10 AI Applications in Nuclear Medicine and Hybrid Imaging

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10.1 Introduction

This chapter provides an overview of AI in nuclear medicine and hybrid imaging applications. It refers to nuclear medicine with its widest definition, as the medical specialty that uses radioactive tracers (radiopharmaceuticals) to assess bodily functions and to diagnose and treat disease. Hybrid imaging refers to the combination of any imaging modality that uses radioactive tracers, along with any other imaging modality, often one that focuses on anatomy, for simultaneous or sequential imaging such as with computed tomography (CT) in positron emission tomography (PET)/CT, single photon emission computed tomography (SPECT)/CT, or magnetic resonance imaging (MRI) in PET/MR. Such hybrid imaging modalities have been increasingly used to diagnose disease with improved accuracy of anatomical localisation compared to the typically poorer spatial resolution in functional diagnostic findings revealed by the radiotracer. The widespread use of hybrid imaging has significantly empowered the role of nuclear medicine imaging in recent years. The co-registration of the images from the two modalities offers a unique combination of functional and anatomical information with advantages, such as more accurate localisation of focal metabolic abnormality, and the potential to use the X-ray imaging data for attenuation correction of the nuclear medicine imaging data.

Recent developments in radiochemistry have led to radiopharmaceuticals where the same molecular target can be labelled with either a predominately gamma photon emitting isotope to drive diagnosis, or a predominately particle emitting isotope such as beta or alpha, to drive a therapeutic intervention aiming at a common biological target. This combined diagnostic and therapeutic approach is often referred to as theranostics, or specifically for radioisotope applications as radio-theranostics. Radio-theranostics are a driving force in modern nuclear medicine and examples include ^{68}Ga-DOTATATE and ^{177}Lu-DOTATATE as a diagnostic (PET/CT) and therapeutic (with post-therapy imaging with SPECT/CT) complimentary pair. These are, respectively, used for the diagnosis and treatment

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of neuro-endocrine tumours (NET) [1, 2] and ^{68}Ga-PSMA and ^{177}Lu-PSMA as a diagnostic (PET/CT), and therapeutic (with post-therapy imaging with SPECT/CT) complementary pair, respectively, for the diagnosis and treatment of metastatic castration-resistant prostate cancer (mCRPC) [3].

Nuclear medicine and hybrid imaging techniques are affected by common challenges and limitations as in other medical imaging modalities, such as patient motion, variability of contrast-defining biological parameters, variability of equipment specifications and imaging protocols, data size, data handling, and reviewer subjectivity. The use of radiotracers often involves additional burdens related to minimising radiation dose, control of image noise (often as a result of limiting injected activity and/or shortening acquisition times), the biological variability of tracer uptake and tracer availability. As with all other healthcare applications and imaging modalities, various computer algorithm methodologies have been employed over the years in nuclear medicine to mitigate those limiting factors and optimise radiotracer imaging, diagnostic outcomes, resource allocation, and personalised patient care. These include statistical analysis, factor analysis, compartmental modelling, image classification techniques, all of which are based on pre-defined assumptions or models, and applied to numerous tasks in image segmentation, noise reduction, tracer kinetic analysis, and data corrections, as discussed further in this chapter.

The emergence of artificial intelligence (AI) in nuclear medicine has occurred over the last 50 years [4] and the integration of AI can be a disruptive addition to offer novel solutions in image acquisition, reconstruction, processing, segmentation, and analysis. AI supports specific tasks, rather than entire processes, and its use has increased rapidly over the past few years. Here we refer to AI as a collective term for machine learning techniques with a deep learning approach based on convolutional neural networks (CNNs) as the forefront of development in the field, as outlined in Chaps. 1 and 2. The introduction of AI approaches in nuclear medicine and hybrid imaging extends to a wide range of applications with potential impact to all stages of the diagnostic process and the patient's journey [5, 6]. These may range from detector level for image acquisition to correction for physics-related processes, for example, photon attenuation and scatter, to image reconstruction, image processing, and analysis including denoising, segmentation, and hybrid image fusion. In addition, AI can be applied in the construction of models to derive diagnosis-specific metrics to aid the clinical decision-making and to pursue further optimisation of the diagnostic or therapeutic process, such as automated feature (lesion) detection or predictive internal radiation dosimetry for personalised therapy. Finally, AI is transforming nuclear medicine by optimising exam planning, reducing costs and resource usage, while also enhancing the patient experience and contributing to more sustainable waste and energy management [7, 8].

10.2 Data Acquisition and Image Formation

10.2.1 Data Acquisition

In data acquisition, the introduction of AI approaches at detector level includes the use of CNNs for sorting PET data into sinograms for large, pixelated crystal arrays to mitigate blurred coarse sampling and large parallax errors [9], thus potentially improving spatial resolution. In the context of PET, the position of a positron annihilation event can be determined more precisely along the line of response if the difference in the timing of the detection of the two photons is used, a methodology referred to as time-of-flight or TOF PET. AI tools can be used to predict the TOF differences from the detector signals themselves, resulting in a 23% increase in timing resolution in one study [10]. In PET imaging, thin-pixelated crystal designs have been proposed to provide higher spatial resolution images, but at the cost of sensitivity. One group proposed an approach to enhance PET image resolution and noise from scanners with large pixelated crystals [9], with potential of achieving comparable image resolution with the larger crystals. Whilst these approaches have been proposed by research-led teams, such advances have been rapidly explored by scanner manufacturers and may be seamlessly incorporated into future system designs and clinical scanning routine in the new generation of scanners. Another area of impact to routine scanning aims at ensuring reproducibility and standardisation of the image acquisition process, involves the introduction of deep learning AI algorithms to apply a specific protocol to both disease and patient characteristics and enable the scanner to define relevant protocol ranges; an example in hybrid imaging being the automated landmarking technology for setting up a patient scan [11]. AI enhances the optimisation of acquisition protocols by selecting the most appropriate settings for the patient, considering factors such as positioning, CT dose modulation, and contrast product injection [12, 13].

