Article

A State-of-the-Art Survey of Deep Learning for Lumbar Spine Image Analysis: X-Ray, CT, and MRI

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Abstract: Lumbar spine diseases not only endanger patients' physical health but also bring about severe psychological impacts and generate substantial medical costs. Reliable lumbar spine image analysis is crucial for diagnosing and treating lumbar spine diseases. In recent years, deep learning has rapidly developed in computer vision and medical imaging, with an increasing number of researchers applying it to the field of lumbar spine imaging. This paper studies the current state of research in deep learning applications across various modalities of lumbar spine image analysis, including X-ray, CT, and MRI. We first review the public datasets available for various tasks involving lumbar spine images. Secondly, we study the different models used in various lumbar spine image modalities (X-ray, CT, and MRI) and their applications in different tasks (classification, detection, segmentation, and reconstruction). Finally, we discuss the challenges of using deep learning in lumbar spine image analysis and provide an outlook on research and development prospects.

Keywords: deep learning; convolutional neural network; X-ray; computed tomography; magnetic resonance imaging

1. Introduction

Lumbar spine disease is one of the leading causes of disability worldwide [1], which includes degenerative diseases, inflammatory conditions, trauma, and tumors [2]. Not only do lumbar spine diseases cause severe physical pain, such as varying degrees of leg pain, weakness, and back pain [3], but also inflict significant psychological and emotional impacts, such as anxiety, depression, and social isolation often experienced by those suffering from chronic pain [4]. Long-term pain may also lead to dependency on pain management strategies, such as the prolonged use of painkillers [5]. Furthermore, lumbar spine diseases are among the major causes of work absenteeism and workers' compensation claims, reducing labor participation and increasing medical and social security costs, thus imposing a significant economic burden on individuals and nations [6]. Therefore, it is important to effectively diagnose and treat lumbar spine disease. With the continuous development of medical imaging technologies, including X-ray, computed tomography (CT), and magnetic resonance imaging (MRI), these imaging methods have become essential tools for diagnosis, treating, and prognosis prediction of lumbar spine diseases. Lumbar spine imaging provides valuable information about bones, joints, and surrounding soft tissues, helping doctors accurately diagnose spinal pathology [7]. Moreover, image-guided surgery, known for its precision and safety, is widely used in spinal surgical surgery [8]. Additionally, lumbar spine imaging also provides effective postoperative spinal assessments and care for healthcare providers [9]. Traditionally, lumbar spine images are visually observed and manually analyzed by radiologists based on their medical knowledge and experience. However, lumbar spine imaging still faces challenges such as limited contrast, insufficient spatial resolution, and artifacts [10–12]. Hence, accurate evaluation requires extensive knowledge and experience, and training such experts takes a considerable amount of time.

To address these problems, researchers have proposed various methods to guide and assist doctors in lumbar spine image analysis. The commonly used techniques include digital image processing and machine learning methods, which often require manually designed feature extraction methods, making them time-consuming but also require expert knowledge [13]. Deep learning has achieved significant breakthroughs in computer vision, image processing, and analysis in recent years. Deep learning models allow for end-to-end training directly from raw data to learn outputs, automatically extracting features from large datasets without manual design or selection [14]. Furthermore, deep learning models can use pre-training and fine-tuning techniques to perform transfer learning between different but related tasks, effectively addressing the problem of scarce annotated data [15]. Due to these advantages, deep learning has achieved excellent results in lumbar spine image analysis.

Qu et al. [16] published a review on deep learning in spinal image analysis in 2022. They comprehensively introduced the application of deep learning in spinal image segmentation, detection and diagnosis. Lee et al. [17] published a review of deep learning for orthopedic diseases based on medical image analysis in 2022. They comprehensively introduced the application of deep learning in spinal image fractures, osteoarthritis, and joint-specific soft tissue diseases. This paper distinguishes itself from other surveys by providing a comprehensive review of the application of deep learning in lumbar spine image analysis across multiple imaging modalities, including X-ray, CT, and MRI. Unlike previous reviews that often focus on a single modality or specific task, our paper systematically covers deep learning techniques across different modalities and tasks, such as classification, detection, segmentation, and reconstruction. We have reviewed standard deep learning models based on task types and compiled the datasets available from the referenced papers. Additionally, we have summarized deep learning applications across different tasks based on imaging modalities. We have also discussed the optimization techniques and challenges deep learning technology faces in lumbar spine image analysis. Table 1 describes the coverage of this lumber spine image research survey paper, including image modalities and deep learning tasks.

