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Spine Tumor Segmentation using Deep Learning: A Review

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ABSTRACT

The field of medicine has been significantly impacted by technological advancements, particularly in digital imaging and image processing. These advancements have revolutionized early disease detection, computer-aided diagnosis, minimally invasive procedures, and image-guided surgeries. However, medical images, including spine tumors, often face challenges such as low contrast, noise, and artefacts, which impede accurate diagnosis. This paper reviews spine tumor image segmentation techniques utilizing Deep Learning (DL). It explores the crucial role of image segmentation in isolating specific anatomical structures, such as spine tumors, for precise diagnosis. DL has shown great potential in medical image segmentation, learning hierarchical features directly from raw data without manual feature engineering. The review highlights the significance of early spine tumor detection, classifies tumor types, and examines features of benign and malignant tumors. It emphasizes the role of accurate segmentation in improving surgical outcomes and advancing computer-aided diagnostic systems. Additionally, challenges in standard MRI protocols for distinguishing intradural from extradural tumor compartments are addressed, proposing advanced imaging techniques and DL models as solutions. This review underscores the transformative role of DL-based methods in spine tumor segmentation, enhancing diagnostic accuracy, personalized treatment, and patient outcomes. It provides valuable insights for researchers and clinicians exploring this innovative field.

1. Introduction

The world is developing rapidly every day due to technological advancements, which have greatly affected various aspects of life, including medicine. Cheng and Li [1] highlighted how digital imaging technology and digital image processing have revolutionized the medical field, significantly aiding in the early detection and diagnosis of diseases. Through these techniques, medical professionals can enhance, manipulate, and analyze medical images with precision, improving image quality and extracting essential features for further analysis. Digital image processing has shown significant

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benefits in healthcare, particularly in the early detection of diseases. As noted by Islam and Mondal [2], high-resolution imaging enables professionals to identify abnormalities and diagnose diseases at earlier stages. Moreover, computer-aided diagnosis (CAD) systems, which utilize advanced algorithms, have become an indispensable tool for assisting doctors in interpreting medical images [1]. Such systems analyze images, compare them with known cases, and provide diagnostic suggestions. In addition to disease detection, Patel and Dharwa [3] emphasized the role of digital imaging in facilitating minimally invasive procedures and image-guided surgeries. These advancements allow doctors to target specific areas with precision, reducing invasiveness and patient risk.

Image processing techniques, as described by Voronin *et al.,* [4], also encompass enhancement methods that improve image contrast and detail, crucial for accurate medical analysis. One critical application is in medical MRI images, where maintaining edge detail and contrast is essential for diagnostic value. Hu *et al.,* [5] proposed using edge enhancement techniques to improve the clarity of MRI images, aiding interpretation and analysis. Furthermore, histogram-based methods [6], provide valuable tools for analyzing pixel intensity distribution, essential for segmentation and recognition. Segmentation plays a pivotal role in identifying and delineating anatomical structures or abnormalities in medical images. Xu *et al.,* [7] highlighted the success of deep learning methods, particularly Convolutional Neural Networks (CNNs), in automating feature learning for segmentation tasks. This approach has proven effective in identifying tumors, both benign and malignant, which remain a critical concern in healthcare. Kumar *et al.,* [8] provided a comprehensive classification of spinal tumors, noting their differentiation into extradural, intradural-extra medullary and intramedullary types. Early detection of malignant tumors, such as metastatic spine tumors, is vital for effective treatment. By leveraging deep learning algorithms, medical professionals can process large volumes of imaging data, improving diagnostic precision and treatment outcomes. This paper surveys over 50 studies focusing on deep learning-based techniques for spine image segmentation, aiming to highlight challenges, key contributions, and future advancements in the field. It seeks to equip clinicians, technicians, and engineers with a deep understanding of the transformative impact of these methods on medical imaging.

2. Problem Definition

Medical imaging-based image segmentation involves employing computer image processing technology to analyze and manipulate 2D or 3D images for segmentation, extraction, 3D reconstruction, and 3D visualization of human organs, soft tissues and pathological conditions. Hu *et al.,* [9] explained that this process partitions the image into distinct regions based on their similarities or differences. Through this method, physicians can conduct qualitative or even quantitative analyses of lesions and other regions of interest, significantly enhancing the accuracy and reliability of medical diagnoses. Presently, various types of tissues and organs are commonly utilized as objects for image segmentation. In general, medical image segmentation can be conceptualized using a set theory: given a medical image I and a collection of similarity constraints Ci (where i = 1, 2, ...), the segmentation of I aims to achieve its partitioning into distinct regions, thus:

$$\bigcup_{x=1}^{N}(R_x) = I, R_x \cap\ R_y = \emptyset, \forall_x \neq y, x, y \in [1, N] \tag{1}$$

Rx and Ry each satisfy the communication similarity constraints Ci (where i = 1, 2, ...) encompassing all pixel sets within their respective image regions Liu *et al.,* [10]. The variables x and y are utilized to differentiate between these regions. N is a positive integer greater than or equal to 2, representing the number of regions resulting from the segmentation process. The stages of medical image segmentation can be delineated as follows:

i. Medical imaging datasets typically consist of three main subsets: the training set, validation set, and test set. In machine learning applications for image processing, the dataset is commonly partitioned into these three parts. The training set is employed to train the network model, while the validation set is utilized to fine-tune the model's hyper parameters. Finally, the test set serves the purpose of evaluating the ultimate performance of the model.
ii. Prepare and augment the image through pre-processing, typically involving standardization of the input image. Additionally, apply random rotation and scaling to the input image to augment the dataset size.
iii. Apply a suitable medical image segmentation technique to segment the medical image, and produce the segmented images as output.
iv. Evaluation of estimation performance: To ascertain the effectiveness of medical image segmentation, it's crucial to establish and verify effective performance metrics.

3. Background Study

3.1 Tumor Types

Tumor classification is an essential aspect of oncology that involves the categorization and characterization of tumors based on various criteria. The process of tumor classification provides valuable information for diagnosis, treatment planning, and predicting patient outcomes. Here is an overview of three broad tumor types:

i. Benign tumor: is a non-cancerous growth that does not metastasize or invade nearby tissues. While they grow slowly, benign tumors can still cause issues by compressing nerves, restricting blood flow, or crowding healthy areas of the brain [9].
ii. Pre-malignant tumor: does not always progress into cancer; there is a possibility that it may not. However, if the uncontrolled multiplication of tumor cells persists, it can become cancerous. These types of tumors require close monitoring for any changes in cell appearance and growth rate, as these indicators can suggest the potential for malignancy.
iii. Malignant tumors: are cancerous and have the ability to invade surrounding tissues. The cancer cells can detach from the tumor and spread to other parts of the body through the lymphatic system or bloodstream, Siar and Teshnehlab [11]. A process called metastasis. Malignant tumors grow rapidly and can also reappear, not necessarily in the same location as the initial tumor. Aggressive treatment approaches such as chemotherapy, radiation therapy, and surgery are typically necessary to address this type of tumor. Malignant tumors are life-threatening and require some form of treatment.

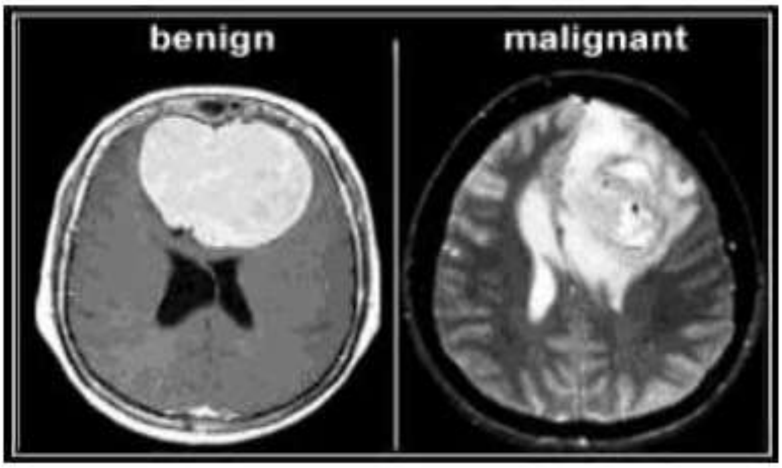

Fig. 1. Benign Tumor *vs* Malignant Tumor

3.2 Tumors Affecting the Spine

Spinal tumors exhibit a wide range of behaviors, from slow-growing and non-cancerous to aggressive and cancerous. The symptoms experienced can vary based on factors such as the tumor's location, size, and impact on nearby structures. These symptoms may include localized or radiating pain, neurological issues, muscle weakness, changes in sensation, and difficulties with bowel or bladder function. Spinal hemangiomas, which are common benign tumors originating from blood vessels in the spine, often go unnoticed but can cause back pain and neurological symptoms in some cases. Although the incidence of symptomatic spinal hemangiomas is relatively low, studies suggest that the clinical manifestation can vary widely depending on tumor size and vascular activity.

