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The role of Artificial intelligence in the assessment of the spine and spinal cord

Abstract:

Artificial intelligence (AI) application development is underway in all areas of radiology where many promising tools are focused on the spine and spinal cord. In the past decade, multiple spine AI algorithms have been created based on radiographs, computed tomography, and magnetic resonance imaging. These algorithms have wide-ranging purposes including automatic labeling of vertebral levels, automated description of disc degenerative changes, detection and classification of spine trauma, identification of osseous lesions, and the assessment of cord pathology. The overarching goals for these algorithms include improved patient throughput, reducing radiologist workload burden, and improving diagnostic accuracy. There are several pre-requisite tasks required in order to achieve these goals, such as automatic image segmentation, facilitating image acquisition and postprocessing. In this narrative review, we discuss some of the important imaging AI solutions that have been developed for the assessment of the spine and spinal cord. We focus on their practical applications and briefly discuss some key requirements for the successful integration of these tools into practice. The potential impact of AI in the imaging assessment of the spine and cord is vast and promises to provide

broad reaching improvements for clinicians, radiologists, and patients alike.

Highlights:

- In the past decade, multiple spine AI algorithms have been created based on radiographs, computed tomography, and magnetic resonance imaging.

- The overarching goals for these algorithms include improved patient throughput, reducing radiologist workload burden, and improving diagnostic accuracy.

- Their practical applications are detailed and briefly discuss some key requirements for the successful integration of these tools into practice.

1. Introduction

Medical practice has seen a rapid recent increase in the development of artificial intelligence (AI) solutions. Medical images, such as those generated in radiology, are data rich and thereby provide an excellent substrate for AI algorithms. As a result, considerable efforts have been directed towards creating and implementing AI applications in radiology, aiming to improve clinical practice. To date, there have been many notable developments in radiology applications for AI, with promising results spanning many different conditions and diverse anatomic regions [1], [2], [3]. To the uninitiated, the AI lexicon can be daunting. Terms such as machine learning (ML), deep learning (DL), and convolutional neural networks (CNNs) have specific and unique definitions, but are often erroneously used interchangeably, compounding confusion [4]. ML is the field of AI responsible for creating algorithms for providing computers the ability to learn automatically without minimal human intervention. DL is the subfield of ML focused on creating algorithms able to process data and create patterns in the human brain. CNNs are a subtype of DL algorithms applied to analize data using a neuron-like pattern.

A primary goal of AI implementation in radiology is to improve and augment the radiologist's workflow, which will, in turn, benefit referring clinicians and positively impact patients. AI has the potential for useful applications throughout all parts of the diagnostic process in radiology, beginning with image acquisition and ending with image postprocessing and automated report generation. In spine imaging, AI algorithms have been developed for several different tasks including improving the overall quality of images, automated labeling of vertebral levels, and the detection, segmentation, and characterization of lesions [5], [6], [7], [8]. AI tools for spine lesion characterization have shown particular promise in the extraction of specific image features that can help to both detect and classify lesions.

Early AI applications in spine have demonstrated remarkable utility in the assessment of the focal lesions. For example, some algorithms have been able to detect early compressive myelopathy changes and demyelinating lesions in the spinal cord, which are otherwise occult on normally appearing MR images [9]. Other AI applications have resulted in an earlier detection of focal or diffuse pathologic marrow involvement. This may prove to have substantial prognostic implications for patients, allowing for more rapid initiation of therapy and, in some cases, additional therapeutic options that would have otherwise not been available with a more advanced disease [4], [5], [10].

We conducted a bibliography search with a review of articles on Spine imaging and Artificial Intelligence in radiology published between 2010 and 2021 using a PubMed search. In this narrative review, we describe some of the main AI solutions that have been developed during this period for the imaging evaluation of the spine and spinal cord and highlight their primary strengths and weaknesses. Further, we review some of the barriers to the eventual, successful integration of these specific AI tools into daily clinical practice.

2. Artificial intelligence applications in the spine

The spine was one of the first anatomic regions for which dedicated AI algorithms were applied to imaging studies. Since the spine is typically included as part of the field of view for a variety of other imaging studies (e.g., neck, thorax, abdomen), there is the potential to either capture, or miss, a considerable amount of additional information. For this reason, there is growing interest in the development of automated AI tools that can be used to assess the vertebra and the spinal cord on these non-spine examinations. Additionally, tools for automated vertebral body labeling are now widely available for both computed tomography (CT) and MRI [11] (Fig. 1). More recently, AI tools for vertebral fracture detection and for the assessment of osteoporosis have been successfully developed for CT as well as plain radiographs with promising early results [1], [12]. Algorithms have also been applied to MRI and CT images in an effort to output automated scoring and reporting of lumbar spine degenerative changes [13], [14]. Furthermore, specific AI tools have been developed for the detection of spinal metastases [15] and the diagnosis of hematologic diseases [16]. Table 1 summarizes the main AI applications for spine evaluation.

2.1 Anatomic localization in the Spine: Vertebral body labeling and segmentation

The first step in many fully automated ML tasks in spine is to label the vertebral bodies on CT or MRI, with several different algorithms having already been developed to this end [17], [18], [19]. Suzani et al. [20] developed a deep neural network for automatic detection and localization (defined in this work as the determination of the center) of specific vertebrae in CT scans. Their work produced results in less than three seconds per CT with an accuracy of 96 %, improving upon the one minute per image computation time using a random forest algorithm previously achieved by Glocker et al. [21]. Based on CT images, Wang et al. [8] developed a solution that decreased localization errors in the cervical and lumbar region due to stronger image contrast but with lower accuracy in the thoracic region due to spine curvature and substantial similarity of thoracic vertebrae. We consider that wrong site spinal surgery percentage as consequence of transitional abnormalities would potentially decrease with the introduction of these AI solutions [22]. Recent studies obtained localization and labeling accuracies of 94.7 % on CT [17], and of 95.6 % for MRI [23]. While some of these applications are already commercially available, considerable research continues in this area to further improve results and reduce computational costs. Similarity of the different vertebrae, spinal curvature, beam hardening or susceptibility artifacts due to orthopedic hardware, the presence of lumbosacral transitional vertebrae or field of view limitations are among the main challenging issues for developing and implementing AI solutions for automatic vertebral bodies labeling [8], [19], [21], [23], [24].

Segmentation, the process in which each pixel is labeled based on its belonging to a specific region or anatomical structure, is a prerequisite for developing more powerful diagnostic and prognostic AI tools. For example, once AI based automated segmentation is mastered, future AI algorithms can then be developed to use this segmented information in order to generate 3D models for surgical planning and navigation among other tasks [25], [26]. In recent years, CNN has emerged as the primary methodology employed for the development of segmentation algorithms. For example, Kuang et al. developed an unsupervised DL pipeline model for vertebral segmentation from MRI images that eliminates time-consuming manual labelling tasks with a segmentation accuracy comparable to manual methods and that also overcomes limitations due to vertebral shape variability or image quality inconsistences derived from the use of different MRI systems or protocols [27]. Extensive experiments will be required to validate these promising results further. In addition to vertebral segmentation, ML algorithms have also been used to segment and measure the neural foramina [28] and the spinal canal [29].

Several authors have explored the application of AI tools to conventional radiographs in order to reduce interpretation times through automation. Successfully screening normal radiographs through the use of AI could markedly reduce radiologist interpretation times, allowing them to focus their effort on more complicated or abnormal studies [30]. In addition, active prioritization of cases with urgent findings on the reading worklist, such as a vertebral fracture, may reduce turnaround times and thereby improve patient outcomes. ML can also help with repetitive tasks such as measuring angles. For example, Zhang et al. [31] used a deep neural network on posteroanterior radiographs of the spine to measure Cobb angles obtaining a high intraclass correlation coefficient. Wu et al. [32] proposed a multi-view correlation network using anteroposterior and lateral radiographs for the automated assessment of adolescent idiopathic scoliosis. Using 526 radiographs from 154 patients, they achieved high accuracy with only a 4.04° mean error in the estimation of AP Coob angle. Additionally, Pan et al. [33] applied a two Mask R-CNN to chest radiographs for the assessment of scoliosis, which was defined as a Cobb angle greater than 10°. They obtained limited results with a sensitivity of 89.5 % and a specificity of 70.3 % and suggest that their models could reduce interobserver variation in scoliosis grading as manual measurements have been shown to depend on the radiologist's experience [34]. Furthermore, Galbusera et al. [35] developed a CNN able to predict the location of several spine landmarks on biplanar radiographs of the spine in order to calculate thoracic kyphosis, lumbar lordosis, Cobb angle, pelvic incidence, sacral slope and pelvic tilt; however, the accurate results reported in this study might be at least partly influenced by the reduced size of the training dataset, the use of distinct localizers for each landmark, and potentially non-negligible measurement errors in the determination of the ground-truth.

ML algorithms can also be used for image reconstruction. For example, the BoneMRI software generates CT-like images from a T1-weighted sequence. This model was trained with paired MRI and CT on a CNN, and can obviate the need to acquire a separate CT for surgical planning or diagnostic purposes, eliminating unnecessary patient radiation exposure and providing both a time and cost savings [36].