Table 1. Lumber Spine Image Research Using Deep Learning.

Image Modality	Deep Learning Tasks
X-Ray	Classification, detection, segmentation
CT	Classification, detection, segmentation, registration, reconstruction
MRI	Classification, detection, segmentation, reconstruction

Note: CT: computed tomography; MRI: magnetic resonance imaging.

The structure of this paper is organized as follows. Section 2 introduces deep learning methods and public datasets. Section 3, 4, and 5 discuss the specific applications of deep learning in various task types across different imaging modalities. Section 6 discusses key optimization methods and challenges affecting existing deep learning methods in the field of lumbar spine image analysis. Section 7 summarizes the advantages and future prospects of deep learning in the field of lumbar spine imaging.

2. Deep Learning Methods and Data

2.1. Classification Models

In 1998, LeCun et al. [18] introduced the LeNet-5 model, which was successfully applied to handwritten digit recognition (MNIST dataset), marked a breakthrough in the practical application of Convolutional Neural Network (CNN). CNNs can automatically learn features with spatial hierarchy from images by stacking convolutional layers, pooling layers, and fully connected layers. This feature learning method fr om local to global enables CNNs to excel in image classification tasks. In 2012, AlexNet [19] achieved overwhelming success in the ImageNet large scale visual recognition challenge (ILSVRC). AlexNet utilized ReLU activation functions, dropout regularization, and GPU acceleration, significantly improving classification accuracy. ResNet [20] addressed the difficulty of deep network training by introducing residual learning. It allows network layers to fit a residual mapping directly, rather than the mapping itself, enabling the network to improve performance by increasing depth without gradient vanishing or exploding issues. Following ResNet, the deep learning community has continuously explored classification models, including deeper and more complex network architectures (such as DenseNet [21], EfficientNet [22]), the introduction of attention mechanisms (such as the application of Transformer [23] in image classification applications), as well as model design optimized for specific tasks or efficiency.

2.2. Detection Models

Detection models are mainly divided into two categories two-stage models and one-stage models. Two-stage models are characterized by first generating candidate regions, and then classifying these regions and regressing their bounding boxes. Region-based Convolutional Neural Network (RCNN) [24] initially extracts candidate regions through a selective search algorithm, then uses CNN to extract features and then classifies them through the SVM classifier. Fast RCNN [25] achieved the sharing of feature extraction by introducing the region of interest (RoI) pooling layer. It inputs the entire image into a CNN to generate a feature map, and then extracts features for each candidate region from this shared feature map for classification and regression. Faster RCNN [26] introduced the region proposal network (RPN) for automatically generating high-quality candidate regions, further improving detection speed and accuracy.

One-stage models directly predict the category and location of objects on the image, omitting the generation step of candidate regions, and thus are usually generally faster. You only look once (YOLO) [27] treated the object detection task as a single regression problem, directly mapping from image pixels to bounding box coordinates and class probabilities. YOLOv2 [28] has made a number of improvements over YOLOv1, including the introduction of batch normalization, use of high-resolution classifiers for pre-training, and improved anchor mechanism. YOLOv3 [29] further improved the accuracy and speed of detection. It introduced multi-scale prediction and used a deep darknet as the feature extractor. Single Shot MultiBox Detector (SSD) [30] performed detection on feature maps of different scales, better-handling objects of various sizes.