10.2.2 Spatial Alignment

Hybrid imaging relies on the co-registration of two datasets from different imaging modalities. Usually, a fixed set of spatial transformation parameters is defined during installation of a hybrid imaging system such as PET/CT or SPECT/CT scanner and periodically checked as part of a quality control program. Whilst such co-registration parameters are expected to show minimal variation with time, unless significant structural changes are introduced in the system, voluntary and involuntary patient motion can affect the spatial alignment between images of the two modalities [14–16]. Furthermore, images from separate imaging sessions may often be required to be co-registered to assist with feature localisation or assessment of progression. Machine learning models can be employed to address the image registration problem. This can be done by estimating the similarities between images, for example, through better intensity correspondences between the two imaging datasets, by comparing corresponding anatomy in the two datasets, by speeding up the optimisation of existing image registration algorithms, or by learning how to approximate the transformations directly [17].

10.2.3 Attenuation Correction (AC)

The CT dataset in hybrid imaging lends itself to attenuation correction of the photons emitted from the PET or SPECT radiotracer as they pass through tissues, because an X-ray image is an indication of how photons are attenuated through different parts of the body. Differences in attenuation properties between the energies of SPECT or PET imaging and the CT X-ray photons are typically addressed by (bi-linear) scaling of these values to match the appropriate energy. However, MR images cannot directly be used for attenuation correction purposes as these are formed by physical processes not related to the electron density in tissues, which would reflect the probability of photon interaction with the matter. Deep learning tools have successfully been used to transform MR images into pseudo-CT images that can be used for attenuation correction [18–20]. Deep learning trained with paired CT and PET/MR images was proposed for pseudo-CT synthesis for the generation of attenuation maps based on Dixon MRI [21] or multiparametric MRI consisting of Dixon and proton-density–weighted zero echo-time (ZTE) MRI [22] and applied to whole-body abdominal or pelvic PET/MR with only minimal bias compared with the CT-based approach, the current standard for attenuation correction.

In fact, current research is being done to investigate whether it is possible to create pseudo-CT images from PET or SPECT images alone. This can potentially be done by using the structural information from the non-attenuation corrected images themselves, which in turn could also lead to a radiation dose reduction. Additionally, if the CT component of a PET/CT is no longer required, it could be speculated that such a new generation of PET scanners could potentially be cheaper to acquire [18]. However, it is probably worth noting that the anatomical component in hybrid imaging, such as the CT in SPECT/CT and PET/CT, typically serves far more than the need for data corrections, such as attenuation and scatter correction, and the impact of anatomical localisation of the radiopharmaceutical uptake often is the dominant requirement for hybrid imaging. Therefore, a departure from the current hybrid imaging model is rather unlikely.

While the above focus on the generation of attenuation maps describes the distribution of the photon attenuation properties across the object, such attenuation maps are typically used as part of iterative image reconstruction in order to apply the actual attenuation correction. As we will see in a section below, the step of attenuation map generation can be incorporated in the image reconstruction step, with an AI approach, which can be expanded to include other corrections such as image registration. As an example of this approach, the use of CNNs trained with whole-body [18] F-FDG PET/CT data has been proposed to simultaneously reconstruct activity and attenuation maps as part of a maximum-likelihood image reconstruction scheme [23], see Fig. 10.1.

10.2.4 Scatter Correction

In the context of PET or SPECT imaging, the result of photon interactions with the tissues may contribute to either photon attenuation, that is, the removal of the photons from the line of site to the detector, or to erroneous entries of photons into the line of site of the detector in the case of photon scattering. Scatter correction methodologies include indirect measurements or modelling of a scatter distribution to estimate the amount of scatter in an image. Images can be obtained in one or several lower energy windows on the energy spectrum to measure the scatter component, typically applicable to SPECT where detector energy resolution is appropriate for this approach. Monte Carlo models of the estimated scatter distribution are often used in both SPECT and PET imaging and tend to be computationally intensive and time-consuming.

Deep learning models can be used to obtain the total scattering distribution. Such models can be trained on Monte Carlo simulated data, which makes the training process initially quite time-consuming [19, 25]; however, they may offer processing time savings to the end-user. As with attenuation correction, scatter correction can lead not only to better quantification of the activity distribution but also to an overall higher accuracy as a result of an improved image reconstruction. This is because the inclusion of all the physical processes involved from the photon emission to its detection will result to a more accurate system matrix, which describes the activity-to-image relationship within the image reconstruction algorithm [26, 27].