2.2 Spine osteoporosis and degenerative changes

AI allows one to leverage previously untapped information on imaging studies in order to achieve purposes that the ordering clinician may not have originally considered. For example, the assessment of osteoporosis based on radiographs or CT (opportunistic screening) examinations acquired for other purposes has become a topic of particular interest in the field of AI (Fig. 2). Zhang et al. developed a deep CNN model to detect osteopenia and osteoporosis on lumbar spine radiographs using dual-energy X-ray absorptiometry-derived bone mineral density as the reference standard. The diagnostic sensitivity was approximately 70 % for osteoporosis and 83 % for osteopenia; however, this model was limited by the narrow study group (only women over 50 years old) and the potential overestimation of the bone mineral density due to the significant variability introduced by patient positioning as well as atherosclerotic and osteophytic calcifications [12]. Summers et al. automatically estimated the bone mineral density, based on Hounsfield Units, of the L1 and L2 vertebral bodies in 475 women ranging from 42 to 79 years-old who had received CT colonography. They were able to obtain reproducible results that successfully differentiated between osteopenic and osteoporotic patients. The authors concluded that their AI solution could be used to simultaneously screen for osteoporosis during standard colorectal cancer screening; nevertheless, further research including a broader, more diverse study group would be required for further validation [37].

Several teams have applied AI to the assessment of degenerative changes on spine MRI intending to obtain high accuracy in feature extraction (Fig. 3). Jamaludin et al. [23] developed a ML algorithm that automatically grades lumbar spine disc degeneration on sagittal T2-weighted sequences using a CNN. Their model first detects and labels vertebrae and discs with an accuracy of 95.6 %, then analyses different features (i.e., disc signal intensity, narrowing, spondylolisthesis, endplate changes, Modic changes, and central canal stenosis), and finally predicts radiologic scores. This entire process is completed in only 1–2 min. Their results were impressive, achieving Pfirrmann grading system predictions and disc narrowing grading with a performance comparable to a radiologist. However, although accuracy was also similar to radiologist scoring for spondylolisthesis, central canal stenosis, and endplate changes, the reliability (overall consistence of measuring) scores were poorer. Similarly, Oktay et al. [38] developed an algorithm based on midsagittal MR images of 102 subjects combining disc intensity, shape, context and texture features. This information was extracted from segmented intervertebral discs classifying them as normal or degenerated using a support vector machine (SVM), resulting in an accuracy of 92.8 %.

AI based tools for automated estimation of spinal canal stenosis (Fig. 4) or intervertebral disc herniation (Fig. 5) have been created to help radiologists in the routine assessment of MRI spine studies. Lu et al. developed a DL algorithm to assess spinal canal and foraminal stenosis grades on axial and sagittal images. They used a natural language processing (NLP) model to establish ground-truth stenosis grade information from MRI free text reports to train their model, obtaining an overall accuracy above 90 % in most of the levels evaluated. Although this model was enough to grade stenosis in most cases, the authors reported the need for further development to properly address problematic cases, for example in patients with severe scoliosis [39]. Lewandrowski et al. used an alternative approach via deep CNN models to produce lumbar MRI free text reports with high accuracy, sensitivity, and specificity for spinal canal stenosis (86.2 %) and disc herniation (85.2 %). This group also used a natural language processing model to generate the report and suggested that their algorithm could be used for routine reporting in spine MRI, a time-consuming process in typical radiology practices compounded by the common nature of these imaging exams. However, this group also stated a need to refine their model further as it had difficulty in detecting foraminal stenosis [40].

2.3 Spine trauma

Multiple AI based solutions have been developed and integrated into routine imaging protocols to assist radiologists in the diagnosis of vertebral body fractures. These tools help in quantifying the severity of vertebral collapse and enable the automated detection of vertebral body fractures. This latter task is particularly useful in the identification of these fractures as incidental findings on CT exams of the chest, abdomen, and pelvis, and also allows for the prioritization of studies containing these urgent unexpected fractures on the worklist (Fig. 6). ML can also be used to screen plain radiographs to identify vertebral fractures. Murata et al. [41] trained a deep CNN on anteroposterior and lateral thoracolumbar radiographs of 300 patients, detecting fractures with an accuracy of 86 % and a sensitivity of 84.7 %. They compared model performance with that of orthopedic surgeons and residents and determined that it was non-inferior to orthopedic surgeons and had superior sensitivity compared to orthopedic residents. The model did not reveal which vertebra was fractured or if the fracture was unstable; however, its high accuracy and sensitivity suggest that it could be a valuable screening tool for clinicians, particularly those without subspecialty training, such as primary care, emergency medicine, or rural physicians.

Several groups have developed different AI algorithms for the diagnosis of compression fractures on CT, some also evaluating fracture morphology and determining the degree of thoracolumbar vertebral body height loss [42], [43], [44]. In addition to these applications, Burns et al. also added to their model the ability to assess fractures in a 3D reconstruction. Using an SVM, they graded the extent of height loss and detected asymmetric lateral height loss, which allowed for the additional assessment of post-compression scoliosis. They reported a sensitivity of 95.7 % for fracture detection and localization. Importantly, their model also found additional mild compression fractures that were missed during the manual annotation of the data set. However, this model is limited by the lack of manual reference standards for the extent of height loss [45].

Several investigators have also developed AI solutions capable of identifying fracture lines. Using CT examinations in trauma patients, Yao et al. [46] developed a model that can detect fracture lines extending through the cortex of thoracic and lumbar vertebral bodies, achieving a sensitivity of 95.3 %. Burns et al. built upon their work mentioned above to further develop their algorithm such that it could determine the location of a vertebral body fracture (i.e., anterior two-thirds or posterior one-third) relative to the Denis three-column classification scheme. Although their model did not evaluate the posterior elements, they still reported a sensitivity of 81 % for detecting and localizing fractures, and a sensitivity for fracture localization to the correct vertebra of 92 %. However, the interobserver agreement between the algorithm and the radiologist interpretation was 79 %. The generalizability of this model is likely limited by several simplifications in its design including narrowing the search for fractures to the vertebral bodies and specifically focusing the algorithm on detecting fracture lines through the cortices [47].

2.4 Metastasis, hematologic disease, and spine infection

AI applications have recently been developed for the automated detection of lytic and sclerotic lesions in the spine [48]. Burns et al. built a system capable of identifying vertebral body sclerotic metastases on thoracolumbar CT, producing results in less than 2 min. They used a SVM to detect sclerotic lesions greater than 0.3 cm3. Their algorithm achieved a sensitivity of 79 %, with 40 % of the false negatives due to lesion proximity to the endplate, low attenuation, or small volume [49]. Wang et al. [15] focused their efforts on the detection of spinal metastases on MRI, applying deep Siamese neural networks to 26 examinations with known osseous metastases and obtaining a true positive rate of 90 %. There is also early ongoing work attempting to characterize metastatic spinal lesions. Lang et al. applied diverse ML analysis methods and radiomics to contrast-enhanced MR sequences in order to classify vertebral metastases as of either lung or non-lung origin. Their efforts yielded an accuracy of 81

% using a convolutional long-short term memory network. The major limitation in this study was the relatively small case number [50].

Frighetto-Pereira et al. used different ML methods including k-nearest-neighbor, a neural network with radial basis functions, and naive Bayer classifier, to classify vertebral compression fractures as either benign or malignant on T1-weighted sequences. They achieved an AUROC of 0.97 in detecting vertebral fractures and of 0.92 in classifying them as benign or malignant. However, their model was limited by their manual segmentation process (introducing intra- and interobserver variability) and their individual analysis of the vertebral bodies, ignoring relevant information such as the presence of epidural masses [51].

Radiomics can also be used to differentiate between metastatic and non-metastatic lesions in the vertebral marrow [52] and to detect osteoporosis [53]. Hwang et al. [16] used a SVM texture classifier to distinguish between pathologic diffuse infiltration of the bone marrow and normal bone marrow on lumbar MRI T1-weighted sequences with a resultant performance that was similar to that of radiologists. Using bone marrow radiomics of T1-weighted lumbar MRI in combination with a least absolute shrinkage and selection operator to select the most relevant radiomics features and random forests for classification, Hwang et al. found that their ML model was more accurate than radiologists in identifying diffuse hematologic marrow diseases. The algorithm’s AUROC was 0.92 compared with 0.86 and 0.76 for radiologists with 1 and 11 years of experience, respectively. The reliability and reproducibility of this model were not tested, and thus further work is needed to ensure robustness [54].

Kim et al. trained a deep CNN to differentiate between tuberculous and pyogenic spondylitis on axial T2-weighted MRI images, concluding that the algorithm's performance was comparable to that of three radiologists. They suggested that their model could be used to identify spondylitis as an incidental finding on spine MRI obtained for reasons other than for the assessment of a suspected infection. However, the DL method used in the model needs further validation with a larger-scale study that utilizes multiplanar MR images [55].

3. Artificial intelligence applications in the spinal cord

The application of AI to spinal cord imaging brings with it the promise of potential advances in many different clinical arenas. To date, initial studies have been focused on the evaluation of common pathology such as multiple sclerosis (MS), assessment of the spinal cord after trauma, and degenerative myelopathy, all with encouraging results [56], [57].

Investigators have also developed AI solutions for cord segmentation as well as lesion characterization and quantification [57], [58], [59]. Unlike the aforementioned AI applications in the osseous spine that include solutions based on MRI, CT, and plain radiography, most of the algorithms developed for spinal cord assessment are only based on MRI datasets. The reason for this is likely the superior contrast resolution of MRI, particularly for soft tissues such as the spinal cord. Investigators have successfully harnessed powerful MR datasets to generate algorithms for spinal cord evaluation using almost every type of MRI sequence, including T1 and T2 weighted sequences and even advanced sequences such as Diffusion Tensor Imaging (DTI). Table 2 summarizes the main AI applications for spinal cord evaluation.