2.3. Segmentation Models

Fully convolutional network (FCN) [31] was the first model to apply deep learning to semantic segmentation successfully. It transformed the fully connected layers in traditional convolutional neural networks into convolutional layers, enabling the network to accept input images of any size and output segmentation maps of corresponding dimensions. FCN is trained end-to-end, significantly improving the accuracy and efficiency of segmentation tasks. U-Net [32], by introducing skip connections, fuses feature maps from the encoder (downsampling) phase with those from the decoder (upsampling) phase, thereby preserving more contextual information. This design enables U-Net to perform exceptionally well on small sample datasets, especially in medical image segmentation. SegNet [33] uses pooling indices from the encoder phase for upsampling in the decoder phase, reducing the model's parameter count while improving segmentation accuracy. DeepLabv1 [34] introduced atrous convolution, which increases the receptive field size without adding parameters, enhancing segmentation precision. Building on v1, DeepLabv2 [35] introduced atrous spatial pyramid pooling (ASPP), further improving the model's ability to segment objects of different scales.

2.4. Evaluation Metrics

Evaluation metrics in deep learning are standards used to measure the performance of deep learning models, aiding in understanding how models perform on specific tasks. Different metrics are employed across various tasks and application scenarios to comprehensively represent a model's performance, enabling a more thorough comparison between models [36]. Typically, evaluation metrics can be defined using a confusion matrix, where true positive (TP) represents the number of samples correctly predicted as positive, false positive (FP) represents the number of samples incorrectly predicted as positive, true negative (TN) represents the number of samples correctly predicted as negative, and false negative (FN) represents the number of samples incorrectly predicted as negative.

Accuracy represents the proportion of samples that are correctly predicted by the model out of the total samples. It is the most fundamental metric for assessing model performance in balanced class situations.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision represents the proportion of actual positives among all samples predicted as positive by the model. A high precision means fewer false positives.

$$Precision = \frac{TP}{TP + FP}$$

Recall represents the proportion of samples predicted as positive by the model among all actual positives. A high recall means fewer false negatives. Recall is also known as sensitivity.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score is the harmonic mean of precision and recall, used when both precision and recall are considered. The F1 score provides a single metric that balances precision and recall, also known as DSC (Dice Similarity Coefficient).

$$F1 - Score = \frac{2TP}{2TP + FP + FN}$$

Average precision (AP) is mainly used to evaluate the performance of models in classification and object detection tasks. In object detection, it specifically measures the precision performance of a model at different recall levels. The Precision-Recall Curve is drawn by calculating the model's precision and recall at different threshold settings. A high AP value indicates the model can detect positive objects with high precision while maintaining a high recall rate. AP is calculated for each class, and the average of all class AP values, known as mean average precision (mAP), indicates overall model performance.

Mean intersection over union (mIoU) is a common metric for evaluating model performance in image segmentation tasks. It calculates the average ratio of the intersection to the union of the predicted segmentation area and the actual segmentation area. Specifically, for a single class, IoU is calculated as follows.

$$IoU = \frac{TP}{TP + FP + FN}$$

After calculating IoU for all classes, mIoU is the average of these IoU values. This metric provides a way to quantify model accuracy in segmenting different classes. A higher mIoU value indicates better segmentation performance of the model.

Table 2 summarizes the evaluation metrics for deep learning models.

Table 2. Evaluation Metrics for Deep Learning Models.

Metric	Description	Formula	Application Tasks
Accuracy	Proportion of correctly predicted samples among the total samples	$\frac{TP + TN}{TP + TN + FP + FN}$	Classification, Detection
Precision	Proportion of true positives among all samples predicted as positive	$\frac{TP}{TP + FP}$	Classification, Detection
Recall (Sensitivity)	Proportion of true positives among all actual positives	$\frac{TP}{TP + FN}$	Classification, Detection
F1-Score	Harmonic mean of precision and recall	$\frac{2TP}{2TP + FP + FN}$	Classification, Detection
Average Precision (AP)	Average precision values at different recall levels	Calculated from the Precision-Recall Curve	Detection
Mean Average Precision (mAP)	Mean of AP values across all classes	Average of AP values for all classes	Detection
Intersection over Union (IoU)	Ratio of the overlap between predicted and actual segmentation areas to their union	$\frac{TP}{TP + FP + FN}$	Segmentation
Dice Similarity Coefficient (DSC)	Measure of overlap between the predicted and actual segments	$\frac{2 * TP}{2 * TP + FP + FN}$	Segmentation

Note: TP: true positive; TN: true negative; FP: false positive; FN: false negative.