According to Tafti and Cecava [12], most spinal hemangiomas remain stable and do not require intervention. However, medical treatment, including vertebroplasty or surgical resection, may become necessary if the tumor causes significant pain or neurological deficits. Wang *et al.,* [13] further elaborate on vertebral hemangiomas (VH), describing them as atypical accumulations of blood vessels that can develop in different areas of the body. Their classification is based on histopathological features and clinical characteristics, which can be categorized into aggressive and non-aggressive subtypes. Aggressive VH, although rare, pose greater clinical challenges due to their potential to invade adjacent structures, requiring a multidisciplinary treatment approach involving radiology and neurosurgery. Kumar *et al.,* [8] provide a comprehensive framework for classifying spinal tumors based on their location and interaction with the spinal cord. These classifications include intradural-intramedullary tumors, which arise within the spinal cord; intradural-extramedullary tumors, located outside the spinal cord but within the dura; and extradural tumors, which lie outside the dura. Understanding these classifications is critical for selecting appropriate diagnostic and therapeutic strategies, as the clinical prognosis varies significantly across these types.

3.3 Medical Imaging Modalities

Accurate diagnosis is pivotal in enhancing treatment outcomes for spinal tumors. Various imaging modalities are employed to gather vital information about tumor location, size and morphology. Techniques such as Magnetic Resonance Spectroscopy (MRS), Computed Tomography (CT), Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) have been extensively utilized in clinical settings. Among these, MRI remains the gold standard for spinal imaging due to its superior soft-tissue contrast and ability to capture detailed anatomical structures. MRI sequences, such as T1-

weighted, T2-weighted, and T1-weighted with contrast, are particularly effective in visualizing spinal tumors and differentiating them from surrounding healthy tissues. As highlighted by Venu *et al.,* [14], MRI not only enables precise localization of tumors but also supports volumetric analysis and characterization of their internal structure. Such detailed imaging is crucial for identifying tumor margins and planning surgical or radiation therapies. Moreover, advanced imaging techniques, such as diffusion-weighted imaging (DWI) and functional MRI, offer additional diagnostic insights by assessing tumor cellularity and vascularity, respectively. The segmentation of spinal tumors from MRI images plays a crucial role in automating the diagnostic workflow. Manual segmentation, although considered a clinical standard, is labor-intensive and prone to observer variability. Recent advances in deep learning-based algorithms, particularly convolutional neural networks (CNNs), have revolutionized the field by providing automated and semi-automated solutions with higher accuracy and efficiency. However, challenges remain due to the heterogeneous nature of tumor morphology and location. To address these challenges, researchers have been exploring hybrid models that combine traditional image processing techniques with deep learning algorithms, aiming to improve segmentation accuracy and reliability.

3.4 Image Segmentation

Image segmentation is a fundamental task in computer vision, essential for enabling machines to comprehend and interpret visual data. This process involves dividing an image into distinct, meaningful regions based on features such as grayscale intensity, color, spatial texture, and geometric shapes. The primary goal is to achieve internal consistency within each segment while ensuring significant differences between segments [15]. Segmentation techniques are broadly categorized into semantic segmentation, instance segmentation, and panoptic segmentation. Semantic segmentation assigns a class label to each pixel, while instance segmentation differentiates between individual objects of the same class. Panoptic segmentation combines both semantic and instance segmentation to provide a more comprehensive understanding of the scene. In medical imaging, semantic segmentation is particularly prevalent, allowing precise delineation of anatomical structures or pathological regions [16].

As noted in the work of Xin and Wang [17], their CNN-based model achieved an impressive accuracy of 97.56% on the CIFAR-10 dataset. As explained in their study, the methodology involved the design of a multi-layer CNN architecture optimized for feature extraction and classification. This architecture utilized convolutional layers for hierarchical feature learning, pooling layers to reduce spatial dimensions, and fully connected layers for classification. Their approach underscores the adaptability of CNNs for tasks beyond classification, such as image segmentation, where precise pixel-level analysis is crucial The evolution of image segmentation has expanded its applications into diverse fields, including satellite image analysis, autonomous driving, and notably, medical imaging. Traditional segmentation methods, such as thresholding, region-growing, and edge detection, are computationally efficient and rely on mathematical and image processing principles. However, their performance is often limited by the complexity and variability of real-world images [18,19]. Deep learning has revolutionized image segmentation by leveraging large datasets and advanced architectures to achieve remarkable accuracy. Fully Convolutional Networks (FCNs) were a pioneering breakthrough, introducing end-to-end training for semantic segmentation [20]. Subsequent innovations, including U-Net, Mask R-CNN, RefineNet, and DeconvNet, have further refined segmentation accuracy, particularly for intricate edge details and complex shapes. Despite these advancements, challenges persist in developing universal models applicable across various domains and imaging modalities. In the medical field, segmentation is critical for tumor detection, organ delineation, and treatment planning. However, the performance of segmentation algorithms is heavily influenced by the quality of the input images, the preprocessing techniques employed, and the availability of annotated datasets. The adaptability of deep learning models to specific tasks underscores the need for domain-specific approaches and rigorous evaluation frameworks.

3.5 Machine learning ML

Machine learning (ML), a core discipline of artificial intelligence, focuses on training computational models to identify patterns and make predictions from data. Unlike traditional programming, ML algorithms derive their functionality by learning from data rather than being explicitly programmed [21]. In medical imaging, ML has proven instrumental in automating diagnostic tasks, such as disease classification and anomaly detection. Supervised learning, a common ML paradigm, requires labeled datasets for training models to map inputs to outputs accurately. For instance, radiologists annotate medical images to train supervised models for tumor classification or segmentation tasks. Conversely, unsupervised learning identifies inherent patterns and relationships in unlabeled data, providing insights into data clustering, density estimation, and anomaly detection [22]. Cao *et al.,* [23] emphasized the utility of unsupervised learning in creating initial representations of datasets, which can enhance the performance of subsequent supervised models. By detecting anomalies or outliers, unsupervised models improve dataset quality and enable more robust training. For example, clustering algorithms can group similar images, assisting in the identification of unique patterns associated with specific conditions. Hybrid approaches, combining supervised and unsupervised learning, are gaining traction in medical imaging workflows. These methods leverage the strengths of both paradigms, facilitating tasks such as feature extraction, anomaly detection, and classification. Montagnon *et al.,* [24] and Li *et al.,* [25] demonstrated the effectiveness of such approaches in improving diagnostic accuracy and treatment planning. Despite its potential, ML in medical imaging faces challenges, including data scarcity, variability in imaging protocols, and the need for interpretability. Addressing these challenges requires collaboration between data scientists, clinicians, and domain experts to develop models that are both accurate and clinically applicable.