3.1 Spinal cord segmentation

AI-driven spinal cord segmentation has been developed not only for delineation of the whole cord contour, but also for specific segmentation of the gray and white matter, providing radiologists and clinicians the opportunity to quantify the volume of subcomponents of the cord more precisely. Furthermore, such previously unobtainable granularity may allow one to more rapidly detect and characterize specific patterns of disease such as that found in MS, amyotrophic lateral sclerosis (ALS), spinal cord degeneration due to trauma, or even physiological aging [59]. Several different methodological approaches have been used to segment the cord. Intensity-based, image-based, and surface-based approaches are the most common. These methods use template deformation based on an atlas, thresholding strategies, or edge/contour detection in order to achieve proper segmentation of the cord [59] (Fig. 7). Perone et al. [7] applied deep dilated convolutions using T2* sequences to automatically segment the gray matter, obtaining better results than traditional approaches based on medical imaging architectures such as U-Nets. Using a T2* sequence has the advantage of providing superior contrast between the gray and white matter compared with other conventional MRI sequences. Alternatively, gray and white matter segmentation can be accomplished using the inherent differences in fractional anisotropy on DTI [59].

Automated detection and segmentation of the cord using CNNs has demonstrated utility in the setting of radiotherapy planning in patients with locally advanced head and neck cancer. The spinal cord is both quite radiosensitive and located close to the intended target, placing it at great risk during radiation therapy [60]. Automated detection during radiation planning could serve to reduce the risk of morbidity due to radiation-induced cord injury. Liu et al. [61] evaluated the accuracy of a CNN for segmenting the spinal cord, obtaining a Dice Similarity Coefficient (a statistical calculation that measures the similarity between two samples, commonly used to quantify the performance of image segmentation algorithms) of 0.83 compared with the gold standard of manual segmentation by radiation oncologists. These automated segmentation approaches, including volumetry studies, would also help to reduce inter- and intra-observer variability, as they minimize the bias inherent in visual or semiqualitative evaluation (i.e., improving radiation oncologists workflow for delimitating target lesions) [60]. Further, these tools would potentially allow radiologists to detect subtle changes in spinal cord volume that could otherwise remain undetected with unaided human visualization alone. For example, early detection of spinal cord atrophy is an important sign of disease progression in a diverse group of neurodegenerative diseases. Specifically, ALS and MS can both result in progressive loss of cord volume, a finding that correlates with both the patient's level of clinical impairment as well as eventual outcomes.

Other groups have taken slightly different approaches toward achieving the same goals of improved sensitivity and earlier detection of cord lesions. Mathias et al. performed spinal cord texture analyses, a specific subtype of radiomics, in patients with MS, finding significant differences compared with healthy controls using MRI fast spoiled gradient echo sequences. More importantly, they identified these cord texture changes before atrophic changes could be visualized on conventional MRI sequences [62]. Further studies are required to determine if this texture analysis could be used to more accurately monitor for otherwise occult imaging changes and if these results would better correlate with MS patient disability. The eventual integration of these spinal cord AI algorithms into routine clinical practice would open the door to potential improvements in diagnostic sensitivity, treatment monitoring, and patient outcomes, with resultant value added for both clinicians and our patients.

3.2 Spinal cord trauma

Traumatic spinal cord injury results in considerable disability and places a substantial financial burden on the healthcare system. Unfortunately, conventional MRI and CT imaging methods are, in most cases, not enough for answering some important questions about a given patient's diagnosis and prognosis [63]. New imaging methods are therefore critically needed. AI may play a substantial role in providing a solution. [64], [65]. Therefore, initiatives such as Open Data Commons for Spinal Cord Injury are working toward creating large datasets through multidisciplinary and multicenter collaboration networks to develop AI algorithms for spinal cord assessment [65].

Several groups have developed AI solutions to assess spinal cord trauma. More notable efforts include those by McCoy et al., who explored the feasibility of using CNN for automatic spinal cord segmentation and contusion injury using T2 fast spin echo (FSE) images. They obtained superior performance with a Dice coefficient of 0.93 for spinal cord segmentation, a significantly higher value than that of manual segmentation tools (0.8) and borderline significant compared to the value for previous segmentation models (0.9) [66]. Additionally, a positive correlation was identified between segmented lesion volumes and the measurement of disability in traumatic spinal cord injury patients [58].

The use of DTI for the assessment of traumatic spinal cord injuries is an area of active investigation. While conventional software analyses have been applied, newer AI algorithms add the potential to extract additional information from this advanced MRI sequence. Tay et al. developed an ML approach for evaluating spinal cord injuries based on DTI acquisitions. Their algorithms analyzed fractional anisotropy values to differentiate between healthy volunteers and patients with spinal cord injuries obtaining a sensitivity of 91 % and a specificity of 95 %. This model was limited by the reduced availability of spinal cord data [57]. Recent animal model studies have addressed the analysis of intraparenchymal signal changes on MRI of spinal cord after trauma using ML approaches. For example, Boudreau et al. [67] found a correlation between low signal areas on T2-WI and poor functional recovery. These promising early studies reveal the potential of AI to eventually substantively affect patient outcomes.

3.3 Degenerative myelopathy

Degenerative spondylosis is a pervasive problem that can lead to myelopathy in the setting of compressive effect on the cord. Before the onset of myelomalacia and permanent disability, however, early changes in cord structure occur [68]. These changes often begin months or years before identifiable signal abnormalities on conventional MRI [69], [70]. There is, therefore, an opportunity for earlier diagnosis and improved patient outcomes via the detection of these cord structural changes.

Current efforts to develop AI algorithms capable of analyzing cord structure based on texture or radiomics analyses are generating considerable enthusiasm. Such solutions could help to objectively explain potential mismatches observed between patient symptoms and the extent of degenerative changes on imaging. Further, one may be able to better predict patient outcomes after surgery by combining clinical and imaging data [71]. While some investigators have employed conventional MRI sequences to generate these AI algorithms, others have turned toward more advanced imaging such as DTI. For example, Jin et al. used DTI data to predict outcomes in patients with cervical degenerative myelopathy. The parameters derived from DTI included fractional anisotropy, mean diffusivity, axial diffusivity, and radial diffusivity, and were analyzed using logistic regression, k-nearest neighbors, and a radial basis function kernel SVM tool with a resultant accuracy of 89.7 % for the prognosis of cervical degenerative myelopathy, predicting surgical outcomes based on the modified Japanese Orthopedic Association scores. Nonetheless, this model could benefit from a larger sample size, and the implementation of an automatic segmentation toolbox to reduce intra- and interobserver variability [72]. Additionally, Wang et al. [73] developed a ML algorithm for classification of DTI metrics in patients without and with clinical criteria for cervical degenerative myelopathy. A SVM was employed obtaining an accuracy of 95.7 % with a sensitivity of 93.4 % and specificity of 98.6 %. We considered that the functional information provided by DTI studies and their advanced AI based analysis would positively impact the management of patients with cervical degenerative myelopathy. Early diagnosis, better clinical-radiological correlation and improve of selection and monitoring of surgical patients are among potential applications of these AI solutions. However, reproducibility and robustness of AI algorithms with different MR vendors and institutions should be tested prior to extrapolate clinical results.

4. Integrating spine Artificial intelligence into practice

Generating AI tools for use in spine imaging in the academic arena is of minimal impact without real world implementation and integration into daily practice. Strategies toward meeting this end should be feasible in order to maximize the probability of success. For example, AI solutions that require complex postprocessing of images, sophisticated software, or the acquisition of new advanced skills by clinicians or radiologists will be more difficult to implement, regardless of their promising results. Eliminating these barriers through strategic “one-click” solutions and simple integration within the normal radiologist workflow will be critical for successful translation from the research domain to practical everyday use.

Many of the AI solutions previously discussed in this review can potentially be integrated into MRI or CT acquisition and the general reading workflow in an automated fashion reducing the barrier to implementation. As previously stated, the use of prioritization reading solutions of urgent findings may improve radiologist́s workflow and improve patient outcomes. Others, such as identifying lesions within vertebral bodies or the cord, require postprocessing via semiautomated software that typically depends on active human input. For example, many require placement of regions of interest to segment and discrimination between anatomic structures. This step limits its real implementation in clinical practice.

A particular challenge that arises when using supervised ML with DL algorithms is the need for large, annotated datasets. Also, a challenge is to train this DL algorithms with multicenter and multivendor data that will probe the reproducibility of their results. Furthermore, obtaining large datasets of advanced techniques, such as DTI, in patients with specific pathologies (i.e., spinal cord trauma) is problematic. Developing such datasets can be extremely time-consuming and often requires dedicated effort from expert radiologists [74]. Fortunately, some publicly available datasets on the internet can be used to develop algorithms and allow teams to compare their results with previously published work [17], [42]. Alternatively, image processing techniques exist to artificially multiply the training set, such as flipping the image, a strategy which could be used in the spine, particularly suitable for this anatomic region due to its symmetry [55]. Natural language processing, a branch of AI dedicated to extract information and insights contained in text and documents, could also be used to mine the free text of radiology reports in order to label the dataset [39], [40], [74].

Another important area to gain confidence in AI algorithms for radiologists, clinicians and even patients is to overcome the black box inherent to this technology. Explainable AI is a branch of this technique that tries to make transparent the used methodology to all kind of users. Its implementation in radiology department is critical to gain confidence in these solutions and increase their clinical use [75].

Collaboration between radiologists, clinicians, technologists, engineers, and other stakeholders integrating multidisciplinary teams will be key for the successful integration of AI solutions into the routine workflow [76]. Each of these individual contributors will be able to provide unique expertise and experience that can inform specific queries and suggested adjustments to the AI solution, maximizing the quality of the final product. The overarching goal in these collaborative efforts should be to minimize inefficiencies in throughput, such as long postprocessing times, which may prevent stakeholder buy in and preclude implementation of this promising new technology.

