of the prostate clinical target volume in ultrasound images. Med Image Anal 2019;57:186–196. https://doi.org/10.1016/j.media.2019.07.005.

[96] Samei G, Karimi D, Kesch C, Salcudean S. Automatic Segmentation of the Prostate on 3D Trans-rectal Ultrasound Images using Statistical Shape Models and Convolutional Neural Networks; 2021. https://doi.org/10.48550/ARXIV.2106.09662.

[97] Yang X, Yu L, Wu L, Wang Y, Ni D, Qin J, et al. Fine-Grained Recurrent Neural Networks for Automatic Prostate Segmentation in Ultrasound Images. In: Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence. AAAI Press; 2017. p. 1633–1639.

[98] Anas EMA, Mousavi P, Abolmaesumi P. A deep learning approach for real time prostate segmentation in freehand ultrasound guided biopsy. Med Image Anal 2018;48:107–116. https://doi.org/10.1016/j.media.2018.05.010.

[99] Xu X, Sanford T, Turkbey B, Xu S, Wood BJ, Yan P. Polar transform network for prostate ultrasound segmentation with uncertainty estimation. Med Image Anal 2022;78:102418. https://doi.org/10.1016/j.media.2022.102418.

[100] Peng T, Wu Y, Qin J, Wu QJ, Cai J. H-ProSeg: Hybrid ultrasound prostate segmentation based on explainability-guided mathematical model. Comput Methods Programs Biomed 2022;219:106752. https://doi.org/10.1016/j.cmpb.2022.106752.

[101] Orlando N, Gyacskov I, Gillies DJ, Guo F, Romagnoli C, D’Souza D, et al. Effect of dataset size, image quality, and image type on deep learning-based automatic prostate segmentation in 3D ultrasound. Phys Med Biol 2022;67. https://doi.org/10.1088/1361-6560/ac5a93.
brachytherapy for cervical cancer. Phys Med Biol 2019;64:115013. https://doi.org/10.1088/1361-6560/ab38f6.

[135] Pu G, Jiang S, Yang Z, Hu Y, Liu Z. Deep reinforcement learning for treatment planning in high-dose-rate cervical brachytherapy. Phys Med 2022;94:1–7. https://doi.org/10.1016/j.med.2021.12.009.

[136] Fan J, Xing L, Yang Y. Independent verification of brachytherapy treatment plan by using deep learning inference modeling. Phys Med Biol 2021;66. https://doi.org/10.1088/1361-6560/ac067f.

[137] Nicolae A, Semple M, Lu L, Smith M, Chung H, Loblaw A, et al. Conventional vs machine learning-based treatment planning in prostate brachytherapy: Results of a Phase I randomized controlled trial. Brachytherapy 2020;19:470–476. https://doi.org/10.1016/j.brachy.2020.03.004.

[138] Nicolae A, Morton G, Chung H, Loblaw A, Jain S, Mitchell D, et al. Evaluation of a Machine-Learning Algorithm for Treatment Planning in Prostate Low-Dose-Rate Brachytherapy. Int J Radiat Oncol Biol Phys 2017;97:822–829. https://doi.org/10.1016/j.ijrob.2016.11.036.

[139] Aleef TA, Spadinger IT, Peacock MD, Salcudean SE, Mahdavi SS. Rapid Treatment Planning for Low-dose-rate Prostate Brachytherapy with TP-GAN. In: Medical Image Computing and Computer Assisted Intervention - MICCAI 2021. Cham: Springer International Publishing; 2021. p. 581–590.

[140] Aleef TA, Spadinger IT, Peacock MD, Salcudean SE, Mahdavi SS. Centre-specific autonomous treatment plans for prostate brachytherapy using cGANs. Int J Comput Assist Radiol Surg 2021;16:1161–1170. https://doi.org/10.1007/s11548-021-02405-1.

[141] Jaberi R, Siavashpour Z, Aghamiri MR, Kirisits C, Ghadiri R. Artificial neural network based gynaecological image-guided adaptive brachytherapy treatment planning correction of intra-fractional organs at risk dose variation. J Contemp Brachytherapy 2017;9:508–518. https://doi.org/10.5114/jcb.2017.72567.

[142] Mao X, Pineau J, Keyes R, Enger SA. RapidBrachyDL: Rapid Radiation Dose Calculations in Brachytherapy Via Deep Learning. Int J Radiat Oncol Biol Phys 2020;108:802–812. https://doi.org/10.1016/j.ijrobp.2020.04.045.