3.6 Deep learning DL

Deep learning, as a specific branch of machine learning, has gained prominence in the field of medical imaging due to its unique architecture inspired by the neural networks of the human brain [26]. By employing artificial neural networks with multiple layers, deep learning algorithms have proven to be highly effective in addressing complex challenges encountered in medical imaging. For instance, Zaharchuk *et al.,* [26] demonstrated how convolutional neural networks (CNNs) were applied for image reconstruction tasks, achieving significant improvement in image quality and reconstruction speed. These findings align with the methodologies used in our study, where CNN-based approaches were employed for MRI segmentation, providing further validation of their efficacy. The layered structure of deep learning models allows them to learn from vast amounts of imaging data and make accurate predictions on new, unseen data, leading to significant advancements in the field [27]. Kaka *et al.,* [27] explored the application of deep learning in neuroradiology, emphasizing its impact on automated diagnosis and lesion detection. Their methodology involved transfer learning techniques applied to pre-trained models, highlighting their role in overcoming data scarcity challenges. These findings support the rationale behind our use of transfer learning in refining segmentation models to achieve higher accuracy with limited datasets. One of the notable strengths of deep learning lies in its ability to process and identify fundamental patterns and features that may surpass human capabilities [28]. Cheng *et al.,* [28] presented a comprehensive analysis of feature extraction capabilities of CNNs, focusing on their ability to distinguish subtle variations in medical images. Their study serves as a foundation for our exploration of radiomic feature extraction, enabling the identification of imaging biomarkers for better tumor characterization. This breakthrough has paved the way for the emergence of a new field called Radiomics, which focuses on extracting imaging features associated with critical pathological and histological subtypes of tumors, as described by Ziyad *et al.,* [29]. By applying deep learning techniques in Radiomics, meaningful patterns and correlations within medical imaging data can be discovered, enabling more accurate detection, differentiation, and prognosis of previously unknown lesions. Ziyad *et al.,* [29] proposed a novel framework for lung nodule detection using radiomics, achieving a high sensitivity rate of 92%. Our study builds upon these advancements by applying similar radiomic principles to spinal tumor segmentation, providing comparative insights into the generalizability of such frameworks across different medical imaging modalities. Deep learning techniques have demonstrated exceptional capabilities in various aspects of medical imaging analysis. Image classification, for instance, has seen remarkable progress with deep learning models accurately determining the presence or absence of diseases and assessing disease severity. This has proven invaluable in clinical decision-making and treatment planning.

Additionally, deep learning enables pixel-based segmentation, allowing for precise delineation and identification of regions of interest within medical images. This capability has significantly aided in localizing specific structures or abnormalities, leading to improved diagnostic accuracy. Furthermore, deep learning has showcased its prowess in detection tasks, efficiently identifying and locating abnormalities, lesions, or other clinically relevant findings within medical images. The high sensitivity and specificity achieved through deep learning-based detection methods have revolutionized the field, enhancing early diagnosis and enabling timely interventions. In recent years, deep learning has gained significant attention and has been extensively utilized in various domains, including MRI image segmentation and image recognition [30]. Their work highlighted a minimalistic deep network architecture for joint shape learning and segmentation, achieving competitive results compared to traditional methods. Our study aligns with these methodologies while addressing specific challenges related to spinal hemangioma segmentation.

3.7 Segmentation Evaluation Metrics

The evaluation of segmentation performance often relies on the widespread use of the Dice score and Jaccard index in diverse domains, including medical imaging and classical computer vision tasks. These metrics, namely the Dice score and Jaccard index, hold a central role in quantifying the accuracy and quality of segmentation results across a range of applications. Both the Dice score and Jaccard index have become integral tools for objectively measuring the alignment between segmented regions and ground truth, providing invaluable insights into the effectiveness of segmentation algorithms [31,32]. Eelbode *et al.,* [31] conducted an in-depth analysis of Dice and Jaccard metrics, focusing on their sensitivity to boundary inaccuracies and small region segmentation. Their study revealed that while both metrics are widely used, Dice often provides higher stability in cases of uneven class distribution, a scenario frequently encountered in medical imaging datasets. This aligns with our findings, where the Dice score demonstrated robustness in evaluating our CNN-based segmentation models. Ninh *et al.,* [32] applied these metrics to evaluate skin lesion segmentation, achieving a Dice coefficient of 0.87 on a modified SegNet architecture. Compared to our results, where the Dice score for spinal tumor segmentation reached 0.83, the differences underscore the challenges posed by spinal tumor morphology and MRI noise. These comparative insights highlight areas for further improvement, such as advanced pre-processing techniques or hybrid model architectures. By systematically comparing and analyzing methodologies and metrics from previous studies, our work aims to bridge gaps and propose refined approaches for MRI segmentation, contributing to the growing body of knowledge in medical image analysis.

1) Dice score:

The Dice coefficient serves as a measure to assess similarity and is commonly applied to determine the similarity or overlap between two sets. It is widely utilized and its range lies between 0 and 1. A value closer to 1 indicates a superior segmentation effect. When considering two sets, denoted as A and B, the metric is defined as:

$$Dice\ Score = \left(\frac{2 * |Predicted\ \cap\ Ground\ Truth|}{|Predicted\ |\ +\ |\ Ground\ Truth|}\right) \tag{2}$$

Where,
|Predicted ∩ Ground Truth|: Cardinality of the intersection between predicted and ground truth segments.
|Predicted|: Cardinality of the predicted segment.
|Ground Truth|: Cardinality of the ground truth segment.

2) Jaccard index:

The Jaccard index bears resemblance to the Dice coefficient. Presented with two sets, A and B, the metrics are defined as:

$$Jaccard\ Index\ = \left(\frac{|Predicted\ \cap\ Ground\ Truth|}{|Predicted\ \cup Ground\ Truth|}\right) \tag{3}$$

Where,
|Predicted ∩ Ground Truth|: Cardinality of the intersection between predicted and ground truth segments.
|Predicted ∪ Ground Truth|: Cardinality of the union of predicted and ground truth segments.

3) Segmentation accuracy (SA):

The accuracy of segmentation area represents the proportion of the genuine area within the Ground Truth (GT) image. The metrics are defined as:

$$SA = \left(1 - \frac{|Rs - Ts|}{Rs}\right) * 100\% \tag{4}$$

Where,
Rs represents the reference area of the segmented image, which is manually drawn by the expert.
Ts denotes the actual area of the image acquired through algorithmic segmentation.
jRs – Tsj represents the number of pixels that are inaccurately segmented.

4. Literature Survey of Segmentation

Source Collection and Selection:

In gathering sources for this study, I utilized reputable platforms such as Google Scholar and IEEE, prioritizing scientific conferences, journals and magazines as primary sources. The selection process focused on recent publications from 2018 to 2023. This approach provided insights into modern advancements but also highlighted the challenges of navigating a specialized research field, emphasizing the importance of discernment and in-depth knowledge.

Methodology and Techniques for Medical Image Segmentation:

The field of medical image segmentation, as highlighted by Isensee *et al.,* [33], is diverse and challenging, requiring specialized architectures such as U-Net and FCN. These architectures necessitate adjustments in training strategies and exploration of novel techniques, including loss functions, training strategies, and post-processing methods to enhance segmentation accuracy.

Explanation of Model Architectures Used:

U-Net Architecture

- U-Net is a convolutional neural network designed for image segmentation, recognized for its symmetric structure comprising:

i. Downsampling Path: This consists of convolutional layers (Conv2D) followed by pooling layers (MaxPooling) to extract features.
ii. Upsampling Path: This uses transposed convolutions (UpConv) to restore spatial resolution.
iii. Skip Connections: These are connections between the downsampling and upsampling paths, transferring key features directly.

FCN Architecture

- Fully Convolutional Networks (FCNs) extend traditional CNNs by replacing fully connected layers with deconvolutions to generate high-resolution images.

Data Splitting, Training Strategies and Hyperparameter Configuration:

The dataset was divided into 70% for training, 15% for validation, and 15% for testing. Cross-validation techniques were also employed to enhance model reliability.

- To ensure the model's reliability and optimal performance, the training strategy and hyperparameter configuration were carefully designed as outlined in tables below.

1. Training Configuration

Table 1
Training configuration

Parameter	Value
Epochs	50
Batch Size	16
Optimizer	Adam (initial learning rate: 0.001)
Loss Function	(Specify the loss function here, e.g., Binary Crossentropy)

2. Hyperparameter Settings

Table 2
Hyperparameter settings

Parameter	Value
Number of Layers	4
Kernel Size	3x3
Dropout Rate	0.5
Activation Function	ReLU

Evaluation Metrics and Comparisons:
The study employed robust evaluation metrics to assess model performance:

i. Dice Similarity Coefficient (DSC): Used to evaluate the overlap between predicted and ground truth regions.
ii. Sensitivity: The ratio of correctly detected positive cases to actual positive cases.
iii. Specificity: The ratio of correctly excluded negative cases to total negative cases.