5. Conclusions

The application of AI solutions to the imaging assessment of the spine and spinal cord has demonstrated early promise throughout a diverse range of clinical scenarios. AI offers the possibility of increased efficiency by reducing the need for time-consuming tasks and may also assist radiologists in determining specific diagnoses. Also, AI may provide new “free” information not usually included in radiological reports, such as the presence of osteopenia or osteoporosis and compression fracture on chest, abdomen and pelvis CT performed for other reasons. Of particular interest is the potential for AI to identify lesions that would otherwise remain undetected by the traditional radiologic interpretation as well as its potential to characterize lesions. These advances could allow for earlier diagnoses and reporting, adjustments in treatment regimens, and may contribute to more personalized medical care. Most of limitations of AI solutions mainly arise from their small sample size, for this reason larger-scale, multi-center studies will allow a more robust analysis. Successful creation and integration of AI algorithms into clinical practice will require collaboration between multiple stakeholders in spine, including radiologists, clinical specialists, engineers, and data scientists in order to develop reproducible, robust, and relevant tools that enhance radiology exams and improve patient care.

References

1. Gorelik N, Gyftopoulos S. Applications of Artificial Intelligence in Musculoskeletal Imaging: From the Request to the Report. Can Assoc Radiol J. 2021;72(1):45–59.

2. Kaka H, Zhang E, Khan N. Artificial Intelligence and Deep Learning in Neuroradiology: Exploring the New Frontier. Can Assoc Radiol J. 2021;72(1):35–44.

3. Mallow GM, Siyaji ZK, Galbusera F, Espinoza-Orías AA, Giers M, Lundberg H, et al. Intelligence-Based Spine Care Model: A New Era of Research and Clinical Decision-Making. Glob Spine J. 2020;

4. Galbusera F, Casaroli G, Bassani T. Artificial intelligence and machine learning in spine research. Jor Spine. 2019;2(1):e1044.

5. Roggen T, Bobic M, Givehchi N, Scheib SG. Deep Learning model for markerless tracking in spinal SBRT. Phys Medica [Internet]. 2020;74(May):66–73. Available from: https://doi.org/10.1016/j.ejmp.2020.04.029

6. Nam KH, Kim DH, Choi BK, Han IH. Internet of things, digital biomarker, and artificial intelligence in spine: Current and future perspectives. Neurospine. 2019;16(4):705–11.

7. Perone CS, Calabrese E, Cohen-Adad J. Spinal cord gray matter segmentation using deep dilated convolutions. Sci Rep. 2018;8(1).

8. Wang X, Zhai S, Niu Y. Automatic Vertebrae Localization and Identification by Combining Deep SSAE Contextual Features and Structured Regression Forest. J Digit Imaging. 2019;32(2):336–48.

9. Moll NM, Rietsch AM, Thomas S, Ransohoff AJ, Lee JC, Fox R, et al. Multiple sclerosis normal-appearing white matter: Pathology-imaging correlations. Ann Neurol. 2011 Nov;70(5):764–73.

10. Khan O, Badhiwala JH, Grasso G, Fehlings MG. Use of Machine Learning and Artificial Intelligence to Drive Personalized Medicine Approaches for Spine Care. World Neurosurg [Internet]. 2020;140:512–8. Available from: https://doi.org/10.1016/j.wneu.2020.04.022

11. Štern D, Vrtovec T, Pernuš F, Likar B. Automated determination of the centers of vertebral bodies and intervertebral discs in CT and MR lumbar spine images. In: Medical Imaging 2010: Image Processing. 2010. p. 762350.

12. Zhang B, Yu K, Ning Z, Wang K, Dong Y, Liu X, et al. Deep learning of lumbar spine X-ray for osteopenia and osteoporosis screening: A multicenter retrospective cohort study. Bone. 2020;140.

13. Lewandrowski KU, Muraleedharan N, Eddy SA, Sobti V, Reece BD, León JFR, et al. Reliability analysis of deep learning algorithms for reporting of routine lumbar MRI scans. Int J Spine Surg. 2020;14:S98–107.

14. Han Z, Wei B, Xi X, Chen B, Yin Y, Li S. Unifying neural learning and symbolic reasoning for spinal medical report generation. Med Image Anal [Internet].

2021;67:101872. Available from: https://doi.org/10.1016/j.media.2020.101872

15. Wang J, Fang Z, Lang N, Yuan H, Su MY, Baldi P. A multi-resolution approach for spinal metastasis detection using deep Siamese neural networks. Comput Biol Med. 2017;84:137–46.

16. Hwang EJ, Jung JY, Lee SK, Lee SE, Jee WH. Machine Learning for Diagnosis of Hematologic Diseases in Magnetic Resonance Imaging of Lumbar Spines. Sci Rep-UK. 2019; 9:6046.

17. Chen Y, Gao Y, Li K, Zhao L, Zhao J. Vertebrae Identification and Localization Utilizing Fully Convolutional Networks and a Hidden Markov Model. IEEE Trans Med Imaging. 2020;39(2):387–99.

18. Glocker B, Feulner J, Criminisi A, Haynor DR, Konukoglu E. Automatic localization and identification of vertebrae in arbitrary field-of-view CT scans. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). 2012. p. 590–8.

19. Chen H, Shen C, Qin J, Ni D, Shi L, Cheng JCY, et al. Automatic localization and identification of vertebrae in spine CT via a joint learning model with deep neural networks. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). 2015. p. 515–22.

20. Suzani A, Seitel A, Liu Y, Fels S, Rohling RN, Abolmaesumi P. Fast automatic vertebrae detection and localization in pathological CT scans - a deep learning approach. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). 2015. p. 678–86.

21. Glocker B, Zikic D, Konukoglu E, Haynor DR, Criminisi A. Vertebrae localization in pathological spine CT via dense classification from sparse annotations. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). 2013. p. 262–70.

22. DeVine JG, Chutkan N, Gloystein D, Jackson K. An Update on Wrong-Site Spine Surgery. Glob Spine J. 2020;10(1_suppl):41S–44S.

23. Jamaludin A, Lootus M, Kadir T, Zisserman A, Urban J, Battié MC, et al. ISSLS PRIZE IN BIOENGINEERING SCIENCE 2017: Automation of reading of radiological features from magnetic resonance images (MRIs) of the lumbar spine without human intervention is comparable with an expert radiologist. Eur Spine J. 2017;26(5):1374–83.

24. Lootus M, Kadir T, Zisserman A. Vertebrae detection and labelling in lumbar MR images. Lect Notes Comput Vis Biomech. 2014;17:219–30.

25. Lessmann N, van Ginneken B, de Jong PA, Išgum I. Iterative fully convolutional neural networks for automatic vertebra segmentation and identification. Med Image Anal. 2019;53:142–55.

26. Vania M, Mureja D, Lee D. Automatic spine segmentation from CT images using Convolutional Neural Network via redundant generation of class labels. J Comput Des Eng. 2019;6(2):224–32.

27. Kuang X, Cheung JPY, Wu H, Dokos S, Zhang T. MRI-SegFlow: A novel unsupervised deep learning pipeline enabling accurate vertebral segmentation of MRI images. Proc Annu Int Conf IEEE Eng Med Biol Soc EMBS. 2020;2020-July:1633–6.

28. Gaonkar B, Beckett J, Villaroman D, Ahn C, Edwards M, Moran S, et al. Quantitative Analysis of Neural Foramina in the Lumbar Spine: An Imaging Informatics and Machine Learning Study. Radiol Artif Intell. 2019;1(2):180037.

29. Gaonkar B, Villaroman D, Beckett J, Ahn C, Attiah M, Babayan D, et al. Quantitative analysis of spinal canal areas in the lumbar spine: An imaging informatics and machine learning study. Am J Neuroradiol. 2019;40(9):1586–91.

30. Veronezi CCD, de Azevedo Simões PWT, dos Santos RL, da Rocha EL, Meláo S, de Mattos MC, et al. Computational Analysis Based on Artificial Neural Networks for Aiding in Diagnosing Osteoarthritis of the Lumbar Spine. Rev Bras Ortop (English Ed. 2011;46(2):195–9.

31. Zhang J, Li H, Lv L, Zhang Y. Computer-Aided Cobb Measurement Based on Automatic Detection of Vertebral Slopes Using Deep Neural Network. Int J Biomed Imaging. 2017;2017.

32. Wu H, Bailey C, Rasoulinejad P, Li S. Automated comprehensive Adolescent Idiopathic Scoliosis assessment using MVC-Net. Med Image Anal. 2018;48:1–11.

33. Pan Y, Chen Q, Chen T, Wang H, Zhu X, Fang Z, et al. Evaluation of a computer-aided method for measuring the Cobb angle on chest X-rays. Eur Spine J. 2019;28(12):3035–43.

34. Sun Y, Xing Y, Zhao Z, Meng X, Xu G, Hai Y. Comparison of manual versus automated measurement of Cobb angle in idiopathic scoliosis based on a deep learning keypoint detection technology. Eur Spine J. 2022;31:1969–78.

35. Galbusera F, Niemeyer F, Wilke HJ, Bassani T, Casaroli G, Anania C, et al. Fully automated radiological analysis of spinal disorders and deformities: a deep learning approach. Eur Spine J. 2019;28:951–60.