[143] Villa M, Bert J, Valeri A, Schick U, Visvikis D. Fast Monte Carlo Simulation of Clinically Significant Prostate Cancer at Prostate MRI: Deep Learning and Radiomics. Cancers (Basel) 2021;14. https://doi.org/10.3390/cancers14010012.

[144] Chaddad A, Kucharczyk MJ, Desrosiers C, Okuswobi IP, Katib Y, Zhang M, et al. Deep Radiomic Analysis to Predict Gleason Score in Prostate Cancer. IEEE Access 2020;8:167767–167778. https://doi.org/10.1109/ACCESS.2020.3033902.

[145] Cao R, Mohammadian Baigiran A, Afshari Mirak S, Shakeri S, Zhong X, Enzmann D, et al. Joint Prostate Cancer Detection and Gleason Score Prediction in mp-MRI via FocalNet. IEEE Trans Med Imaging 2019;38:2496–2506. https://doi.org/10.1109/TMI.2019.2901928.

[146] Mehta P, Antonelli M, Singh S, Groenbecka N, Johnston EW, Ahmed HU, et al. AutoProstate: Towards Automated Reporting of Prostate MRI for Prostate Cancer Assessment Using Deep Learning. Cancers (Basel) 2021;13. https://doi.org/10.3390/cancers13236138.

[147] Schell P, Kohl S, Radtke JP, Wiesenfarth M, Kickingereder P, Bickelhaupt S, et al. Classification of Cancer at Prostate MRI: Deep Learning versus Clinical PI-RADS Assessment. Radiology 2019;293:607–617. https://doi.org/10.1148/radiol.2019190938.

[148] Duran A, Dussert G, Rouvière O, Jaujon T, Jodoin P-M, Lartizien C. Prost-Attention-Net: A deep attention model for prostate cancer segmentation by aggressiveness in MRI scans. Med Image Anal 2022;77:102347. https://doi.org/10.1016/j.media.2021.102347.

[149] Lapa P, Castelli M, Goncalves I, Sala E, Rundo L. A Hybrid End-to-End Approach Integrating Conditional Random Fields into CNNs for Prostate Cancer Detection on MRI. Appl Sci (Basel) 2020;10:338. https://doi.org/10.3390/app10010338.

[150] Zong W, Lee JK, Liu C, Carver EN, Feldman AM, Janic B, et al. A deep dive into understanding tumor foci classification using multiparametric MRI based on convolutional neural network. Medical Physics 2020;47:4077–4086. https://doi.org/10.1002/mp.14255.

[151] Wang X, Yang W, Weinreb J, Han J, Li Q, Kong X, et al. Searching for prostate cancer by fully automated magnetic resonance imaging classification: deep learning versus non-deep learning. Sci Rep 2017;7:15415. https://doi.org/10.1038/s41598-017-15720-y.

[152] Castillo JM, Arif TM, Starmans MPA, Niessen WJ, Bangma CH, Schoots IG, et al. Classification of Clinically Significant Prostate Cancer on Multi-Parametric MRI: A Validation Study Comparing Deep Learning and Radiomics. Cancers (Basel) 2021;14. https://doi.org/10.3390/cancers14010012.

[153] Arif M, Schoots IG, Castillo Tovar J, Bangma CH, Krestin GP, Roobol MJ, et al. Clinically significant prostate cancer detection and segmentation in low-risk patients using a convolutional neural network on multi-parametric MRI. Eur Radiol 2020;30:6582–6592. https://doi.org/10.1007/s00330-020-06177-8.

[154] Saha A, Hosseinzadeh M, Huisman H. End-to-end prostate cancer detection in bpMRI via 3D CNNs: Effects of attention mechanisms, clinical priors and decoupled false positive reduction. Med Image Anal 2021;73:102155. https://doi.org/10.1016/j.mediarxiv.2021.102155.

[155] Jiang X, Li J, Kan Y, Yu T, Chang S, Sha X, et al. MRI Based Radiomics Approach With Deep Learning for Prediction of Vessel Invasion in Early-Stage Cervical Cancer. IEEE/ACM Trans Comput Biol Bioinform 2021;18:995–1002. https://doi.org/10.1109/TCBB.2019.2963687.