2.5. Data

Data is crucial for deep learning models. Deep learning models rely on large data for training and validation. They learn features from the datasets through multi-level feature extraction to further enhance their generalizability and robustness, thereby enabling effective classification and prediction [37]. Conversely, when datasets are insufficient, models may only learn specific data features, leading to overfitting [38].

In the medical field, it is difficult to collect high-quality datasets. First, medical data involves patients' health information, which is subject to strict privacy protections and legal regulations, and current healthcare systems are yet to have the capability to provide the necessary protection for patient privacy [39]. Secondly, there are limitations in the cost and resources of collecting and processing medical data. Typically, experienced doctors are needed to analyze and annotate the data, and annotating large datasets also incurs a significant time cost [40]. Additionally, collecting sufficient data for rare diseases is challenging due to the scarcity of cases [41].

To develop deep learning applications in the field of lumbar spine images, it is imperative to construct public datasets. Public datasets can, to some extent, compensate for the lack of data in private datasets, while improving the generalizability and robustness of models. Moreover, they provide a fair comparison of the performance of models trained on different datasets. Additionally, even images of the same type but different parts can assist model training through transfer learning. Al-kubaisi et al. [42] used MRI images of brain tumors to train a VGG model from scratch and used the transferred weights for training a classification task on lumbar MRI images. The results showed further improvement in model performance.

Table 3 shows the public datasets collected in the papers we reviewed. The Lumbar Spine MRI Dataset [43] is the most used dataset among the papers reviewed, with Masood et al. [44] using it for MRI image vertebral segmentation tasks, Liawrungrueang et al. [45] for MRI image disc detection tasks, and Le Van et al. [46] for simulating X-ray data for image classification tasks. Spineweb [47] is an online collaborative platform that includes 16 spine image datasets for various modalities and tasks. Scoliosis Test Dataset [48] is MICCAI 2019 Challenge dataset containing 98 X-ray images of the spine. VerSe2020 [49], VerSe2019 [50], xVertSeg Challenge [51] are CT spine image datasets from different challenges, containing 300, 160, and 25 images, respectively. BUU Spine Dataset [52] is a Burapha University dataset containing 400 labeled X-ray images of the spine.

Table 3. Lumbar Datasets.

Dataset	Image Type	Size	Labeled	Citation
Lumbar Spine MRI Dataset	MRI	515	No	[43]
Scoliosis Test Dataset	X-ray	98	No	[48]
BUU Spine Dataset	X-ray	400	Yes	[52]
VerSe2020	CT	300	Yes	[49]
VerSe2019	CT	160	Yes	[50]
xVertSeg Challenge	CT	25	Yes	[51]
Spineweb	X-ray/ CT/MRI	-	-	[47]

3. X-Ray

3.1. Classification

Classification tasks based on deep learning are widely used in lumbar X-ray images and are used mainly for classifying various diseases, including spondylolisthesis, stenosis, osteoporosis, etc. Khare et al. [53] employed the DenseNet-201 model to predict vertebral slippage in the lumbar spine. In the preprocessing stage, they used contrast stretching to eliminate incorrect boundaries and adaptive histogram equalization to reduce the impact of image noise. In comparative experiments with four other models (LumbarNet, VGG19, AlexNet, and GoogleNet), the DenseNet-201 model achieved the highest classification accuracy. Varçin et al. [54] predicted lumbar spondylolisthesis through a deep learning system. The model first detected the L4, L5 vertebrae, and S1 sacrum using the YOLOv3 model, followed by the classification of lumbar spondylolisthesis through a fine-tuned MobileNet model.

Multiclass prediction tasks are also applicable to lumbar X-ray imaging. Sugiura et al. [55] used AlexNet to measure the tangential incident X-ray angles of the intervertebral disc space (IDS). They constructed a deep learning model using neural network console (NNC) and performed data augmentation and automatic model parameter selection through NNC. The study results demonstrated the effectiveness of deep learning in automatically classifying lumbar spine X-ray deflection angles, reducing patient burden, and improving imaging process efficiency. Nissinen et al. [56] analyzed and predicted pathological features in lumbar spine X-ray images using deep learning techniques, including scoliosis, instability, and fractures. They employed various visualization techniques to qualitatively evaluate the model's performance, including generating image heatmaps with gradient-weighted class activation mapping, indicating shapes and textures extracted by the network using the vanilla gradient method, rendering feature maps of individual input samples, and generating artificial input samples to visualize specific layers and kernels using activation maximization. Zhang et al. [57] proposed a DCNN model for osteopenia and osteoporosis screening. The model includes two channels for processing anteroposterior and lateral films and classifies patients from three sets of views: anteroposterior, lateral, and anteroposterior-lateral. Results indicate that the model can be effectively applied to identify osteopenia and osteoporosis in postmenopausal women. Table 4 summarizes the applications of deep learning models for classifying lumbar X-ray images.