36. Staartjes VE, Seevinck PR, Vandertop WP, van Stralen M, Schröder ML. Magnetic resonance imaging–based synthetic computed tomography of the lumbar spine for surgical planning: a clinical proof-of-concept. Neurosurg Focus. 2021;50(1):1–7.

37. Summers RM, Baecher N, Yao J, Liu J, Pickhardt PJ, Choi JR, et al. Feasibility of simultaneous computed tomographic colonography and fully automated bone mineral densitometry in a single examination. J Comput Assist Tomogr. 2011;35(2):212–6.

38. Oktay AB, Albayrak NB, Akgul YS. Computer aided diagnosis of degenerative intervertebral disc diseases from lumbar MR images. Comput

Med Imaging Graph [Internet]. 2014;38(7):613–9. Available from: http://dx.doi.org/10.1016/j.compmedimag.2014.04.006

39. Lu JT, Pedemonte S, Bizzo B, Doyle S, Andriole KP, Michalski MH, et al. Deep spine: Automated lumbar vertebral segmentation, disc-level designation, and spinal stenosis grading using deep learning. arXiv. 2018.

40. Lewandrowski KU, Muraleedharan N, Eddy SA, Sobti V, Reece BD, León JFR, et al. Feasibility of deep learning algorithms for reporting in routine spine magnetic resonance imaging. Int J Spine Surg. 2020;14:S86–97.

41. Murata K, Endo K, Aihara T, Suzuki H, Sawaji Y, Matsuoka Y, et al. Artificial intelligence for the detection of vertebral fractures on plain spinal radiography. Sci Rep. 2020;10(1).

42. Löffler MT, Sekuboyina A, Jacob A, Grau A-L, Scharr A, El Husseini M, et al. A Vertebral Segmentation Dataset with Fracture Grading. Radiol Artif Intell. 2020;2(4):e190138.

43. Yao J, Burns JE, Wiese T, Summers RM. Quantitative vertebral compression fracture evaluation using a height compass. In: Medical Imaging 2012: Computer-Aided Diagnosis. 2012. p. 83151X.

44. Baum T, Bauer JS, Klinder T, Dobritz M, Rummeny EJ, Noël PB, et al. Automatic detection of osteoporotic vertebral fractures in routine thoracic and abdominal MDCT. Eur Radiol. 2014;24(4):872–80.

45. Burns JE, Yao J, Summers RM. Vertebral body compression fractures and bone density: Automated detection and classification on CT Images. Radiology. 2017;284(3):788–97.

46. Muñoz HE, Yao J, Burns JE, Summers RM. Detection of vertebral degenerative disc disease based on cortical shell unwrapping. In: Medical Imaging 2013: Computer-Aided Diagnosis. 2013. p. 86700C.

47. Burns JE, Yao J, Muñoz H, Summers RM. Automated detection, localization, and classification of traumatic vertebral body fractures in the thoracic and lumbar spine at CT. Radiology. 2016;278(1):64–73.

48. Hammon M, Dankerl P, Tsymbal A, Wels M, Kelm M, May M, et al. Automatic detection of lytic and blastic thoracolumbar spine metastases on computed tomography. Eur Radiol. 2013;23(7):1862–70.

49. Burns JE, Yao J, Wiese TS, Muñoz HE, Jones EC, Summers RM. Automated detection of sclerotic metastases in the thoracolumbar spine at CT. Radiology. 2013;268(1):69–78.

50. Lang N, Zhang Y, Zhang E, Zhang J, Chow D, Chang P, et al. Differentiation of spinal metastases originated from lung and other cancers using radiomics and deep learning based on DCE-MRI. Magn Reson Imaging. 2019;64:4–12.

51. Frighetto-Pereira L, Rangayyan RM, Metzner GA, de Azevedo-Marques PM, Nogueira-Barbosa MH. Shape, texture and statistical features for

classification of benign and malignant vertebral compression fractures in magnetic resonance images. Comput Biol Med. 2016;73:147–56.

52. Filograna L, Lenkowicz J, Cellini F, Dinapoli N, Manfrida S, Magarelli N, et al. Identification of the most significant magnetic resonance imaging (MRI) radiomic features in oncological patients with vertebral bone marrow metastatic disease: a feasibility study. Radiol Medica. 2019;124(1):50–7.

53. He L, Liu Z, Liu C, Gao Z, Ren Q, Lei L, et al. Radiomics Based on Lumbar Spine Magnetic Resonance Imaging to Detect Osteoporosis. Acad Radiol. 2020;28(6):e165–e171.

54. Hwang EJ, Kim S, Jung JY. Bone Marrow Radiomics of T1-Weighted Lumber Spinal MRI to Identify Diffuse Hematologic Marrow Diseases: Comparison with Human Readings. IEEE Access. 2020;8:133321–9.

55. Kim K, Kim S, Lee YH, Lee SH, Lee HS, Kim S. Performance of the deep convolutional neural network based magnetic resonance image scoring algorithm for differentiating between tuberculous and pyogenic spondylitis. Sci Rep. 2018;8(1).

56. Afzal HMR, Luo S, Ramadan S, Lechner-Scott J. The emerging role of artificial intelligence in multiple sclerosis imaging. Multiple Sclerosis Journal. 2020.

57. Tay B, Hyun JK, Oh S. A machine learning approach for specification of spinal cord injuries using fractional anisotropy values obtained from diffusion tensor images. Comput Math Methods Med. 2014;2014.

58. McCoy DB, Dupont SM, Gros C, Cohen-Adad J, Huie RJ, Ferguson A, et al. Convolutional neural network–based automated segmentation of the spinal cord and contusion injury: Deep learning biomarker correlates of motor impairment in acute spinal cord injury. Am J Neuroradiol. 2019;40(4):737–44.

59. De Leener B, Taso M, Cohen-Adad J, Callot V. Segmentation of the human spinal cord. Magn Reson Mater Physics, Biol Med. 2016;29(2):125–53.

60. Vrtovec T, Močnik D, Strojan P, Pernuš F, Ibragimov B. Auto-segmentation of organs at risk for head and neck radiotherapy planning: From atlas-based to deep learning methods. Vol. 47, Medical Physics. 2020. p. e929–50.

61. Liu Z, Liu X, Xiao B, Wang S, Miao Z, Sun Y, et al. Segmentation of organs-at-risk in cervical cancer CT images with a convolutional neural network. Phys Medica [Internet]. 2020;69(April 2019):184–91. Available from: https://doi.org/10.1016/j.ejmp.2019.12.008

62. Mathias JM, Tofts PS, Losseff NA. Texture analysis of spinal cord pathology in multiple sclerosis. Magn Reson Med. 1999;42(5):929–35.

63. Khan O, Badhiwala JH, Wilson JRF, Jiang F, Martin AR, Fehlings MG. Predictive modeling of outcomes after traumatic and nontraumatic spinal cord injury using machine learning: Review of current progress and future directions. Neurospine. 2019;16(4):678–85.

64. Russell Huie J, Almeida CA, Ferguson AR. Neurotrauma as a big-data problem. Curr Opin Neurol. 2018;31(6):702–8.

65. Callahan A, Anderson KD, Beattie MS, Bixby JL, Ferguson AR, Fouad K, et al. Developing a data sharing community for spinal cord injury research. Vol. 295, Experimental Neurology. 2017. p. 135–43.

66. Cook DJ, Gladowski DA, Acuff HE, Yeager MS, Cheng BC. Variability of manual lumbar spine segmentation. Int J Spine Surg. 2012;6(1):167–73.

67. Boudreau E, Otamendi A, Levine J, Griffin JF, Gilmour L, Jeffery N. Relationship between Machine-Learning Image Classification of T 2 -Weighted Intramedullary Hypointensity on 3 Tesla Magnetic Resonance Imaging and Clinical Outcome in Dogs with Severe Spinal Cord Injury . J Neurotrauma. 2020;

68. Badhiwala JH, Wilson JR. The Natural History of Degenerative Cervical Myelopathy. Neurosurgery Clinics of North America. 2018.

69. Kato S, Fehlings M. Degenerative cervical myelopathy. Current Reviews in Musculoskeletal Medicine. 2016.

70. Keřkovský M, Bednařík J, Jurová B, Dušek L, Kadaňka Z, Kadaňka Z, et al. Spinal Cord MR Diffusion Properties in Patients with Degenerative Cervical Cord Compression. J Neuroimaging. 2017;27(1):149–57.

71. Wilson JRF, Badhiwala JH, Moghaddamjou A, Martin AR, Fehlings MG. Degenerative cervical myelopathy; A review of the latest advances and future directions in management. Neurospine. 2019;16(3):494–505.

72. Jin R, Luk KD, Cheung JPY, Hu Y. Prognosis of cervical myelopathy based on diffusion tensor imaging with artificial intelligence methods. NMR Biomed. 2019;32(8).

73. Wang S, Hu Y, Shen Y, Li H. Classification of Diffusion Tensor Metrics for the Diagnosis of a Myelopathic Cord Using Machine Learning. Int J Neural Syst. 2018;28(2).

74. Shin HC, Roth HR, Gao M, Lu L, Xu Z, Nogues I, et al. Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning. IEEE Trans Med Imaging. 2016;35(5):1285–98.

75. Xu F, Uszkoreit H, Du Y, Fan W, Zhao D, Zhu J. Explainable AI: A Brief Survey on History, Research Areas, Approaches and Challenges. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). 2019. p. 563–74.

76. Martín-Noguerol T, Paulano-Godino F, López-Ortega R, Górriz JM, Riascos RF, Luna A. Artificial intelligence in radiology: relevance of collaborative work between radiologists and engineers for building a multidisciplinary team. Clin Radiol. 2020;(xxxx).