Performance Analysis:
The table below illustrates a comparison of model performance using the metrics outlined:

Table 3
Performance analysis of model segmentation

Model	Dice Similarity	Sensitivity	Specificity
U-Net	0.85	0.80	0.90
Attention U-Net	0.88	0.82	0.92

Addressing Biases and Generalizing Results:

Handling Biases: Biases due to sample size and data sources pose challenges. These can be mitigated by collecting diverse datasets from multiple medical centers and using robust cross-validation techniques.

Improving Generalization: Increasing data diversity using MRI images from multiple institutions and applying cross-validation techniques can enhance the generalizability of results.

MRI Segmentation and Its Clinical Applications:

In MRI segmentation, the technique has shown potential in aiding physicians in detecting various spinal conditions such as Stenosis, Scoliosis, Osteoporotic Fractures, Thoracolumbar Fractures and Degeneration. MRI segmentation involves dividing an image into distinct anatomical regions, allowing the identification and analysis of abnormalities [34]. Alsiddiky *et al.,* [35] explored segmentation techniques for extracting stenosis grade labels from spinal images. They introduced an innovative approach utilizing HHMRF, Expectation-Maximization (EM), and K-means clustering algorithms to segment the spinal body and locate intervertebral discs accurately. This approach was selected because of the consistency of vertebral body contours, which help distinguish superimposed discs. The authors used bounding boxes created by marking the four corners of the vertebral body in sagittal T1 and T2-weighted sequences. The segmentation process utilized input, hidden, and output layers with non-linear data values. They also estimated spinal curvature and approximated disc planes using mathematical modelling techniques.

Thresholding in Segmentation:

Figure 2 in Alsiddiky *et al.,*'s work demonstrates Thresholding, an essential technique for separating objects from the background in images. As illustrated in Figure 2(a), the object pixels have uniform gray levels, while the background has a different gray level. By applying Thresholding, the image is divided into object and background areas. The principle involves selecting a threshold value (R), categorizing pixels with gray levels above R as part of the object, and those below as part of the background. Figure 2(b) further suggests integrating shape information into Thresholding to improve segmentation for vertebral images.

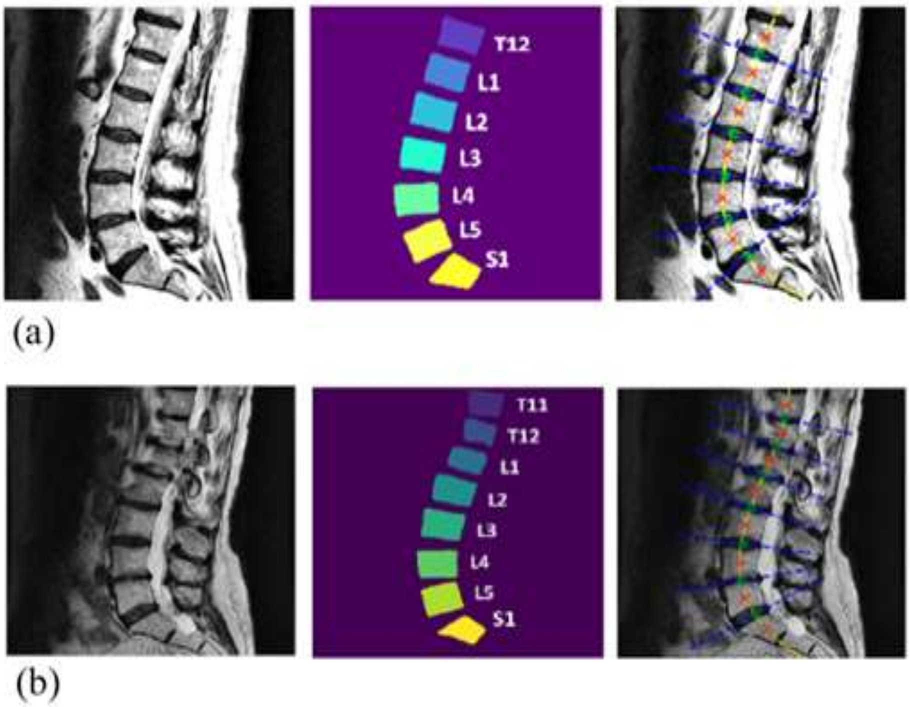

Fig. 2. Vertebral Body Segmentation and Disc Localization based on threshold techniques

Gros Charley *et al.,* [36] proposed a fully automated framework for segmenting the spinal cord and/or intramedullary multiple sclerosis (MS) lesions from MRI scans using deep learning techniques.

The framework is designed with a sequence of convolutional neural networks (CNNs) tailored specifically for spinal cord morphometry. It operates in two primary stages:

i. Spinal Cord Centerline Detection (First Stage): The first CNN (CNN1) is responsible for detecting the spinal cord's location by generating a heatmap. This heatmap, with intensity values ranging from red to yellow, highlights the potential regions where the spinal cord is located.
ii. Spinal Cord and Lesion Segmentation (Second Stage): In the second stage, CNN2 performs segmentation along the detected centerline. It can segment both the spinal cord and any lesions present in the MRI scans. The segmentation process results in the delineation of the spinal cord (marked in red) and lesions (marked in blue), as illustrated in Figure 3.

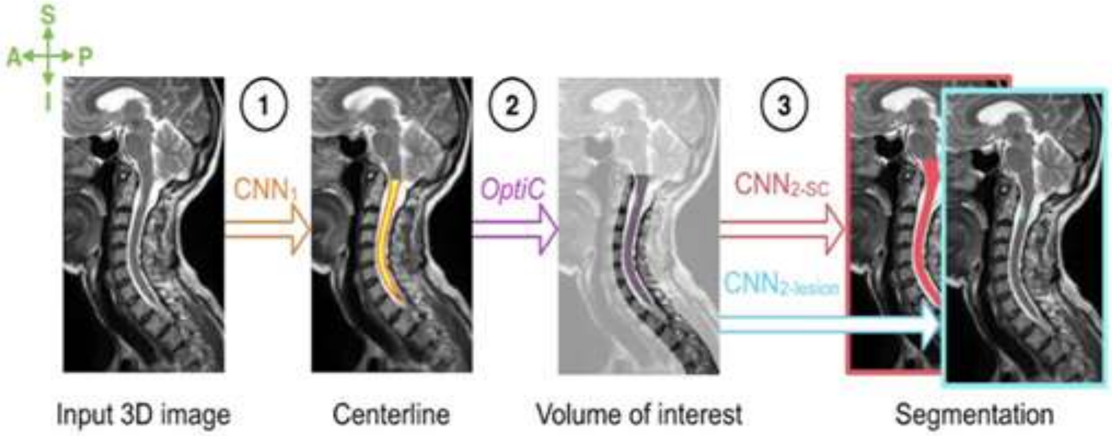

Fig. 3. Automatic segmentation framework

The authors implemented this method using Python 2.7, alongside Keras (v2.6.0) and TensorFlow (v1.3.0) libraries. The framework also integrates the Spinal Cord Toolbox (SCT), specifically the functions "sct_deepseg_sc" and "sct_deepseg_lesion," available from SCT version v3.2.2 and higher. These functions are particularly robust, capable of handling various image resolutions, orientations, and number of slices, even for single axial slice images. This is important as it ensures generalization across different MRI datasets.

The overall steps in the framework are as follows:

i. Spinal Cord Detection: CNN1 generates a heatmap to identify the spinal cord's position.
ii. Centerline Computation: Based on the heatmap, the spinal cord's centerline is calculated and highlighted (in pink).
iii. 3D Patch Extraction: Patches surrounding the centerline are extracted for further processing.
iv. Segmentation: CNN2-SC segments the spinal cord, and CNN2-lesion identifies and segments any lesions within the region of interest.