10.2.5 Image Reconstruction

Traditional image reconstruction techniques include filtered back-projection (FBP) and iterative reconstruction algorithms. In FBP, the projection data acquired at each imaging angle are back-projected into an empty matrix to obtain images of the activity distribution which can be

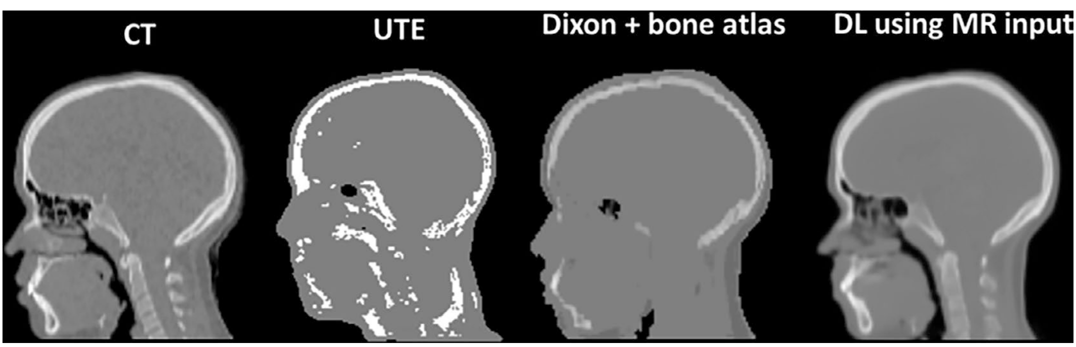

Fig. 10.1 Example of a patient scanned on both PET/CT and PET/MR. Shown from left to right are a sagittal view of the CT image, UTE image, Dixon image with atlas-based bone structure, and an image from a deep learning (DL) model [24] trained using 106 patients to predict a CT from T1 and T2 images. The current MR-based attenuation correction (MRAC) images provided from the scanner for comparison are the Dixon with a bone atlas and UTE. (Data courtesy Dr. Georgios Krokos, The Clinical PET Centre, King's College London)

viewed at transverse, coronal, or sagittal orientation. Inherently, any noise in the projection data is also back-projected, and thus amplified into the final image. To reduce this, a filter can be applied to each projection before the back-projection step. The filter can be modified based on the clinical task, for example, to obtain optimal images of the myocardium or the skeleton, with the applied filter optimised for the specific clinical application.

In iterative reconstruction, the acquired projections of an object or a patient are compared to projections of an estimate of the object or the patient. Corrections are applied to the estimate until the projections of the estimate closely match the acquired projections. Iterative reconstruction techniques are more computationally intensive than FBP, but also much more versatile, as various corrections for physical effects such as photon attenuation, scatter, or spatial resolution can be incorporated into the image reconstruction algorithm [26, 27].

Several AI approaches to image reconstruction for emission tomography have been described in literature [28, 29], see also Fig. 10.2. It is possible that a deep learning algorithm can

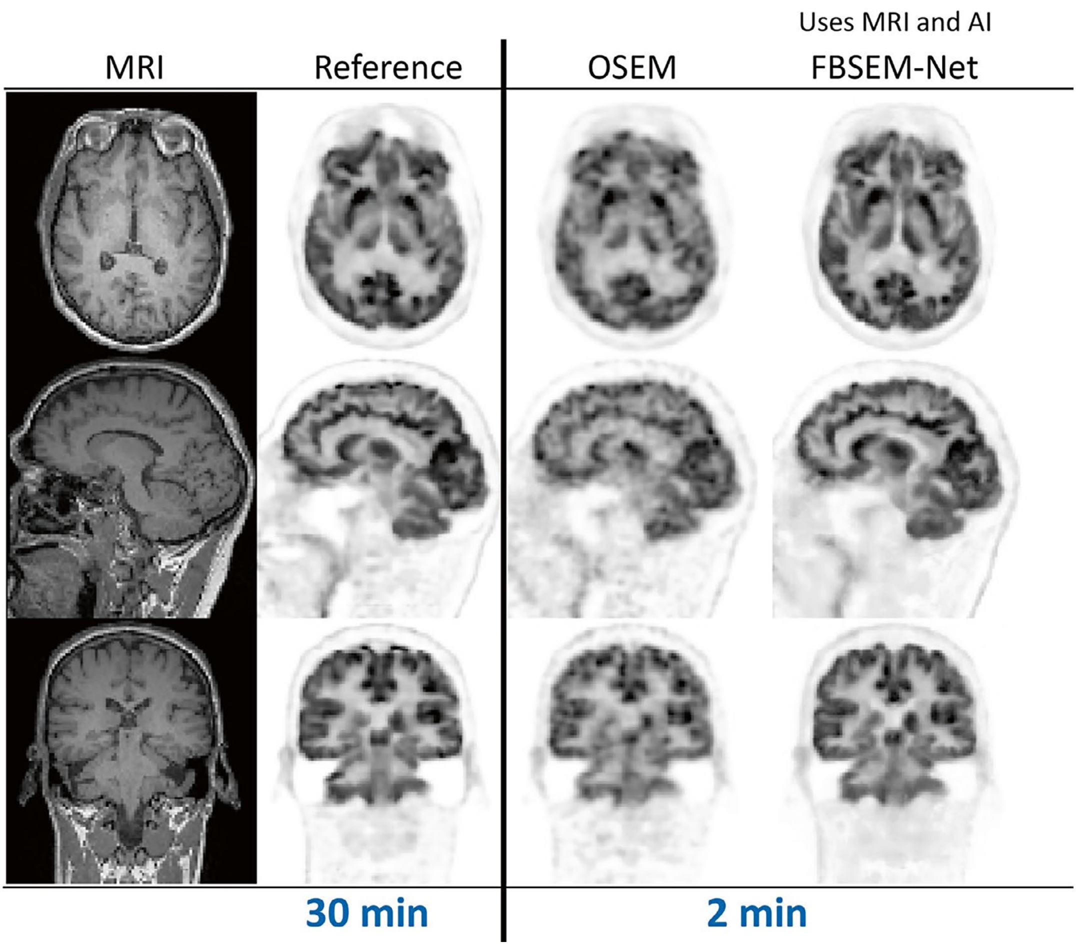

Fig. 10.2 Example of AI-based image reconstruction in PET from FBSEM-Net [28, 33, 34], which offers improved image quality at shorter acquisition times. The images demonstrate this in reconstructing data equivalent to just 2 min of scanning time, with image quality competitive to the reference reconstruction from 30 min of data. OSEM: ordered subsets expectation maximisation; FBSEM: forward backward splitting expectation maximisation