77. Ruiz M, Julià A, Boada I. Starviewer and its comparison with other open-source DICOM viewers using a novel hierarchical evaluation framework. Int J Med Inform. 2020;137.

78. Ahrens J, Geveci B, Law C. ParaView: An end-user tool for large-data visualization. In: Visualization Handbook. 2005. p. 717–31.

Tables

Table 1. Summary of the main spine AI applications.			
AI application	**Ready for its clinical use**	**Impact on clinical practice**	**Imaging modality**
Vertebral body segmentation	Yes	- Generation of 3D models	CT, MRI
Vertebral body labeling	Yes	- Automatic vertebral numbering - Decrease localization errors	CT, MRI
Angle measurement	Yes	- Save radiologist time - Reproducible measurements	X-ray
CT-like images	No	- Improve cortical bone assessment - No radiation	MRI
Osteoporosis	Yes	- Opportunistic screening	X-ray, CT
Lumbar spine assessment	No	- Automatic evaluation of degenerative lumbar disease - Spinal canal stenosis - Automatic radiology reports	MRI
Spine trauma	Yes	- Automatic detection and assessment of vertebral fractures	X-ray, CT
Bone marrow involvement	No	- Metastasis detection. - Hematological diseases - Spine infection	CT, MRI

Table 2. Summary of the main spinal cord AI applications.			
AI application	**Ready for its clinical use**	**Impact on clinical practice**	**Imaging modality**
Spinal cord segmentation	No	- Automatic segmentation of spinal cord - Radiotherapy planning - Spinal cord volume follow up - Multiple sclerosis assessment	MRI
Spinal cord trauma	No	- Correlation of automatic segmentation with disability - Advanced analysis of DTI data	MRI
Degenerative myelopathy	No	- Detect changes prior to conventional approach - Better clinical-radiological correlation	MRI

Figure legends

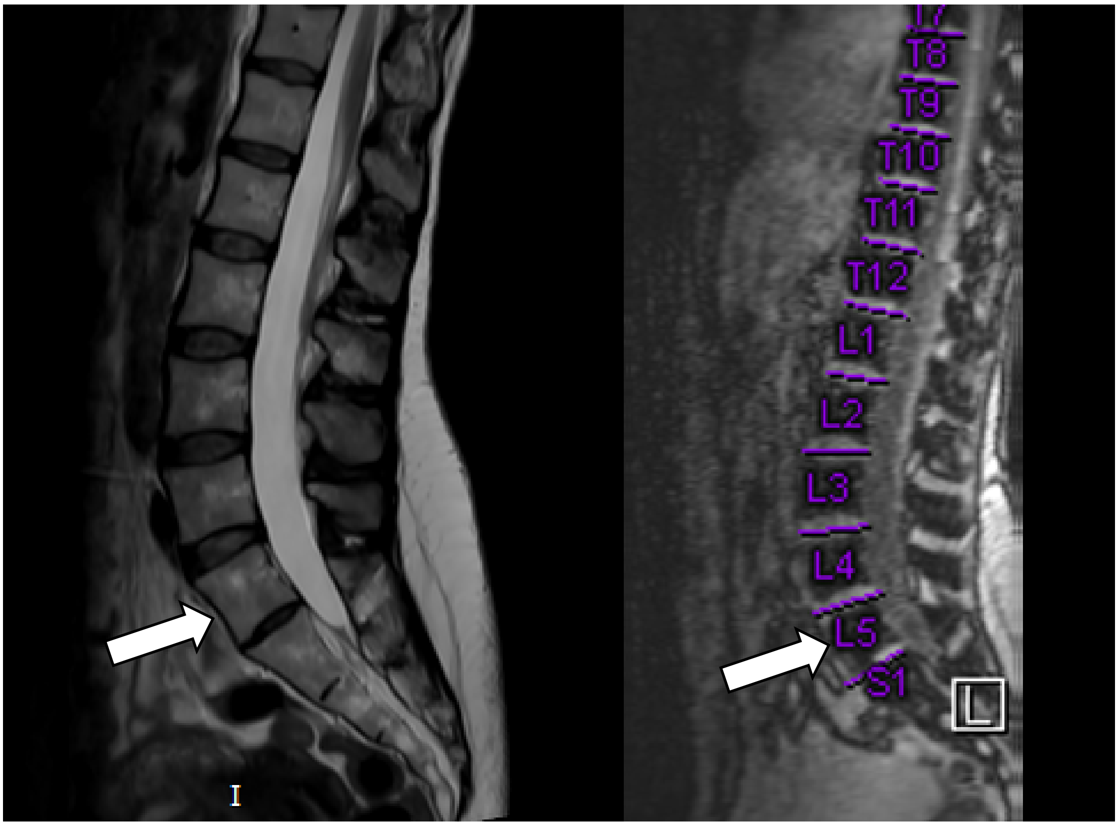

Figure 1. Artificial intelligence for automatic vertebral numbering. A 49-year-old female submitted to lumbar MRI for back pain. No signs of degenerative disk disease were found. However, a transitional vertebrae was identified. An AI algorithm (Spine Dot Engine by Siemens Healthineers) performed during the acquisition process enables an automatic identification and numbering of every vertebral body. This solution enabled not only to identify the transitional abnormality, but also to correctly label it as a L5 sacralized vertebrae (arrow).

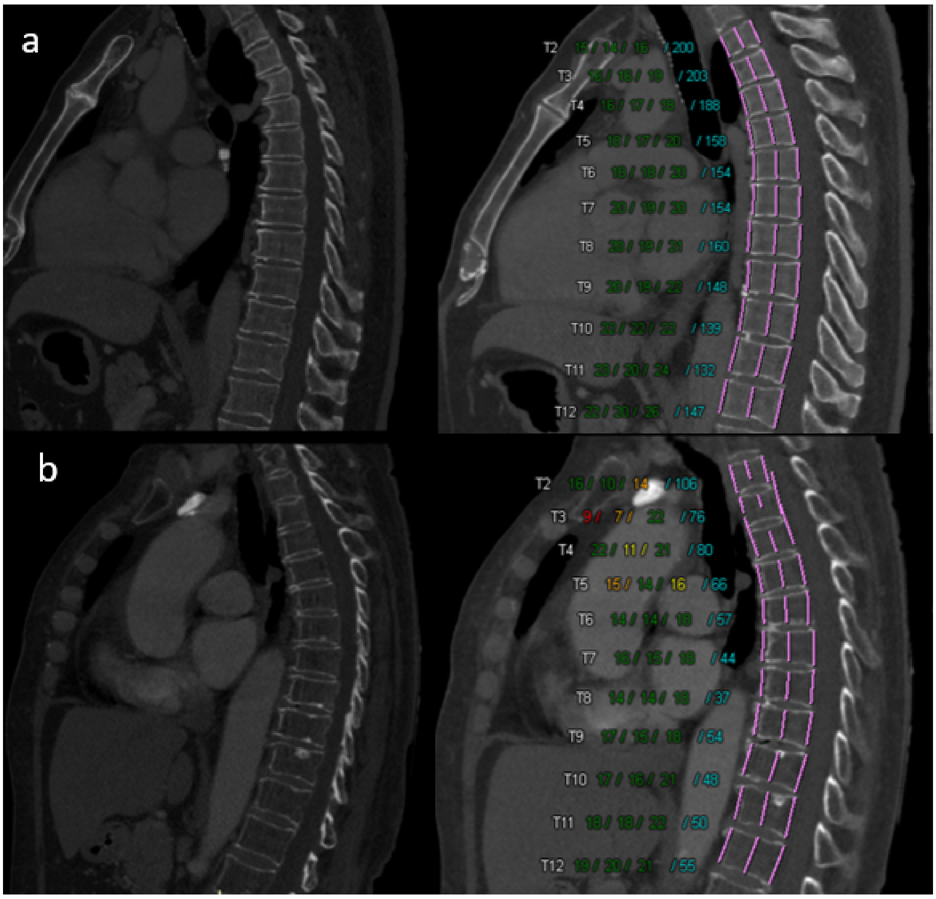

Figure 2. Artificial intelligence for automatic assessment of bone mineral density. (a) 50-year-old male with fever and dyspnea underwent a chest CT. Automatic assessment of bone mineral density based on Hounsfield units (HU) by an AI algorithm (AI-Rad Companion by Siemens Healthineers) did not show significant decrease of HU (coded in blue numbers) within thoracic vertebral bodies. (b) 90-year-old female with constitutional syndrome underwent a chest CT study, finding significant decrease of HU (coded in blue numbers) within all vertebral bodies. Although changes in vertebral bone density can be detected in a qualitative assessment of CT source images, this AI tool facilitates an automatic quantification of bone density.