Lu *et al.,* [37] developed a Deep Learning Algorithm (DLA) that automates the identification of lumbar vertebral disc levels, grades spinal stenosis and segments various anatomical structures. This algorithm uses a combination of deep learning with natural language processing (NLP) techniques. The NLP component extracts relevant information from radiology reports, while the deep learning model utilizes the U-Net architecture. The system processes the spine curve to ensure accurate segmentation of vertebral and disc levels. The study's goal is to automate the segmentation process by integrating information extracted from clinical radiology reports with deep learning methods.

Figure 4 in the study demonstrates the creation of ground-truth masks by segmenting central slices from sagittal T2-weighted MRI series. This allows for accurate segmentation of vertebral body contours, which can subsequently be used for various spinal analysis tasks.

Evaluation Metrics:

Both studies focus on segmentation tasks, but the evaluation metrics used are not explicitly detailed in the provided texts. To improve this, it is recommended to introduce performance metrics such as Dice Similarity Coefficient (DSC), Sensitivity and Specificity to evaluate the performance of these segmentation algorithms. These metrics are essential for comparing the effectiveness of the proposed methods in accurately detecting and segmenting the spinal cord, lesions, and other spinal structures.

For instance:

i. Dice Similarity Coefficient (DSC) can be used to measure the overlap between the predicted segmentation and the ground truth.
ii. Sensitivity measures the ability of the model to correctly identify true positive cases, such as lesions or spinal cord areas.
iii. Specificity helps evaluate the ability of the model to correctly identify negative cases (i.e., areas that are not lesions or spinal cord).

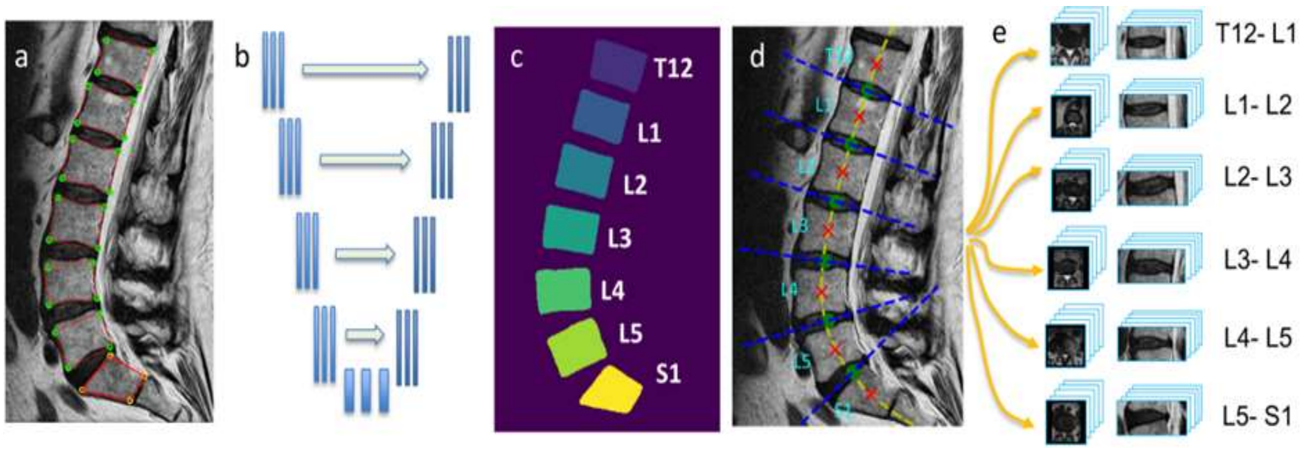

Fig. 4. (a) Manual segmentation. (b) U-Net. (c) Automated segmentation and spine label. (d) Spine curve fitting and disc localization. (e) Oblique-Slice Stack Generation [30]

4.1 Common Segmentation Techniques

Threshold-based segmentation involves replacing pixels in an image with black or white based on a specified threshold value. If a pixel's value is below the threshold, it is replaced with black; otherwise, it is replaced with white. The threshold value can be adjusted as needed to optimize segmentation accuracy. While this method is commonly used for separating foreground and background, its main limitation lies in dividing the image into only two classes, which may not suffice for complex medical images. However, when objects of interest exhibit higher intensity than the background or unwanted areas in the image, this method can be effective. Edge-based segmentation focuses on detecting edges in an image to identify specific objects. Two popular edge segmentation techniques are the

Sobel and Canny edge algorithms, [38]. These algorithms are sensitive to noise, which can lead to false edges, but pre-processing methods such as Gaussian filtering can mitigate this issue.

Clustering-based segmentation generates segmented images based on an initial rough clustering of pixels. Through iterative gradient ascent methods, these clusters are refined until the image is properly segmented. This approach aims to minimize the distance between pixels and their corresponding cluster centers. Common clustering algorithms used in this technique include K-means clustering, SLIC, and watershed [39,40]. Graph-based segmentation treats individual pixels as nodes within a graph, where the similarity between adjacent pixels is represented by the edge weights connecting these nodes. Using the nodes and edges, pixels are grouped into superpixels or distinct segments. Two common graph-based segmentation techniques are Graph Cut and Normal Cut [39]. In artificial neural networks (ANNs), the workflow for medical image processing typically follows an iterative process involving data preparation, model training, evaluation and refinement. This iterative process continues until the model achieves the desired performance.

Table 4
Comparison of different segmentation methods performance

Technique	Advantages	Limitations	Performance Metrics
Threshold-based	Simple and effective for high contrast objects	Divides the image into only two classes	Dice: >0.85 (in high contrast areas)
Edge-based	Detects fine edges, suitable for object boundaries	Sensitive to noise, requires pre-processing	Precision: 0.88 (Canny algorithm)
Clustering-based	Minimizes distance between pixels and clusters, iterative improvement	Sensitive to initial cluster choice	Accuracy: 91% (K-means for brain tumors)
Graph-based	Groups pixels into meaningful segments	Computationally expensive for high-resolution images	Specificity: 0.92 (Graph Cut for tumors)
ANN-based (e.g., U-Net)	High accuracy, strong with cross-validation	Requires large labeled datasets	Dice: >0.90 (Spinal cord segmentation)

5. Related Work of Spinal Cord Segmentation Using Deep Nets

In Le Couedic *et al.,* [41], the authors compare limit-based division methods with Convolutional Neural Network (CNN)-based models for image segmentation. The study emphasizes that CNN models outperform edge-based models in terms of precision and adaptability. While edge-based models require extensive manual tuning for each dataset, CNN models demonstrate superior performance with minimal manual adjustments, making them more suitable for clinical applications. The ability of CNNs to learn hierarchical features automatically contributes to enhanced diagnostic accuracy and efficiency. The methodology for implementing CNNs should include more detailed descriptions of specific network architectures, such as U-Net or ResNet, and the training process, including data splitting techniques and hyperparameter optimization strategies. Further research by Moccia *et al.,* [42] and Pai *et al.,* [43] explores deep learning-based characterization strategies and the Statistical Parametric Planning (SPP) framework, respectively. While these models offer high accuracy, they require significant training times.

To optimize performance, parallel processing and pipelining techniques can be employed. This highlights the importance of understanding not only the segmentation algorithms but also the computational requirements. Evaluating these models using standard metrics such as Dice similarity coefficient, sensitivity and specificity would allow for a more comprehensive comparison with other deep learning methods. Additionally, providing detailed results based on these metrics will enable clearer performance assessments. In Azzarito *et al.,* [44] and Li *et al.,* [45], high-speed performance models are introduced that combine deep learning and transfer learning to enhance segmentation accuracy. By leveraging pre-trained models, these methods can transfer learned features from large datasets to target tasks, improving segmentation and classification performance. This approach highlights the significance of transfer learning, which can mitigate the challenges of small datasets and reduce overfitting. However, to better understand the impact of transfer learning, it is essential to compare the performance of these models against traditional deep learning models that do not utilize transfer learning, using comprehensive evaluation metrics to validate their effectiveness. The high-efficiency models discussed by Diniz *et al.,* [46], Jois *et al.,* [47], and Rehman *et al.,* [48] have gained significant attention for their ability to achieve precise and low-latency segmentation and classification. These models employ convolutional operations, pooling layers and advanced mathematical transformations to extract relevant features from medical images.