learn the iterative reconstruction process directly, without any intermediate steps describing in detail the system matrix. This can lead to vastly reduced processing times (potentially 100-fold) [18] and reduced image noise [30]. AI technology cannot solve the inverse problem, which is encountered in image reconstruction, but can provide a mapping relationship to solve problems in reconstruction. One such example is the transformation between the sinogram (projection data) domain and the image domain that can be achieved through AI technology [19]. While the training of a model that does this is very time-consuming, the direct AI reconstruction afterwards is very efficient for the end-user.

It should be noted that, independently of the exact approach used, the responsibility of performance assessment, quality assurance, and optimisation remains with the end-user. Consequently, AI approaches in data corrections and image reconstruction remain subject to the same rigorous quality control and optimisation as defined by the latest standards, regulations, or professional best practices, though approaches specific to AI performance may also be pursued [31, 32].

10.3 AI in Image Processing and Analysis

10.3.1 Radiation Dose Reduction and Signal-to-Noise Improvements

Reduction of noise, or improvements in signal to noise as part of the imaging optimisation process, can lead to improvements in image quality, which may be translated to reduction of radiation dose or image acquisition times. This has been an area of development for AI approaches, for example, to generate full-dose PET images from low-dose data [35] or to directly filter reconstructed PET images [36]. Similar AI approaches for noise control have been proposed in SPECT imaging [29]. It is possible to train a deep learning algorithm on how to create higher-count images from lower-count images. Intuitively, this can be explained using two matched datasets of the same object – one with lower counts (and thus lower image quality) and one with more counts (and thus less noise). Once the deep learning algorithm is trained on an adequate number of matched datasets, this information can then be used to create images of higher quality from images of lower quality [37]. In real terms, this means that one can either (a) reduce image acquisition time, particularly for patients who are unable to tolerate the full scanning process due to factors such as pain, claustrophobia, or specific populations like paediatric patients, individuals with dementia, and others who may struggle with the procedure or (b) reduce the injected activity, since it is possible to obtain good quality images from a lower quality acquisition. This has led to extreme dose reductions of up to 99% having been reported [38]. This approach is particularly valuable for paediatric patients, or when there are problems with radiotracer availability, as well as in terms of economic and environmental sustainability. See Case Study 10.1 and Fig. 10.3 for more information and insight.