Table 4. Deep Learning (DL) in Classification of Lumbar X-ray Images.

Target Class	Dataset Size	DL Model	Performance (%)		Paper List
			Accuracy	Recall	
Spondylolisthesis, and normal	299	VGG16	98	100	[58]
Anterior slippage, and normal	200	DenseNet-201	95.2	96.5	[53]
Stenosis, and normal	12442	VGG19	82.8	81.0	[59]
Scoliosis, and normal	598	DenseNet	93.5	97	[46]
Scoliosis, unreliability, and fracture	2949	CNN	94.1 (Scoliosis); 82.4 (Unreliability); 58.9 (Fracture)	70.5 (Scoliosis) 78.3 (Unreliability); 60.0 (Fracture)	[56]

Note: VGG: visual geometry group; CNN: convolutional neural network; DCNN: deep convolutional neural network.

Table 4. *Cont.*

Target Class	Dataset Size	DL Model	Performance (%)		Paper List
			Accuracy	Recall	
Osteoporosis, and normal	162	CNN	100	100	[60]
Spondylolisthesis, and normal	272	GoogleLeNet	93.7	91.6	[61]
Osteoporosis, osteopenia, and normal	1616	DCNN	>72.6 (Osteoporosis) >78.7 (Osteopenia)	>68.4 (Osteoporosis) >81.8 (Osteopenia)	[57]
Five classes of deflection angle	500	AlexNet	83.0	83.0	[55]
Anteroposterior view, and Lateral view	1000	CNN	99.4	-	[62]
Spondylolisthesis, and normal	2707	MobileNet	99	98	[54]

3.2. Detection

Detecting vertebrae in lumbar spine images allows for rapid and effective localization of the vertebrae, enabling further analysis of parameters or diseases. An et al. [63] designed a novel landmark detection network for detecting lumbar vertebrae. The network is divided into two parts: first, the centers of the lumbar vertebrae and sacrum are detected based on Pose-Net, followed by the detection of landmarks on the lumbar vertebrae and sacrum using M-Net. In the first part, they proposed a random spinal incision enhancement technique to improve detection robustness, and in the second part, they enhanced detection accuracy through CoordConv and partial affinity fields. Nguyen et al. [64] used a deep learning system to detect keypoints on vertebral angles to calculate specific angles between vertebrae. First, a VGG model was trained to predict keypoints. Since the model did not perform well in cases of severe slippage in extension and bending between adjacent vertebrae, a second CNN regression model was subsequently used to predict the left and right boundaries of the vertebrae and align them with the center predictions of the first model. Experimental results indicate that this method is effectively applicable for Meyerding classification. Zhou et al. [65] developed a deep learning-based model for detecting the L5 vertebra and S1 sacrum to measure lumbar-sacral anatomical parameters further. Based on the EfficientDet model structure, local keypoints localization was enhanced with skip connection modules, and heatmap regression was used instead of direct coordinate regression.

In addition to vertebrae, automatic detection is also applicable to other lumbar spine structures. Sa et al. [66] automatically detected intervertebral discs based on Faster-RCNN. They conducted shallow and deep tuning of the model, specifically adjusting the last two and four layers, and evaluated the performance changes through smooth L1 Loss. Experimental results indicated that fine-tuning deeper layers of the model results in better detection performance. Table 5 summarizes the applications of deep learning models for detecting lumbar X-ray images.

Table 5. Deep Learning in Detection of Lumbar X-ray Images.