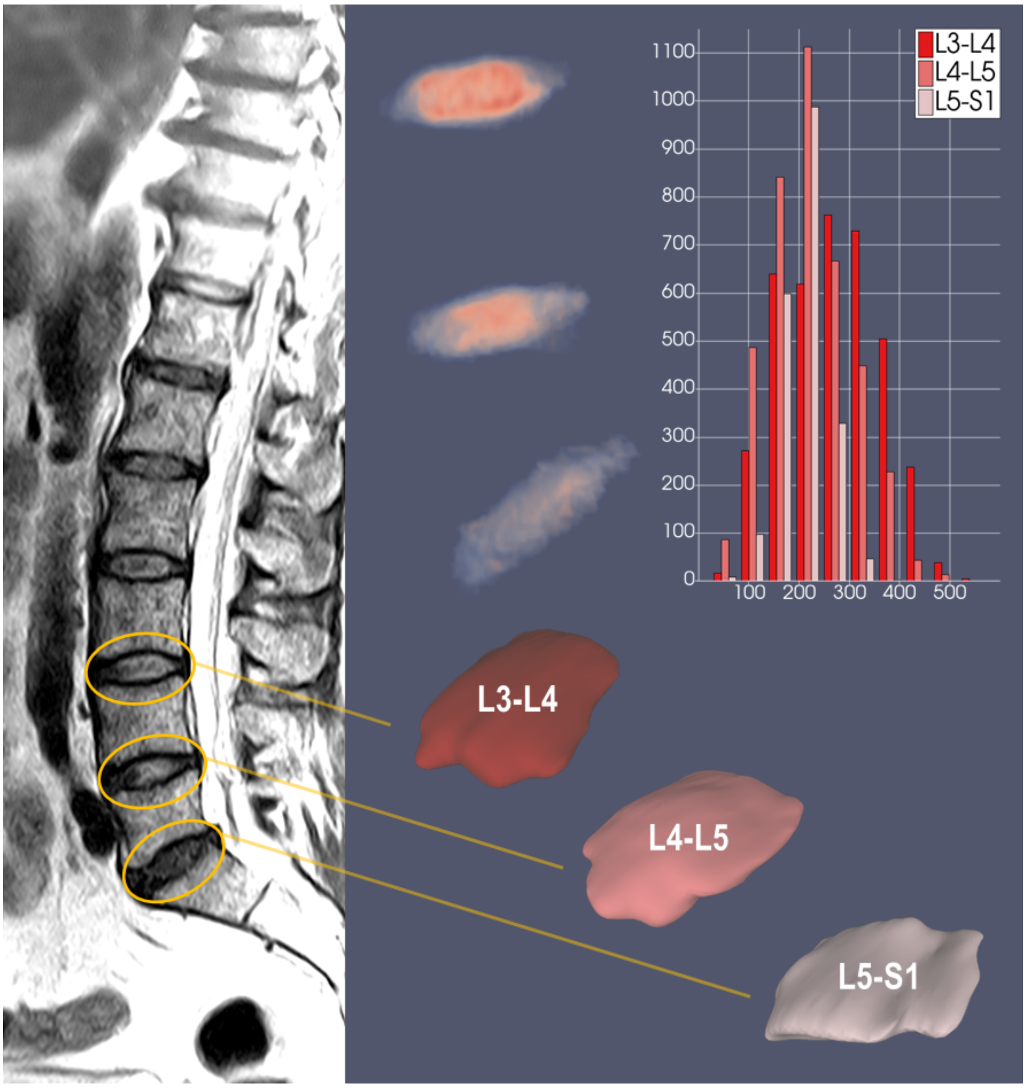

Figure 3. Intended result for automatic assessment of degenerative disc disease by means of artificial intelligence techniques. Example of intervertebral disc analysis on MRI images to assess disc degeneration, with 3D representation of L3-L4, L4-L5 and L5-S1, and their corresponding histogram, where bright red indicates more intensity, i.e., less degeneration. Notice the reduction in size and signal intensity of the highly degenerated L5-S1 disk. Figure obtained using Starviewer© software for image segmentation [77] and ParaView© software for improved segmentation visualization [78].

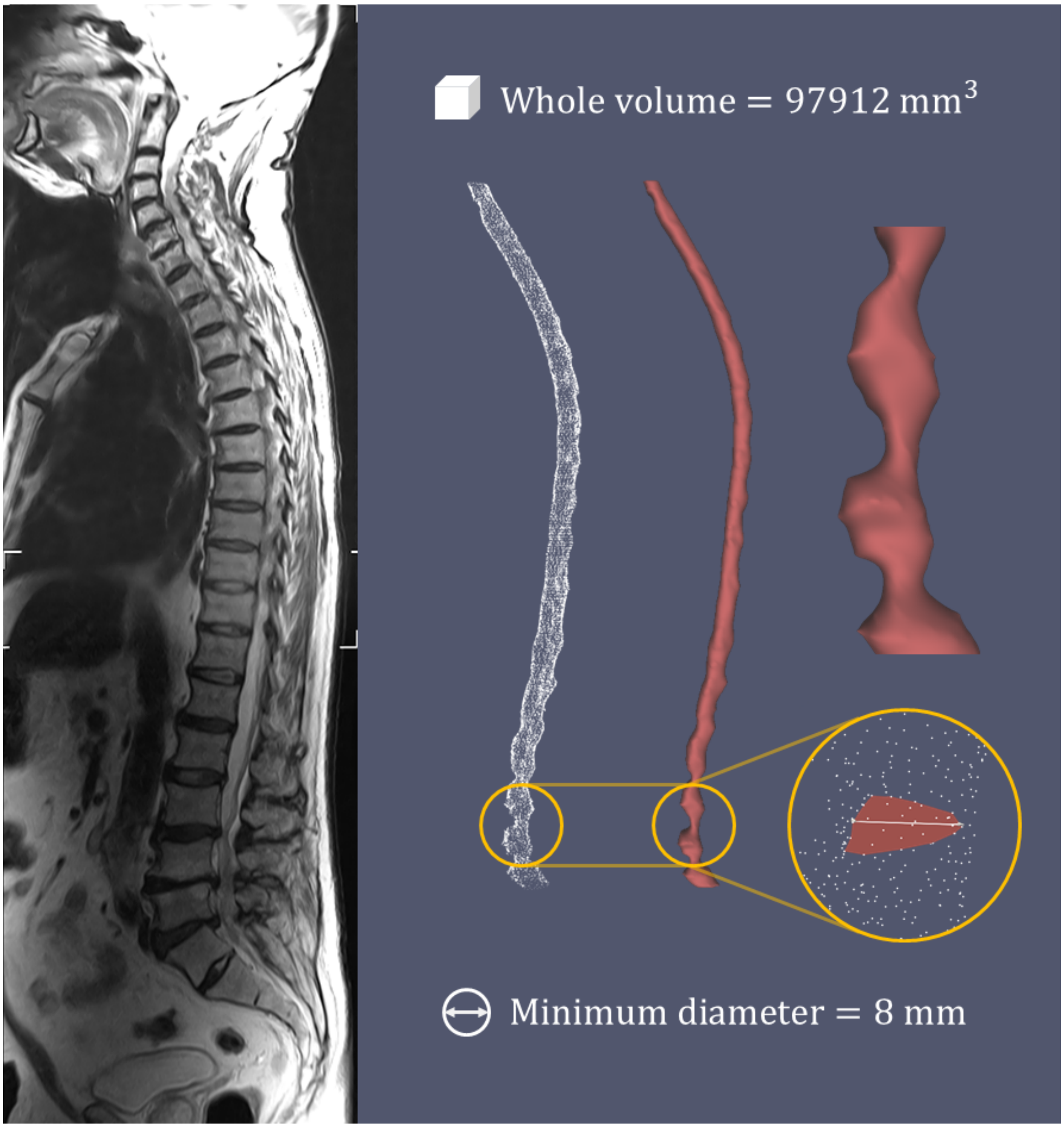

Figure 4. Intended result for automatic assessment of spinal canal stenosis by means of artificial intelligence techniques. Example of spinal canal segmentation on MRI images to assess canal stenosis, with 3D representations and quantification of parameters such as the spinal canal volume and its minimum diameter. Figure obtained using Starviewer© software for image segmentation [77] and ParaView© software for improved segmentation visualization [78].