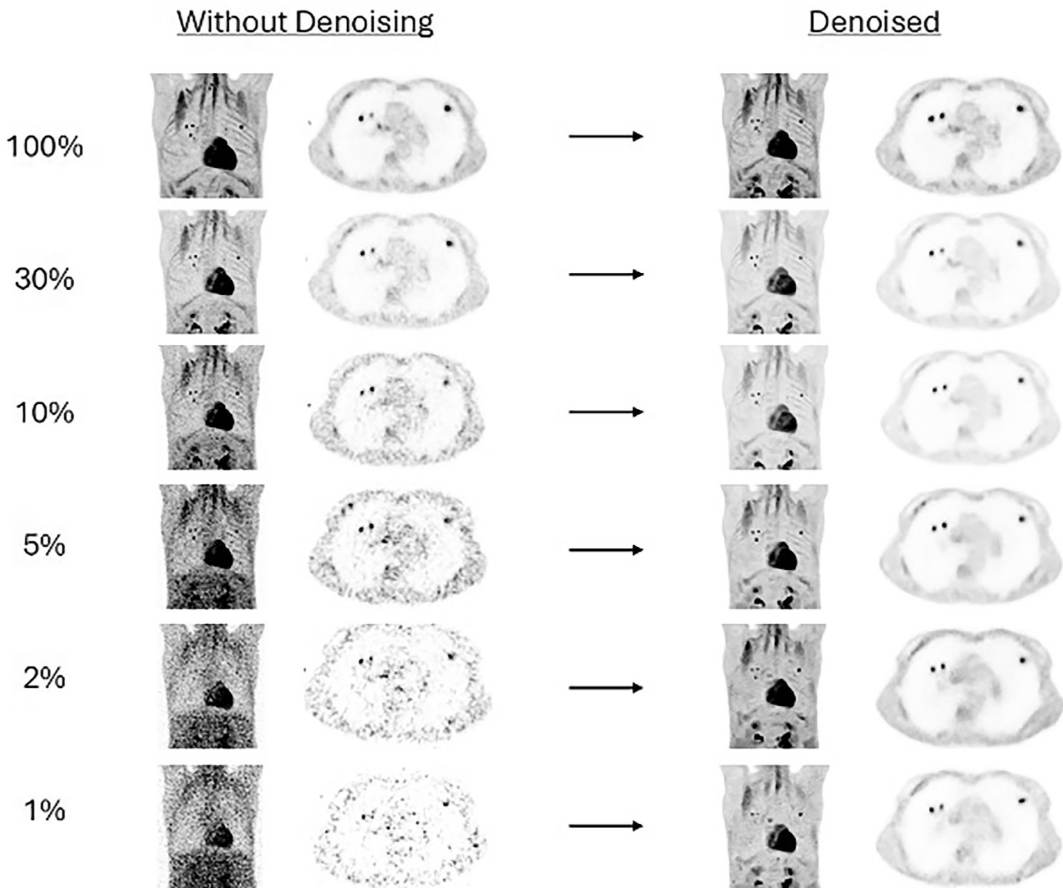

Fig. 10.3 Use of AI denoising in PET imaging. (Images courtesy Prof John Olivier Prior & Dr. Daphné Faist, Department of Nuclear Medicine and Molecular Imaging, Lausanne University Hospital and University of Lausanne, Lausanne, Switzerland)

10.3.2 Image Segmentation—*Automated Lesion Detection*

Case Study 10.1

Clinical challenge: Use of F-18 FDG PET/CT for lung cancer screening. In this context, a reduction in the injected activity is essential. This reduction will have a negative effect on the quality of the PET image, with a lower signal-to-noise ratio (SNR) [39].

AI-enabled solution: To address this issue, a 3D convolutional neural network (CNN) is employed to enhance the quality of FDG PET images through denoising [40]. A simulation of the reduction in injected activity from 100% to 1% was carried out (Fig. 10.3, left). The CNN was then used to reconstruct the degraded images (on the right side). The ground truth, framed in green, represents the PET acquired with 100% of the injected activity.

Benefits: In this scenario, the detectability of pulmonary nodules is maintained while simultaneously reducing the dose received by the patient. This approach can be applied to other clinical situations where a reduction in injected activity is necessary, such as in paediatric patients or during

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radiopharmaceutical shortages. Additionally, it is possible to shorten the acquisition time, which would also require the use of a denoising algorithm. This is particularly beneficial for patients with claustrophobia, those suffering from painful conditions, or children who have difficulty staying still.

Challenges: In the case of small nodules and very noisy images, AI -elated hallucinations may occur, as the nodule fades into the noise and is detected as such. As a result, it may disappear from the image reconstructed by the denoising AI. In the literature, cases of reverse hallucinations have been documented, with the apparition of false lesions in the reconstructed images that were not present in the original ground truth [41]. Additionally, denoised images tend to appear smoother compared to the ground truth.

One area where AI has shown to be extremely beneficial is in automated organ or lesion detection and segmentation. Fast and accurate lesion identification may be critical for an appropriate intervention [42, 43]. Image segmentation and automated definition of regions-of-interest (ROIs) to specify a volume or for organ delineation on a single or hybrid modality may have a significant impact in efficiency of applications such as the calculation of standardised uptake value (SUV), lesion evaluation, or radiation dosimetry derived from radionuclide imaging and therapy.

Numerous medical image segmentation tools have been developed for use on nuclear medicine and the functional, anatomical, or combined modalities of hybrid images [44–47] usually developed around the U-NET architecture [48], while V-Net, a volumetric network, uses 3D slices as input, unlike U-Net, which uses 2D slices. AI approaches previously proposed for image segmentation are often based on a CNN requiring a large amount of input data to be able to create an accurate segmentation model. U-NET-based algorithms aim to achieve accurate segmentation with smaller training datasets. This is particularly applicable to medical images where there is often limited access to well-characterised image datasets, and memory, storage, and processing requirements may be demanding. U-NET architecture consists of a contracting path, as moving through the CNN layers, information is lost via down-sampling. A symmetric expanding path mirrors the encoding part of the algorithm but replaces convolutions with up-convolutions resulting to the output segmentation map. The addition of an up-sampling path gives information to the decoding part on where in the image a feature is extracted from by the use of skip connections [49] allowing for features present in the contracting path to be passed to the expanding path, which recovers the initially lost spatial information from down-sampling [48]. This architecture achieves a higher resolution output whilst maintaining an accurate and robust outcome. In hybrid imaging, the use of both modalities improves segmentation performance by using both anatomical (CT) and physiological (PET or SPECT) information [50].

Automated approaches to image segmentation can have a significant efficiency impact to organ and lesion delineation for applications related to the extraction of clinical image metrics and indices, such as SUV calculation [51], tumour characterisation, or the derivation of organ time activity curves as in internal radiation dosimetry applications in theranostics [52], which could considerably contribute towards personalised therapy [53]. See further information presented in Case Study 10.2 and Fig. 10.4. In radiation oncology, some of these AI approaches have already been commercialised and clinically approved for contouring of organs at risk in radiotherapy [54, 55]. See Chap. 11 for more information.

Further uses of AI-based automated segmentation and classification techniques include the clinical evaluation and automated identification of Parkinson's disease from I^{123}-Ioflupane (FP-CIT) or DaTSCAN SPECT imaging where machine learning approaches have been used to train models based on well-characterised data [56–58]. In such cases, authors have pointed out the use of training datasets that sufficiently reflect