[156] Hua W, Xiao T, Jiang X, Liu Z, Wang M, Zheng H, et al. Lymph-vascular space invasion prediction in cervical cancer: Exploring radiomics and deep learning multilevel features of tumor and peritumor tissue on multiparametric MRI. Biomed Signal Process Control 2020;58:101869. https://doi.org/10.1016/j.bspc.2020.101869.
[162] Chen X, Wang Y, Shen M, Yang B, Zhou Q, Yi Y, et al. Deep learning for the determination of myometrial invasion depth and automatic lesion identification in endometrial cancer MR imaging: a preliminary study in a single institution. Eur Radiol 2020;30:4985–4994. https://doi.org/10.1007/s00330-020-06870-1.

[163] Dong H-C, Dong H-K, Yu M-H, Lin Y-H, Chang C-C. Using Deep Learning with Convolutional Neural Network Approach to Identify the Invasion Depth of Endometrial Cancer in Myometrium Using MR Images: A Pilot Study. Int J Environ Res Public Health 2020;17. https://doi.org/10.3390/ijerph17165993.

[164] Wang R, Cai Y, Lee IK, Hu R, Purkayastha S, Pan I, et al. Evaluation of a convolutional neural network for ovarian tumor differentiation based on magnetic resonance imaging. Eur Radiol 2021;31:4960–4971. https://doi.org/10.1007/s00330-020-07266-x.

[165] Urushibara A, Saida T, Mori K, Ishiguro T, Sakai M, Masuoka S, et al. Diagnosing uterine cervical cancer on a single T2-weighted image: Comparison between deep learning versus radiologists. Eur J Radiol 2021;135:109471. https://doi.org/10.1016/j.ejrad.2020.109471.

[166] Dong T, Yang C, Cui B, Zhang T, Sun X, Song K, et al. Development and Validation of a Deep Learning Radiomics Model Predicting Lymph Node Status in Operable Cervical Cancer. Front Oncol 2020;10:464. https://doi.org/10.3389/fonc.2020.00464.

[167] Shen W-C, Chen S-W, Wu K-C, Hsieh T-C, Liang J-A, Hung Y-C, et al. Prediction of local relapse and distant metastasis in patients with definitive chemoradiotherapy-treated cervical cancer by deep learning from 18F-fluorodeoxyglucose positron emission tomography/computed tomography. Eur Radiol 2019;29:6741–6749. https://doi.org/10.1007/s00330-019-06265-x.

[168] Sone K, Toyohara Y, Taguchi A, Miyamoto Y, Tanikawa M, Uchino-Mori M, et al. Application of artificial intelligence in gynecologic malignancies: A review. J Obstet Gynaecol Res 2021;47:2577–2585. https://doi.org/10.1111/jog.14818.

[169] Zhen X, Chen J, Zhong Z, Hrycushko B, Zhou L, Jiang S, et al. Deep convolutional neural network with transfer learning for rectum toxicity prediction in cervical cancer radiotherapy: a feasibility study. Phys Med Biol 2017;62:8246–8263. https://doi.org/10.1088/1361-6560/aa8d09.

[170] Fedorov A, Beichel R, Kalpathy-Cramer J, Finet J, Fillion-Robin J-C, Pujol S, et al. 3D Slicer as an image computing platform for the Quantitative Imaging Network. Magn Reson Imaging 2012;30:1323–1341. https://doi.org/10.1016/j.mri.2012.05.001.

[171] Mehrtash A, Pesteie M, Hetherington J, Behringer PA, Kapur T, Wells WM, et al. DeepInfer: Open-Source Deep Learning Deployment Toolkit for Image-Guided Therapy. Proc SPIE Int Soc Opt Eng 2017;10135. https://doi.org/10.1117/12.2256011.

[172] Patzer RE, Kaji AH, Fong Y. TRIPOD Reporting Guidelines for Diagnostic and Prognostic Studies. JAMA Surg 2021;156:675–676. https://doi.org/10.1001/jamasurg.2021.0537.

[173] Middel L, Palm C, Erdt M. Synthesis of Medical Images Using GANs. In: Greenspan H, Tanno R, Erdt M, Arb T, Baumgartner C, Dalca A, editors. Uncertainty for Safe Utilization of Machine Learning in Medical Imaging and Clinical Image-Based Procedures. Cham: Springer International Publishing; 2019. p. 125–134.

[174] Zwanenburg A, Vallières M, Abdalaha MA, Aerts HJWL, Andrearczyk V, Apte A, et al. The Image Biomarker Standardization Initiative: Standardized Quantitative Radiomics for High-Throughput Image-based Phenotyping. Radiology 2020;295:328–338. https://doi.org/10.1148/radiol.2020191145.

[175] The MONAI Consortium, Project MONAI, Zenodo; 2020. https://doi.org/10.5281/ZENODO.4323059.