Target Class	Dataset Size	DL Model	Performance (%)		Paper List
			Accuracy	AP	
Vertebrae	1524	Pose-net, M-Net	98.38	-	[63]
Vertebrae	1000	SSD, MobileNet	95.6 (AP) 93.5 (LA)	-	[62]
Vertebrae	100	CNN	99.7	-	[67]
Vertebrae	1000	VGG, CNN	-	-	[64]
Intervertebral discs	1082	Faster-RCNN	-	90.5	[66]
L5 vertebra and S1 sacrum	1791	EfficientDet	>90	-	[65]
L4, L5 vertebra and S1 sacrum	2707	YOLOv3	-	-	[54]

Note: SSD: single shot multiBox detector.

3.3. Segmentation

Automatic segmentation of the lumbar vertebrae can further assist doctors in accurately measuring structural parameters, or further predicting disease states, thus improving their work efficiency. Kim et al. [68] combined deep learning techniques and level set methods to segment the lumbar vertebrae. First, the five lumbar vertebrae were located using Pose-net, followed by segmentation of the located vertebrae through M-net. The level set method was used for fine-tuning the results segmented by M-net. Trinh et al. [69] designed the LumbarNet model for segmenting the lumbar vertebrae and sacrum. Based on the U-net structure, they added a feature fusion module (FFM) to the encoder module to enhance the encoder's efficiency. After obtaining the segmentation results, they calculated the P-grade of the vertebrae based on pedicle slope detection (PSD) and dynamic shift (DS) to determine the presence of lumbar spondylolisthesis.

For more complex structural analysis requirements, Chen et al. [70] used the scSE U-net model to segment various anatomical features of the lumbar spine, such as the lumbar vertebrae, pelvis, spinous processes, and intervertebral foramina. This model implements spatial and channel squeeze & excitation (scSE) blocks in the U-net structure, which recalibrate the feature maps along spatial and channel dimensions, respectively. The model includes two U-shaped networks, the first for segmenting anatomical features and the second for identifying them. Tran et al. [71] designed MBNet for lumbar spine segmentation and prediction of related parameters. This model includes two branches. The first branch performs semantic segmentation of the vertebrae using BiLuNet, which is based on an improved U-Net, and the second branch calculates relevant parameters based on the segmentation results to assist doctors in diagnosing low back pain. Table 6 summarizes the applications of deep learning models for the segmentation of lumbar X-ray images.

Table 6. Deep Learning in Segmentation of Lumbar X-ray Images.

Target Class	Dataset Size	DL Model	Performance (%)		Paper List
			mIoU	DSC	
Multiple anatomical features of the lumbar spine	2782	U-net	-	91 (AP) 87 (LA) 80 (OP)	[70]
Vertebrae	797	Pose-net, M-Net	-	91.6	[68]
Vertebrae	830	Comprehensive	-	-	[72]
Vertebrae, sacrum, and femoral heads	750	U-net	85.0	-	[71]
Vertebrae, and sacrum	706	U-net	88	-	[69]
Vertebrae, and sacrum	780	U-Net	-	82.1	[73]
Vertebrae, sacrum, and femoral heads	1000	ResNet	88.5	-	[74]
Vertebrae	2073	U-Net	-	>94	[75]

4. CT

Automatic classification for lumbar CT images is primarily used for gender classification and bone mineral density (BMD) prediction. Malatong et al. [76] applied a deep learning model to classify gender based on the upper and lower endplates of the L3 lumbar vertebra. They adjusted the last two layers of GoogLeNet, including modifying the parameters of the fully connected layer and replacing the new classification layer. Random rotations, reflections, and horizontal translations were employed during training to prevent model overfitting. Yasaka et al. [77] predicted lumbar spine BMD using deep learning techniques. They trained the model using the L2-L4 vertebrae of patients and tested it using the L1 vertebra. Finally, the BMD prediction results were used to assess whether patients had osteoporosis.

Thoracic and lumbar spine injuries pose significant risks to human health. Automated vertebra detection can effectively locate the vertebrae and predict the damage and severity simultaneously. Doerr et al. [78] used the Faster R-CNN model to locate the lumbar spine, and simultaneously perform a five-category classification of thoracolumbar injury classification and severity score (TLICS) morphology types and binary classification of posterior ligamentous complex (PLC) integrity scores. They trained two models for the two respective localization and classification tasks. Research findings showed that deep learning methods effectively predict PLC and morphological components of TLICS.