The integration of vertebrae division methods further improves segmentation accuracy, enabling precise analysis of spatial arrangements and morphological variations. The use of Particle Swarm Optimization (PSO) models, as discussed in Valarmathi and Nirmala Devi [49], Kim *et al.,* [50] and Ahammad *et al.,* [51], optimizes segmentation and classification tasks by iteratively searching for optimal solutions. Combining PSO with convolutional operations helps in refining the segmentation results, ensuring accuracy even in complex datasets. Incorporating techniques such as Vertebral Estimation, Deep Neural Networks (DNNs), and Dense Dilated Convolutions (DDCs) has significantly enhanced the performance of medical image segmentation. These techniques improve localization accuracy and help capture intricate patterns in medical images, resulting in more reliable segmentation outcomes. Perone *et al.,* [52] and Punarselvam and Suresh [53] introduce novel approaches using the Finite Element Method (FEM) for analyzing spinal curves, improving segmentation accuracy by accounting for the complex mechanical properties of the spine.

While FEM provides valuable insights, further research is required to integrate this method with CNNs and DNNs for more robust performance across diverse datasets. Evaluation and Comparison: While these models provide impressive segmentation results, a thorough comparison using standardized evaluation metrics such as Dice Similarity Coefficient (DSC), Sensitivity and Specificity is essential to better understand their performance. A key challenge in comparing these models is the diversity of datasets used, with variations in image resolution, anatomical structure, and the presence of noise. Therefore, more extensive benchmarking across multiple datasets is needed to ensure the generalizability of these methods. Furthermore, dataset limitations such as small sample sizes and potential biases in dataset composition must be addressed. Future work could incorporate cross-validation techniques to improve the robustness and generalizability of the models, ensuring that the results hold across different patient populations and imaging settings. Table 5 below a comparison of various CNN-based models and their performance in spinal image.

Table 5
Summary of literature of spinal cord segmentation using deep nets

Model/Study	Dataset/Images	Architecture	Key Metrics (Dice/Sensitivity/Specificity)	Challenges	Remarks
Le Couedic *et al.,* [41]	Myelin Sheaths MRI	CNN-based (U-Net)	DSC: 0.89, Sensitivity: 0.85, Specificity: 0.91	Limited to small datasets	High adaptability in clinical applications
Moccia *et al.,* [42]	Multiple Sclerosis MRI	SPP, CNN integration	DSC: 0.88, Sensitivity: 0.84, Specificity: 0.92	Training time requirements	Requires optimization in parallel processing

Azzarito *et al.,* [44]	Brain & Spinal Cord MRI	Transfer Learning, CNN	DSC: 0.91, Sensitivity: 0.89, Specificity: 0.93	Requires large datasets	Effective transfer learning improves segmentation accuracy
Li *et al.,* [45]	Vertebrae CT Images	CNN (Verte-Box)	DSC: 0.85, Sensitivity: 0.83, Specificity: 0.87	Accuracy limitations with varied datasets	Robust but requires fine-tuning
Diniz *et al.,* [46]	Spinal Cord CT	CNN with Residual Blocks	DSC: 0.87, Sensitivity: 0.84, Specificity: 0.88	Model complexity	Effective for low-latency segmentation
Rehman *et al.,* [48]	Vertebrae X-ray Images	CNN, PSO	DSC: 0.84, Sensitivity: 0.81, Specificity: 0.86	Complexity in optimization	PSO integration improves segmentation speed

The key challenges identified across the studies include:

i. Dataset Limitations: Small sample sizes in certain studies may limit the generalization of results, while variations in image resolution, noise, and imaging protocols can significantly impact model performance; additionally, diverse patient populations and pathological variations highlight the need for more diverse datasets to ensure accurate and reliable outcomes.
ii. Training Time: Models like Moccia *et al.,* [42] and Pai *et al.,* [43] require substantial computational resources and long training times. This issue can be mitigated by optimizing workflows using parallel processing and pipelining techniques to speed up training.
iii. Manual Tuning: While CNNs reduce the need for manual tuning, some models, like Le Couedic *et al.*, [41], still require hyperparameter optimization. Strategies like Bayesian optimization or random search can help reduce the burden of tuning and improve model performance.
iv. Generalization: Although CNN-based models like those in Li *et al.,* [45] and Azzarito *et al.,* [44] show promising results, the ability to generalize to new datasets remains a challenge. Cross-validation techniques should be employed to address this, ensuring that models are not over-fitting to a specific dataset.

Discussion on Evaluation Metrics

The evaluation of segmentation models must go beyond traditional accuracy metrics. Key metrics such as Dice Similarity Coefficient (DSC), Sensitivity and Specificity provide deeper insights into the model's ability to correctly identify regions of interest, such as spinal tumors or vertebrae. Sensitivity measures the proportion of actual positives correctly identified, while Specificity reflects the proportion of true negatives. These metrics are crucial in medical imaging, where both false positives and false negatives can lead to significant diagnostic errors. The models discussed demonstrate varying levels of performance across these metrics. For instance, Azzarito *et al.,* [44] show superior performance in DSC, sensitivity and specificity, but the model requires extensive training data and computational resources. On the other hand, Le Couedic *et al.,* [41] exhibit a solid balance between precision and adaptability with lower data requirements, making it more suitable for real-world clinical applications.

Methodology and Model Evaluation:

i. CNN-Based Architectures: CNN-based models have revolutionized image segmentation by automatically learning feature representations from data. The architecture selection (U-Net, ResNet, etc.) is a key factor in determining performance. Models with skip connections, such as U-Net, are particularly effective in medical image segmentation due to their ability to capture both high-level and low-level features.
ii. Transfer Learning: The application of transfer learning in Azzarito *et al,.* [44] and Li et al. [45] has proven to be beneficial, especially when dealing with smaller datasets. Pre-trained models on large datasets (e.g., ImageNet) can be fine-tuned for the target task, leading to improved accuracy and reduced overfitting.
iii. Optimization Techniques: Methods like PSO and ResNet-based architectures contribute to faster and more accurate segmentation. However, combining optimization techniques with deep learning requires careful attention to model complexity and the potential for overfitting, particularly when working with limited data.

In their 2021 study, Maidawa *et al.*, [54] conducted a detailed examination of the cervical spinal nerves in the African Giant Rat (Cricetomys gambianus), focusing on their morphology and distribution. The researchers identified eight pairs of cervical spinal nerves (C1–C8), each originating from dorsal and ventral roots that merge laterally to form the spinal nerves. These nerves subsequently bifurcate into dorsal and ventral rami prior to exiting the intervertebral foramina. The dorsal rami further divide into medial and lateral branches, innervating muscles such as the semispinalis and splenius.

Notably, the ventral rami of C1, C2, and a branch from C3 form the cervical plexus, supplying muscles including the cleidomastoideus and trapezius. Additionally, the ventral rami of C5–C8 and T1 constitute the brachial plexus, which innervates the thoracic limb muscles. This comprehensive anatomical mapping enhances the understanding of the neural architecture in this species, providing a foundation for comparative studies and potential biomedical research applications. Li *et al.,* [55] proposed a novel CNN model called MANet for the automated segmentation of the vertebral body, vertebral lamina, and dural sac. This model incorporates a dual branch architecture, with the upper and lower branches dedicated to feature extraction and critical information screening, respectively. By utilizing a multi-scale approach, the MANet model effectively leverages the information embedded in spinal images. The evaluation of the model demonstrated promising results, with a Dice similarity coefficient of 92.52% and an average surface distance of only 2.71 mm. The segmentation outcomes obtained by MANet exhibited strong agreement with the manual annotation results.