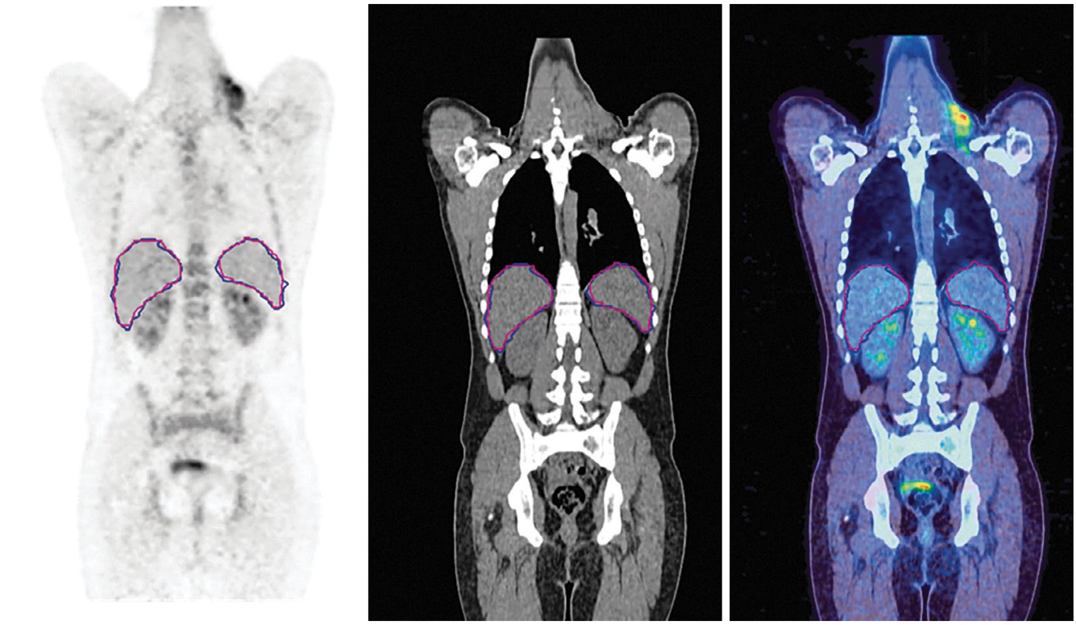

Fig. 10.4 Examples of manually defined liver and spleen regions on CT (blue line) and by AI model (red line) trained on 40 patients [51] to predict those regions. Regions shown on PET (left), CT (middle), and PET/CT (right) modalities. (Data courtesy Dr. Georgios Krokos, The Clinical PET Centre, King's College London)

the variability of scanning protocols, such as gamma cameras, collimators, and reconstruction parameters, to achieve robust and accurate outcomes.

Case Study 10.2: (Fig. 10.4) Use of Deep Learning-Based Image Segmentation in PET/CT

Clinical challenge: Organ segmentation is often required in order to report quantitative metrics, such as SUV (standardised uptake value) in PET and SPECT to express the level of radiopharmaceutical uptake normalised for the injected activity and patient body weight. In hybrid imaging, such as PET/CT and SPECT/CT, the availability of a spatially aligned anatomical modality allows the definition of organs with good anatomical accuracy; however, this manual process can be very time-consuming due to organs extending over many image slices and its accuracy may be subject to variability across different users.

AI-enabled solution: Use of deep learning-based image segmentation by an AI model (red line) trained on 40 patients [51] of manually segmented regions (blue line) to predict liver and spleen regions. Regions shown on PET (left), CT (middle), and PET/CT (right) modalities (Fig. 10.4).

Benefits: Organ segmentation can be achieved at significantly shorter times compared to manual organ delineation, for example, in seconds rather than several minutes (>20 min when organs extend to several image slices). The automated segmentation process is likely to avoid variability of the operation across multiple users [59].

Challenges: The accuracy of the results can vary depending on the complexity of the anatomy presented. Cases which might differ significantly from those used to train the

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model may lead to unexpected results. Cohorts of cases, for example, patient groups with differences in pathophysiology, compared to the training dataset, due to disease, ethnicity, etc., may lead to biased results such as those reported in other modalities [46]. These can be mitigated by carefully balanced training datasets and careful consideration of the required testing and quality assurance for the implementation of AI in the context of the application intended.

10.4 AI in Theranostics

Internal radiation dosimetry is a key aspect to personalised treatments in nuclear medicine theranostics. Individual dose estimates may contribute to reducing the risk of radiation-related toxicities. Whilst Monte Carlo simulations or other voxel-based dosimetry methods may be the gold standard for internal dosimetry [53] moving away from standard geometry pre-calculated dosimetric estimates of the MIRD (medical internal radiation dosimetry) model [60], these techniques are very time-consuming and often not clinically feasible. Furthermore, current clinical practice with molecular radiotherapy suggests that only limited imaging is performed as part of patient treatment planning. This imposes restrictions on the ability to provide dosimetric estimates, given the typically insufficient imaging time points. Therefore, there is a role for machine learning approaches that go beyond the automation of organ segmentation discussed in the previous section, in order to achieve accurate dosimetric estimates under current clinical limitations [52, 53]. Furthermore, a number of steps in the dosimetry estimation process can potentially be enhanced by AI methodologies. These include multi-modality image registration, multiple time-point image registration, segmentation of organs and tumours, curve fitting of time-activity curves, and conversion of time-integrated activity into absorbed dose. This will lead to comprehensive patient dose profiling [53, 61]. See Case Study 10.3 and Fig. 10.5 to explore this AI application further.

In applications of radio-theranostics outside dosimetry, there have been a number of AI approaches in focusing on diagnostic ability or prediction of therapy outcomes; for example, in thyroid cancer where there is a well-established use of radionuclides at diagnostic and therapeutic stages, data from fine-needle aspiration biopsy samples [62], or imaging [63] together with other approaches have been used in machine learning methodologies to improve diagnosis of thyroid cancer [64].