Accurate vertebrae segmentation from CT images is important for many tasks, including vertebral morphological analysis and disease prediction. Lu et al. [79] designed a deep learning-based 3D multi-scale spinal segmentation method. First, the lumbar spine was located and cropped using U-Net, followed by 3D vertebral segmentation using XUNet. XUNet incorporated inception blocks for feature extraction, aggregating features across different semantic scales and improving the network's expressive ability. Malinda et al. [80] proposed a hybrid deep segmentation generative adversarial network for lumbar image segmentation. To increase data usability, they improved the training scheme on the CycleGAN model, combining paired and unpaired training data.

Image-guided surgery is now widely applied in spinal surgery, and image registration allows surgeons to observe real-time changes during surgery better. Gao et al. [81] registered lumbar vertebrae using a deep learning model. They proposed an end-to-end framework named ACSGRegNet, which is mainly divided into two parts. The first is an affine registration network to calculate affine transformation parameters. The second is a deformable registration network, which includes self-attention modules, cross-attention modules, and gated fusion modules to output the final dense deformation field.

Image reconstruction for CT images can reduce noise and improve image quality, obtaining high-quality CT images with reduced radiation doses, and enabling conversions between CT images and other image types. Greffier et al. [82] used both deep learning and hybrid iterative reconstruction algorithms for image reconstruction. Through quantitative analysis of image quality and dose, it was verified that the deep learning reconstruction algorithm can optimize the CT dose plan. Morbée et al. [83] reconstructed CT images from MRI images based on deep learning methods and compared them with traditional CT images, demonstrating their equivalence. Yeoh et al. [84] applied a deep learning reconstruction algorithm to low-dose CT images. The experimental results from the quantitative and qualitative analysis showed that this method could achieve both image denoising and edge-sharpening effects. Table 7 summarizes the applications of deep learning models for lumbar CT images.

Table 7. Deep Learning for Lumbar CT Images.

Task	Target Class	Dataset Size	DL Model	Performance (%)	Paper List
Classification	Female, and male	1100	GoogLeNet	Accuracy = 92.5	[76]
	Female, and male	117	LeNet5	Accuracy = 86.4	[85]
	BMD	1665	CNN	PCCs > 84.0 (p < 0.001)	[77]
Detection	Vertebrae	111	Faster R-CNN	DSC = 92 (morphology), 88 (PLC)	[78]
Segmentation	Vertebrae	522	CNN	DSC > 90	[86]
	Bone, disc, and nerve	1681	U-net	DSC = 94 (Bone), 92 (Disc), 92 (Nerve)	[87]
	Vertebrae	656	U-net	DSC > 88.8	[79]
	Vertebrae	8040	CycleGAN	DSC = 94.2	[80]
Registration	Vertebrae	15	FCN	DSC = 95.77	[88]
	Vertebrae	61	CNN	DSC = 96.3	[81]
Reconstruction	Vertebrae	3	Integrated	Noise magnitude < i4	[82]
	Vertebrae	30	Integrated	Quantitative image noise analysis	[89]
	Full image	30	Integrated	Bland Altman analysis	[83]
	Vertebrae	52	Integrated	Quantitative image noise analysis	[84]

Note: FCN: fully convolutional network.

5. MRI

5.1. Classification

Spinal stenosis and disc herniation are among the causes of lower back pain (LBP) and are two of the most common lumbar disorders. This task is typically performed by radiologists or orthopedic doctors through imaging analysis. Al-kubaisi et al. [42] used a deep learning model to classify lumbar disc status as normal or abnormal. They analyzed the impact of transfer learning and model fine-tuning on image classification through comparative experiments, including training with ImageNet images and brain tumor MRI images, and incorporated Grad-CAM visualization technique to explain the model. Experimental results showed that transfer learning using datasets from the same field could improve model performance and mitigate the effects of dataset limitations.