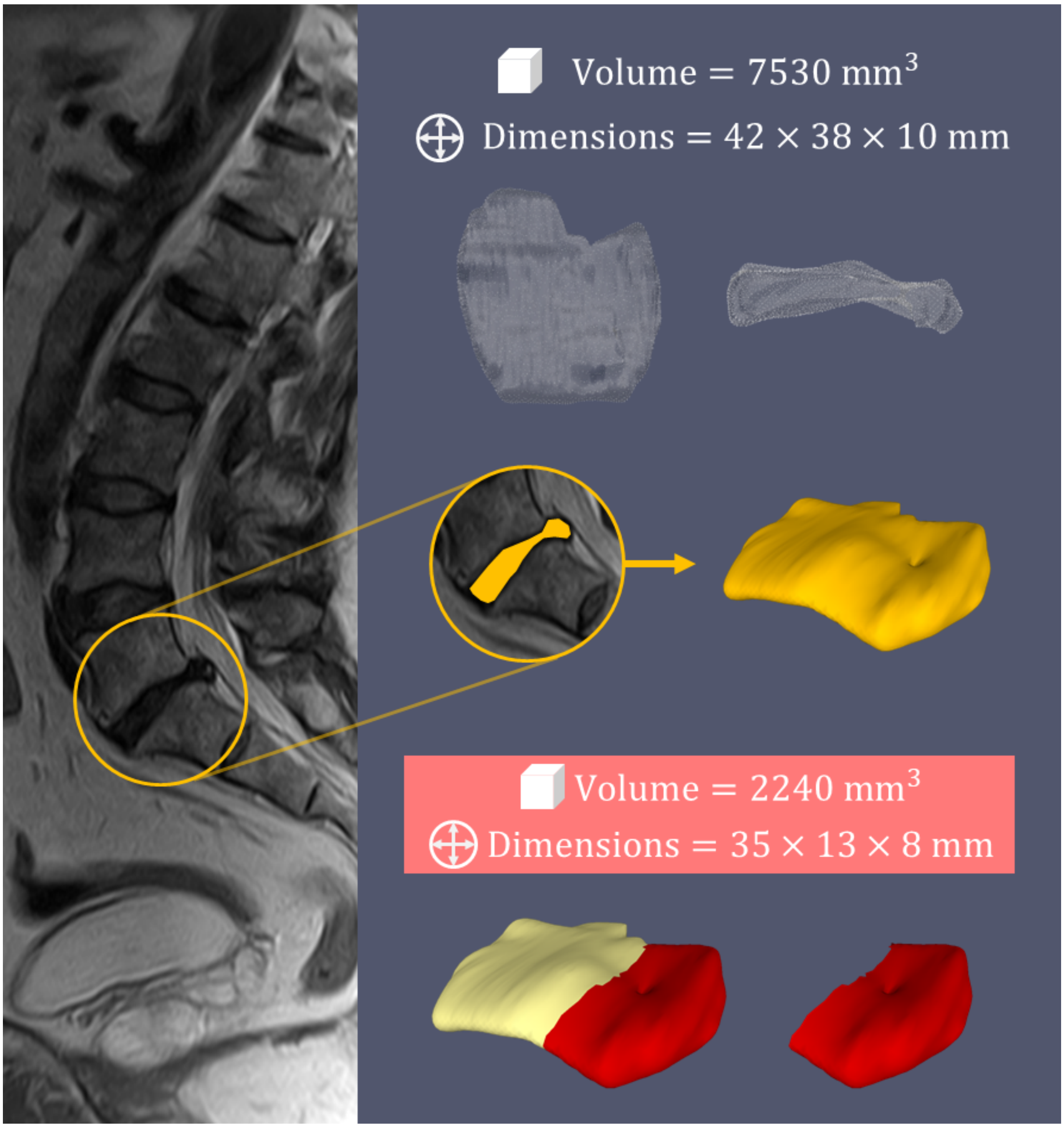

Figure 5. Intended result for automatic assessment of disc herniation by means of artificial intelligence techniques. Example of intervertebral disc segmentation on MRI images to assess disc herniation, with 3D representations and quantification of some parameters, such as the volume and dimensions of the whole disc and the herniated fragment (represented in red). Figure obtained using Starviewer© software for image segmentation [77] and ParaView© software for improved segmentation visualization [78].

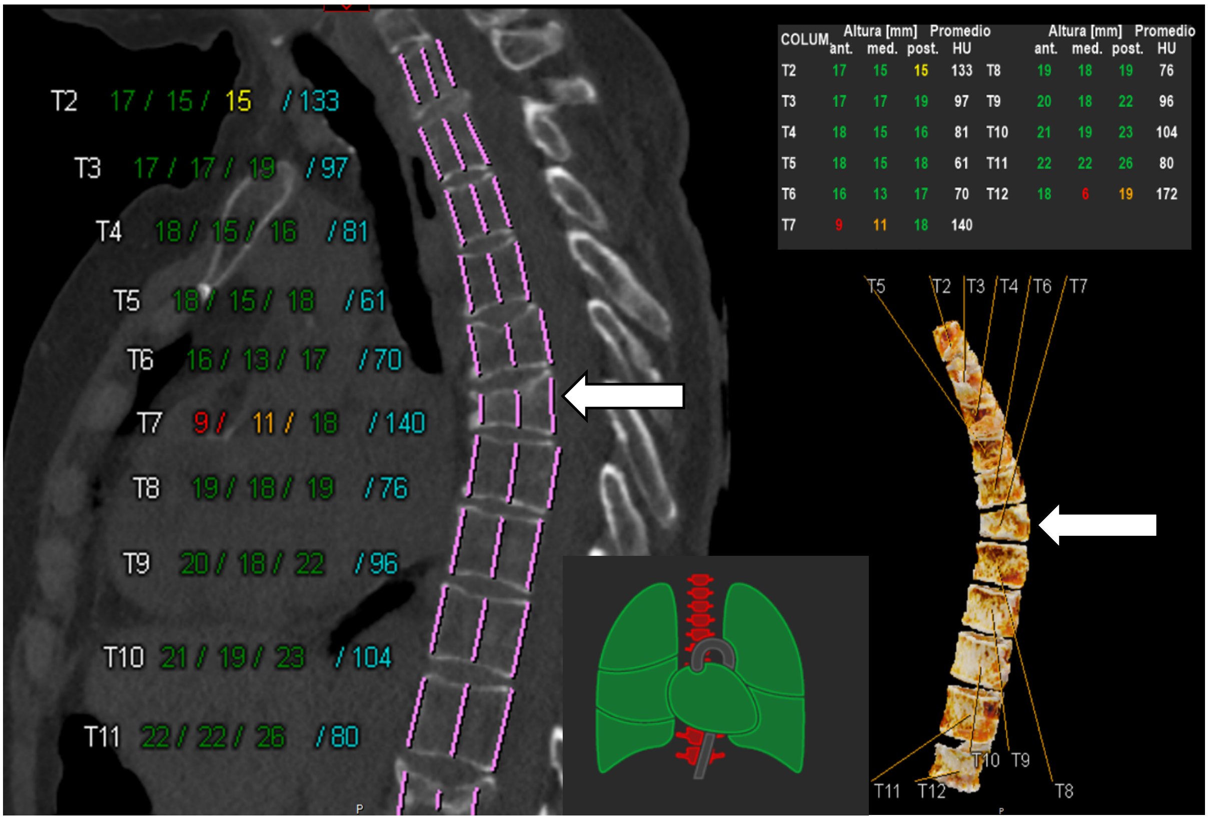

Figure 6. Artificial intelligence for automatic detection of vertebral fracture. A 75-year-old female underwent a chest CT study for suspicion of COVID-19 lung involvement. An AI system (AI-Rad Companion by Siemens Healthineers) performed an automatic sagittal reconstruction of thoracic spine, including volume rendering reconstructions, as well as an automatic estimation of vertebral body height at its anterior, middle, and posterior aspect, pointing out those vertebral body that show significant height loss. In this case, an osteoporotic chronic fracture of T7 vertebral body (arrows) with a loos of height of 50% was identified. This kind of tools may help to number and detect not only vertebral fracture in the setting of chest trauma, but also assist radiologists in detecting fractures as unexpected findings in patients that undergo CT studies for other clinical indications.

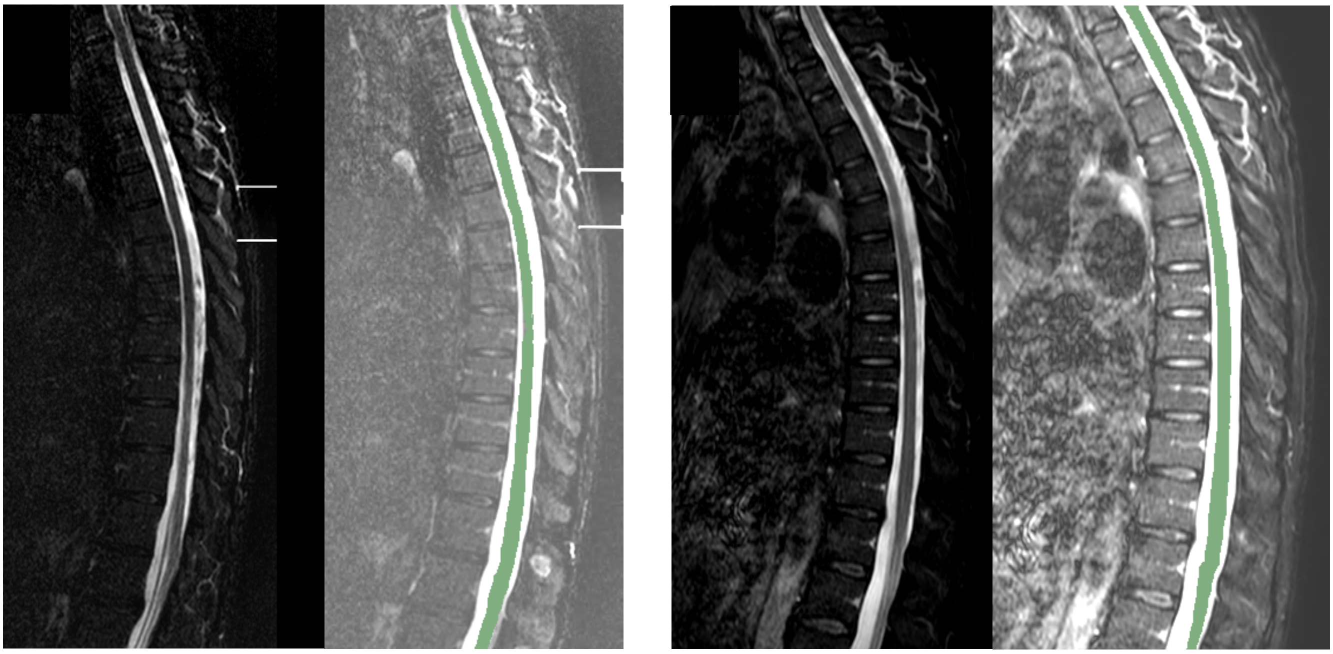

Figure 7. Artificial intelligence for spine involvement assessment in a 55-year-old female with multiple sclerosis. (a) Image and segmentation corresponding to 2019 sagittal STIR sequence with an average cross-sectional area of 40.115 mm2. (b) Image and segmentation corresponding to 2021 sagittal STIR sequence with an average cross-sectional area of 34.1925 mm2. Both segmentations have been generated with the sct_propseg tool included in Spinal Cord Toolbox (https://spinalcordtoolbox.com/). In this case, the use of AI based tools can help radiologists to identify subtle changes in the average volume of spinal cord, otherwise not detectable in a qualitative conventional manner.