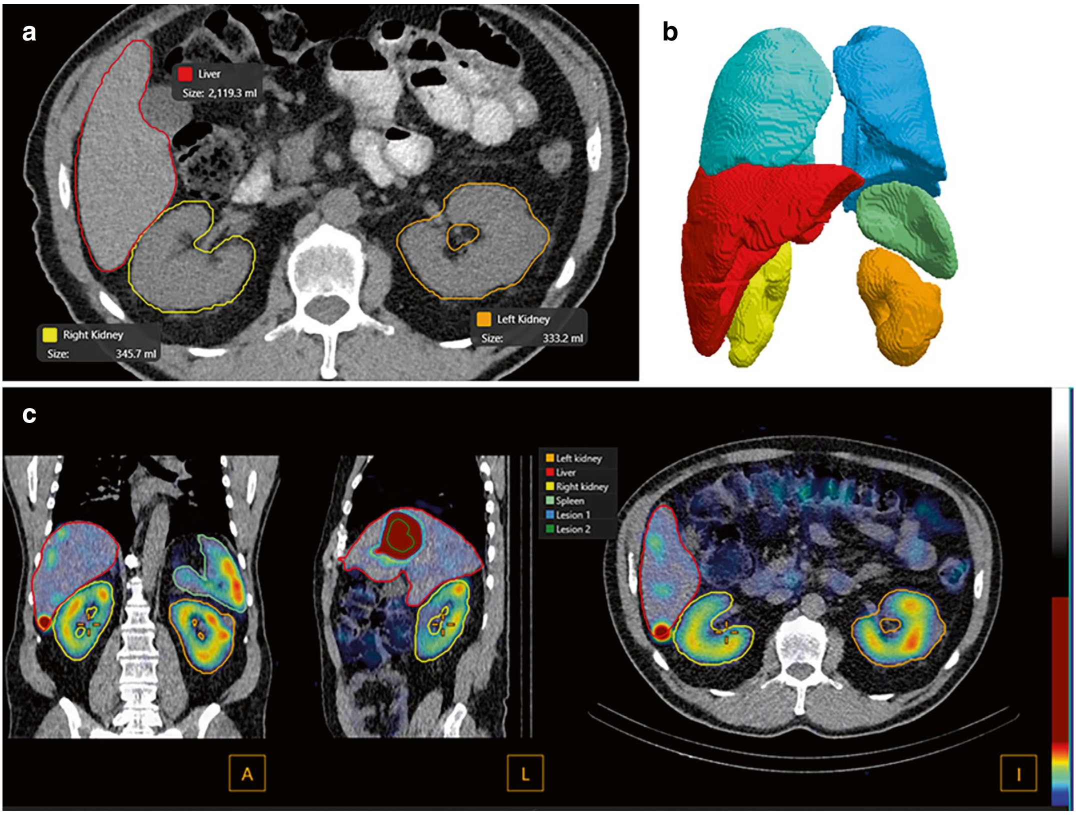

Fig. 10.5 Example of organ segmentation for dosimetry applications in molecular radiotherapy. (**a**) CT-based segmentation of liver, spleen, and left and right kidney shown on a transverse CT slice and (**b**) as 3D rendered volumes. (**c**) Segmentations applied onto a radiation dose map for ^{177}Lu-DOTATATE peptide receptor radiotherapy (PRRT) to derive personalised organ-level radiation dose metrics. Application implemented on the HERMIA (Hermes Medical Solutions, Sweden) software platform based on a CNN deep learning model, substantially expediting the image analysis process (<1 min on a regular current system) compared to the manual segmentation which remains significantly time-consuming due to its requirement to define several regions over a number of slices. Images courtesy Hermes Medical Solutions, Sweden

Case Study 10.3: (Fig. 10.5) Deep Learning-Based Organ Segmentation for Dosimetry in Molecular Radiotherapy

Clinical challenge: Organ segmentation is often required as part of internal radiation dosimetry to define absorbed radiation doses, for example, as part of molecular radiotherapy. Various organs should be defined in order to determine the radiopharmaceutical uptake throughout the course of the therapy, based on SPECT/CT or PET/CT imaging. Organs may have to be defined multiple times, for example, when a series of images is acquired at various time points. As discussed already, this manual process can be very time-consuming and subject to inter-operator variability.

AI-enabled solution: A CNN deep learning model trained on appropriate datasets can substantially expedite the volume of interest (VOI) definition part of the data analysis process for radiation dosimetry. As an example, Fig. 10.5 shows AI-based

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automated segmentation of organs (liver, spleen, kidneys) as part of the dosimetry workup for ^{177}Lu-DOTATATE peptide receptor radiotherapy (PRRT) to derive personalised organ-level radiation dose metrics. Organ VOIs can be applied to the images or directly to dose maps (Fig. 10.5).

Benefits: Organ segmentation in radiation dosimetry is a particularly time-consuming process, so, expediting this stage, from >1 h to <1 min with automated segmentation, may allow the implementation of personalised therapy within clinically relevant time frames and without excessive additional requirements in expert resources. Furthermore, automated organ segmentation may contribute to lower variability in the dosimetric calculations due to reduced intra-operator variability.

Challenges: As stated, the accuracy of results can vary depending on the complexity of the anatomy and the presence of 'outliers' from the datasets used for training the model. Careful consideration of the appropriate testing and on-going quality assurance of AI in the context of its clinical use is crucial for the successful implementation of the application.