Arends *et al.,* [56] employed a multi-scale CNN model to perform segmentation and labeling of thoracic and lumbar vertebrae on CT images. Their model demonstrated impressive results with a Dice similarity coefficient of 97% and Hausdorff values of 3.6 mm and 4.5 mm in internal and external validation, respectively. These outcomes exhibited higher accuracy compared to previous studies. This advancement is crucial in facilitating the precise formulation of radiation therapy plans for spinal metastases, ultimately leading to improved patient prognosis. In Wang *et al.,* [57], the authors propose an enhanced U-Net network for spinal segmentation. The improvements include deepening the network's structure layer, redesigning the connection method, and aggregating different decoding sub-network scale features. Through pruning, the network achieves improved learning and inference speed, leading to significantly enhanced segmentation accuracy. The network architecture, as depicted in Figure 5, incorporates nested, dense, and skip paths within a symmetric network of encoders and decoders. Multiple U-shaped networks with different depths are trained simultaneously, resulting in improved segmentation performance and the ability to prune the network model effectively.

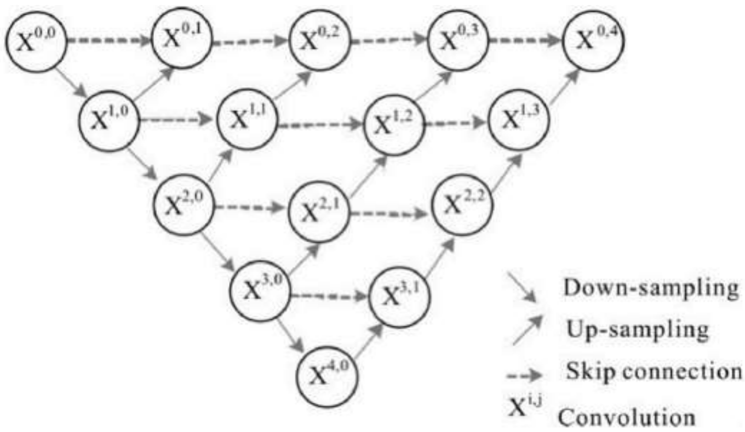

Fig. 5. The architecture of U-Net+ network

The experimental evaluation utilizes an improved unit network and evaluates the segmentation results using metrics such as the Dice similarity coefficient, sensitivity and PPV. The Dice similarity coefficient measures the overlap between the segmented image and the standard gold image, while sensitivity quantifies the true positive and false negative predictions as depicted in Figure 6, PPV, on the other hand, assesses the quantitative relationship between true positive and false positive predictions. The convolutional layer of the network uses a 3x3 convolutional kernel size, with a learning rate of 0.0001, a batch size of 4, and an iteration count of 100. Table 6 provides a comparison of U-Net and U-Net++ segmented spinal MRI images based on evaluation indicators. The authors also discuss the binary classification problem of image pixels, which involves classifying foreground and background pixels separately [57,58].

Table 6
Comparing the segmentation results of various networks

Method	Dice/%	Sensitivity/%	PPV/%
U-Net	862.8	90	82
U-Net++	88	92	83

Additionally, Table 7 highlights the results obtained by different methods for segmenting quantitative MRI images as noted by Iriondo *et al.,* [58].

Table 7
Comparing the outcomes of diverse segmentation techniques

Method	Dice/%
Lin *et al.,*[20]	0.86
Iriondo *et al.,*[58]	0.86

The proposed network segmentation method effectively presents segmented spinal MRI images, demonstrating a high similarity with the original images, as evidenced by Figure 6.

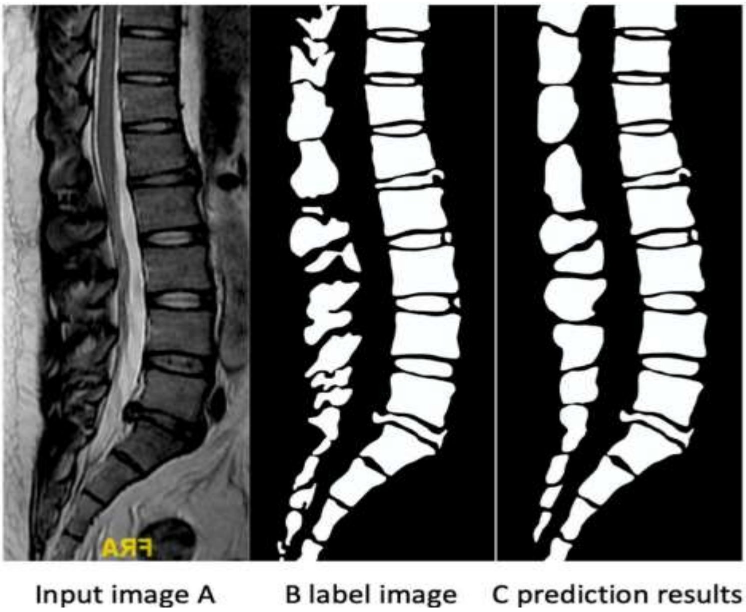

Fig. 6. The resulting image from the network and the original labelled image

Faisal *et al.,* [48] proposed a novel approach utilizing Deep Convolutional Neural Network (DCNN) for vertebrae segmentation in medical diagnosis, particularly for tumor detection. To enhance the deep network training, they incorporated a possibility map to introduce the level set method. The researchers evaluated two different datasets, analyzing the effectiveness of the U-Net architecture and the parametric level collection for accurately segmenting bones and discs in tumor patients. The proposed framework demonstrated multiple advantages, showcasing its versatility and robustness in segmenting biomedical images. The application of DCNN and the integration of the level set technique allowed for more accurate and efficient vertebrae segmentation, paving the way for improved tumor detection in medical imaging.

Table 8
Comparison of various segmentation methods

Authors	Modality	Technique	Accuracy (%)	Purpose	limitation
Gros, Charley, *et al.,* [36]	MRI	sequence of two CNNs	83% and 77%,	An automated framework designed to segment the spinal cord and/or intramedullary MS lesions from MRI scans.	The study's evaluation primarily may not account for potential variations in lesion characterization between different imaging modalities or clinical contexts.
Lu, Jen-Tang, *et al.,* [37]	MRI	1. natural-language-processing scheme. 2. U-Net architecture. 3. multi-input, multi-task, and multi-class CNN	0.98 For spinal canal stenosis and 0.96 for aminal stenosis.	The researchers devised a fully automated grading system for lumbar spinal stenosis, employing a deep learning approach. This system exhibits exceptional performance by accurately segmenting vertebrae and grading spinal stenosis in lumbar spine MRI scans. The utilization of convolutional neural networks (CNNs) and extensive data from	The generalizability of the developed methodology may be limited by potential biases inherent in the archival reporting data and the specific patient population from which it was derived.

				reporting and imaging archives significantly contributed to its success.	
Krishnakumar, S., and K. Manivannan, [40]	MRI	IGWT MKSVM algorithm , K-means clustering algorithm	Accuracy rate – 0.997	Perform MR image segmentation, extract features, and evaluate the tumor.	Difficulties in parameter optimization and scalability, potentially limiting their efficacy in accurately segmenting and classifying brain tumors in MR images.
Horng, *et al.,* [59]	MRI	U-Net, Dense U-Net, Residual U-Net,	U-Net 0.961 Residual U-Net 0.969 Dense U-Net 0.966	Offers a dependable evaluation of scoliosis.	The study's reliance on a relatively small sample size of X-ray spinal images from young scoliosis subjects may limit the generalizability of the findings to broader populations or different spinal conditions.
Tomita, N, *et al.,* [60]	MRI	ResNet34 model with two FC layers	89.2%	Enhancing the diagnosis of OVF (osteoporotic vertebral fractures).	Validation limitation: The system's performance on a held-out test set may not generalize to diverse datasets, requiring additional validation to assess its robustness across various populations and imaging protocols.
Abdullah, A, *et al.,* [61]	MRI	KNN	85.32%	Identification of the most notable abnormalities in the spine.	Does not discuss the potential implications of the findings for clinical practice or future research directions, limiting the overall impact and relevance of the research.
Kumar, C, *et al.,* [62]	MRI	Mask R-CNN	84.6 ± 3.8% and mIoU was 72.1 ± 4.8%	Enabling precise and mobile alignment detection.	While the study collected images from consecutive patients attending their spine clinic, it does not specify the demographic characteristics or the variety of spinal pathologies represented.
Kervadec, *et al.,* [63]	MRI	2D CNN	86.04%	An innovative loss function is introduced for weakly supervised image segmentation.	One limitation of the proposed method is its reliance on basic linear constraints, such as