10.5 AI in Other Nuclear Medicine Applications

10.5.1 Radiopharmaceutical Development

The prediction of drug-target interactions can inform the application of a radiotracer in nuclear medicine. Usually, the development of a new tracer is a time-consuming and expensive undertaking, but AI-based methods are being used to assist with this process [65–67]. This can be done, for example, by predicting the binding affinity of a new radiopharmaceutical for its target, or by predicting its pharmacokinetics [68].

10.5.2 Workflow Optimisation

One study showed the feasibility of predicting non-shows in an imaging department by training a model on 16 data elements from the electronic medical record system [69]. AI may help in patient scheduling and resource use [70], as well as device monitoring to detect errors [71]. It should be noted that the various AI solutions discussed above can significantly impact workflow optimisation. For instance, the use of denoising AI to reduce acquisition time, or AI solutions that automate time-consuming tasks, can streamline different stages of the process, thereby improving overall workflow efficiency.

10.5.3 Clinical Trials

AI can be used to observe clinical trial pipelines, including a wide variety of aspects, ranging from reasons for regulatory approval or refusal, safety issues, or strategic and financial aspects [72]. The potential of human error in data collection can be reduced. Data consistency affects the performance of machine learning algorithms, and therefore hospitals have to be very vigilant to ensure consistent data collection, curation and safe storage. Clear protocols are especially helpful in this regard. Machine learning has also been investigated for detecting centre-level irregularities in randomised controlled trials [73].

10.5.4 Education and Training

Aspects of the use of artificial neural network (ANN)-based tools were proposed early on in nuclear medicine and their role in training was envisaged as support systems in clinical decision-making. Examples include early applications in myocardial perfusion SPECT [74], where AI tools were proposed in clinical decision support as part of a semi-supervised training framework for reporting.

10.5.5 Sustainability

Artificial intelligence offers the potential to improve the sustainability of nuclear medicine in its various pillars. AI can promote social sustainability by reducing inequality and improving patient care. In human terms, it can increase efficiency and reduce practitioner burnout. Economic sustainability is addressed by optimising resources and reducing costs. In terms of ecological and environmental sustainability, AI can help to reduce waste and the use of energy in the production of radiotracers and the production of images [75]. However, the development of AI tools should consider actions to reduce the carbon footprint, energy consumption, and the use of computational resources [76].

10.6 Considerations for AI Implementation

As with other automated techniques, the introduction of machine learning methodologies may pose challenges. The clinical implementation of AI algorithms requires, similar to other new technologies introduced into clinical routine, appropriate testing and the knowledge of its limitations and shortcomings. As examples from AI applications in nuclear medicine and hybrid imaging emerge, some areas of potential concern have been reported in the literature. The potential introduction of artefacts has been reported in AI-based image reconstruction, which might cause false-positive and false-negative results [77]. AI-based denoising may 'remove' lesions [78], and AI-based lesion segmentation may wrongly identify healthy tissue as a lesion [79]. Such examples suggest that there may still be a need for further optimisation and refinement of the newly developed deep learning methodologies. Furthermore, AI algorithms trained on one dataset and performing well on similar data cohorts may perform worse on a new, unseen dataset, such as from a different scanner, population group, or one that experienced a change in patient demographics and imaging protocols [80–82].

Strategies should be developed for rigorous evaluation of AI algorithms in nuclear medicine and hybrid imaging. Key best practices were published by the Society of Nuclear Medicine and Molecular Imaging AI Task Force Evaluation team and are known as the RELAINCE guidelines (Recommendations for EvaLuation of AI for NuClear medicinE) [83]. The authors propose a framework to evaluate AI algorithms for promise, technical task-specific efficacy, clinical decision-making, and post-deployment efficacy. These include, amongst others, checking that the ground-truth quality is reasonable, that the training and testing datasets for the algorithm do not overlap, that appropriate clinically relevant tasks are chosen, that the collected clinical data represents the target population, and that data drift should be regularly monitored (see Chap. 4 for more information about post-market surveillance).

The generalisation of AI requires large amounts of data, which raises ethical questions around consent and data anonymisation. Regulatory pathways are also lagging behind the developments in the field [84]. Some of these aspects may particularly affect applications in nuclear medicine as an area often endemic to limited access to clinical trial data and a variability of scanners and protocols. For these reasons, standardisation of data and protocols and wider availability of open access data may be important for future developments, both in innovation and clinical implementation and testing of AI. More generic information on AI implementation considerations in medical imaging can also be found in Chap. 4.

It is also essential to consider the impact on healthcare professionals, particularly nuclear medicine technologists and radiographers. One study [85] showed that the implementation of an AI denoising algorithm for PET/CT faces barriers such as workflow challenges, professional resistance and lack of education. Facilitating factors include clear explanations and support, such as a 'local AI champion'. Thinking through procedures, workload, and resources, together with appropriate training and support to overcome these barriers, is crucial to success.

10.7 Chapter Summary

There is a wide range of AI in nuclear medicine to support both imaging-related tasks such as acquisition, analysis and therapeutic planning, and tasks relating to the optimisation of patient care processes. However, regulatory pathways are also lagging behind the developments in the field and standardisation of data and protocols and wider availability of open access data may be important for future developments, both in innovation and clinical implementation and testing of AI. Additionally, considering the needs and concerns of users during the implementation of these AI solutions is crucial to facilitate their adoption.

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Artificial Intelligence for Radiographers

Basic Principles, Clinical Applications and Implementation Considerations

Foreword by
Charlotte Beardmore, Edward H. T. Chan,
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