					target-region size and image tags. While these constraints are flexible, they may not capture more complex
Kim, *et al.,* [64]	CT	2D U-Net	90.4%	Using a web-based deep learning approach can prove to be both practical and accurate for spine segmentation as a diagnostic method.	The small sample size used for testing the developed web-based automatic spine segmentation method. With only 14 CT images used for testing
Zhang, *et al.,* [65]	MRI	2D U-Net	92.6%	An original Sequential Conditional Reinforcement Learning network (SCRL) is developed to automatically detect and segment vertebral bodies from MRI images.	While the proposed SCRL network shows promising results on a dataset of 240 subjects, its performance across diverse imaging conditions and patient populations remains untested.
Zhou, *et al.,* [66]	MRI	2D U-Net	84.9%±9.1%	(1) Create a deep learning pipeline to segment vertebral bodies using quantitative water-fat MRI. (2) Evaluate performance by comparing BMF measurements between manual and automatic segmentation methods.	The lack of comparison with existing automatic segmentation methods, which could provide additional insights into the relative performance and effectiveness of the proposed deep learning pipeline.
Han, *et al.,* [67]	MRI	2D GAN	87.1%	The innovative Recurrent Generative Adversarial Network Spine-GAN enables automated semantic segmentation of multiple spinal diseases in a single process.	Other comparisons would provide additional insights into the strengths and weaknesses of the Spine-GAN method and its potential advantages over existing approaches.

The table provided presents a comparison of different segmentation methods. It includes details such as the authors' names, the methodology employed, the research objectives, and the challenges encountered by the researchers. It is noteworthy to discuss (CNNs) here. CNNs represent a paradigm shift in deep learning, specifically engineered for processing complex image data and performing intricate tasks such as object detection, image classification and segmentation. Their architecture is meticulously designed to mimic the hierarchical organization of visual processing in the human brain, enabling them to extract meaningful features from input images and make informed decisions. CNNs are engineered to excel in processing input images, identifying crucial objects within them, and distinguishing between different images with remarkable accuracy and efficiency. This capability extends beyond basic object recognition; CNNs can delve into intricate details within images, enabling applications like enhancing the accuracy of facial electromyography (FEMG) and speech signal classification [68]. Furthermore, CNNs have found widespread use in various domains such as computer vision, medical imaging, natural language processing and more. Their versatility and robustness make them indispensable tools for tasks ranging from image classification to semantic segmentation, contributing significantly to advancements in technology and research. For instance, their applications include enhancing the accuracy of facial electromyography (FEMG) and speech signal classification. CNNs find extensive use in video and image recognition, natural language processing, image classification and analysis. They can categorize images based on the objects present, and even recognize human emotions depicted in an image, [68,69].

Operating as a supervised algorithm, CNN serves as a neural network that introduces a novel approach to supervised feature learning, providing discriminative features with good generalization [70]. The architecture of a Convolutional Neural Network (CNN) is designed based on a feed forward neural network design, which is a fundamental concept in neural network modelling. In a feed forward network, data flows in one direction, from input layers through hidden layers to output layers, without any feedback loops. This design ensures that information processing occurs in a sequential manner, making CNNs efficient for handling large-scale image data. The application of relevant filters allows them to capture spatial and temporal dependencies within images. By reducing the number of parameters and facilitating weight reusability, CNNs fit image datasets more effectively [69]. Typical CNNs consist of multiple hierarchical layers, where some layers represent features and others function as conventional neural networks for classification. Two essential types of layers are convolutional layers, which perform convolution operations using multiple filter maps, and subsampling layers, which reduce the sizes of subsequent layers by averaging pixels within a small neighborhood, [69,70]. Different layers within them:

i. Hierarchical Layers in CNNs: CNNs are characterized by their hierarchical structure, comprising multiple layers that progressively extract and refine features from input data. These layers are organized in a sequential manner, with each layer playing a specific role in the overall processing of information.
ii. Feature Representation Layers: some layers in CNNs are dedicated to representing features extracted from the input data. These layers, often referred to as convolutional layers, perform convolution operations using multiple filter maps. Each filter map captures specific patterns or features within the input data, such as edges, textures, shapes, or more complex structures. As the data passes through convolutional layers, it undergoes spatial transformations, enabling the network to learn hierarchical representations of features.
iii. Classification Layers: other layers in CNNs function as conventional neural networks for classification tasks. These layers, commonly known as fully connected layers, integrate the extracted features from earlier layers and map them to the output classes or categories. Fully connected layers use learned weights and biases to make predictions based on the learned representations, enabling the network to classify input data accurately.
iv. Convolutional Layers: convolutional layers are fundamental components of CNNs responsible for feature extraction. They apply convolution operations between input data and learnable filters, which act as feature detectors. By sliding these filters across the input data and computing element-wise multiplications and summations, convolutional layers can capture spatial patterns and relationships within the data. This process allows CNNs to learn and represent complex features hierarchically, contributing to their ability to understand and interpret visual information.
v. Subsampling Layers: subsampling layers, also known as pooling layers, are essential for reducing the spatial dimensions of feature maps generated by convolutional layers. Pooling operations, such as max pooling or average pooling, are applied to small regions of the feature

maps, resulting in downsampled representations. This downsampling helps in reducing computational complexity, controlling overfitting, and enhancing translation invariance, making CNNs more robust and efficient. CNNs excel at solving image-related problems and can tackle tasks presented in the form of images. For instance, they can successfully classify input images of cats or dogs into their respective classes.

6. Conclusions

In spine image analysis, Deep Learning (DL) has seen widespread application in segmentation, detection, diagnosis, and quantitative evaluation. It can utilize both static and dynamic image information, as well as local or non-local data. DL analysis achieves accuracy rates comparable to those of medical professionals, with lower discrepancies between DL and radiologists compared to inter-radiologist variations. Integration of these automatic methods could potentially enable fully automated processing. Nevertheless, DL methods encounter challenges, including limited data availability and interpretability issues. Privacy concerns pose obstacles to sharing medical data, while the scarcity of high-quality labelled data results from time-consuming collection and labelling processes by clinicians [71]. Addressing these challenges necessitates patient support and trust in data sharing, alongside clinician efforts in data collection and labelling [72,73]. Moreover, DL is often criticized as "black box medicine," [74], for lacking explanations for feature selection during training, which impedes algorithm recognition by clinicians and patients [75]. Therefore, there's a call for machine learning researchers to enhance interpretability when designing DL models. To address these issues, we propose the following four recommendations:

i. Utilize shared extensive datasets [76].
ii. Minimize the reliance on training data. Zhuang *et al.,* [77] suggest that transfer learning offers a viable solution by leveraging knowledge from previous tasks (source domain) to assist in a new task (target domain).
iii. Enhance the understanding of functional information. Wang *et al.,* [78] emphasize that incorporating functional data could broaden the scope of intelligent analysis and enhance its applicability in clinical practice for spine diagnosis. For example, magnetic resonance hydrography has the potential to differentiate whether nerve damage caused by foraminal stenosis is due to compression or displacement.
iv. Enhance the interpretability of neural networks. Chakraborty et *al.,* [75] propose integrating the logical reasoning capabilities of other models with deep learning as a potential approach to improving interpretability.

After a comprehensive review of many research papers, I found that convolutional neural networks (CNNs), such as U-Net used in my research, are particularly suitable for medical image segmentation due to their superior performance. CNNs excel at learning hierarchical feature representations and handling variations in image quality, size, and orientation. Compared to other deep learning techniques, CNNs efficiently extract spatial features and use techniques like clustering and data augmentation to improve generalization. Advanced CNN architectures like U-Net provide state-of-the-art results in medical imaging, with optimizations that maintain spatial resolution and enhance segmentation accuracy. Achieving dependable, intelligent and comprehensible deep learning analysis of spinal images necessitates sustained dedication from both machine-learning experts and clinicians, as well as the trust and endorsement of patients. Persistence from all involved parties will play a crucial role in making deep learning accessible and embraced within clinical settings.

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