Grading specific diseases is also a typical application of deep learning in lumbar MRI images. Chen et al. [90] designed an auxiliary diagnostic system for lumbar disc herniation (LDH) based on the CDCGAN model, capable of outputting six indicators for quantitative analysis of MRI images. In the model, they combined Tanh and ReLU activation functions to enhance the model's classification efficiency. Cheung et al. [91] assessed lumbar disc degeneration using a deep learning model. They employed the integrated MRI-SegFlow and visual geometry group-medium (VGG-M) to predict Schneiderman scores, disc bulging, and Pfirrmann grading. Experimental results demonstrated that deep learning models could be effectively applied in lumbar disc degeneration (LDD) prediction tasks. Table 8 summarizes the applications of deep learning models for classifying lumbar MRI images.

Table 8. Deep Learning in Classification of Lumbar MRI Images.

Target Class	Dataset Size	DL Model	Performance (%)		Paper List
			Accuracy	Recall	
Normal, and abnormal	1448	VGG	87.91	> 90.91	[42]
Six indexes of lumbar disc herniation	-	CDCGAN	-	-	[90]
Four classes of Schneiderman score; disc bulging, and normal; Five classes of Pfirrmann grade	2686	CNN	90.2 (Schneiderman) 90.4 (Disc bulging) 89.9 (Pfirrmann)	96.0 (Schneiderman) 76.5 (Disc bulging) 60.4 (Pfirrmann)	[91]
Five classes of Pfirrmann grade	2500	CNN	86	-	[92]
Five classes of Pfirrmann grade; four classes of spondylolisthesis; four classes of central canal stenosis	882	SpineNet	-	-	[93]
Three classes of foraminal stenosis severity	22796	ResNet	>80	-	[93]

Note: CDCGAN: conditional deep convolutional generative adversarial network.

5.2. Detection

Vertebral detection tasks include center localization and candidate bounding box localization. Deep learning-based vertebral image detection can provide doctors with effective localization of vertebral segments or disease areas. Zhou et al. [94] designed a deep learning method to detect and locate the L1-S1 lumbar vertebrae. The proposed method includes two phases of image detection: the first detects the S1 vertebra, and the second detects the L1-L5 vertebrae. The detection model is trained only on public datasets and does not require annotated MRI images as a training set. Compared to other deep learning methods, this model learns the similarities between vertebrae. Mushtaq et al. [95] combined the YOLOv5 and HED U-Net models to detect and diagnose the lumbar spine. First, YOLOv5 is used to detect the vertebrae, then L1, L5, and S1 are extracted from the detection results to calculate the lumbar lordosis angle (LLA) using L1 and S1, and the lumbosacral angle (LSA) using L5 and S1.

To detect more vertebral structures, effective diagnosis of diseases should be pursued, including lumbar disc herniation and intervertebral disc degeneration. Tsai et al. [96] used deep learning to detect lumbar disc herniation. Due to a small training set size, they used data augmentation methods such as rotation, contrast, and brightness adjustments and employed multiple strategies to expand the volume and features of images. The model can detect abnormalities in the lumbar, sacral, and fifth lumbar vertebral regions. Yi et al. [97] used deep learning models to detect degenerative cervical diseases. They trained two modified 3D Resnet18 networks, one for sagittal view MR images and the other for axial view MR images. A multi-modal cross-attention module from Transformer was introduced in the models, and AdamW was used as the optimizer. Table 9 summarizes the applications of deep learning models for detecting lumbar MRI images.

Table 9. Deep Learning in Detection of Lumbar MRI Images.

Target Class	Dataset Size	DL Model	Performance (%)			Paper List
			Accuracy	Precision	mAP	
Vertebrae	903	CNN	>99.3	>99.6	-	[98]
Disc	1000	YOLOv5	95	-	-	[45]
Vertebrae, sacrum, disc	714	YOLOv3	81.1	87.2	-	[96]
Vertebrae, disc	804	Resnet18	-	>73.7	-	[97]
Disc	80	Faster RCNN	96.25	-	-	[99]
Vertebrae	2739	CNN	98.6	98.9	-	[94]
Vertebrae	575	YOLOv5	-	-	95.2	[95]

5.3. Segmentation

Automatic segmentation of MRI lumbar spine images can help doctors more accurately identify the different structures of the lumbar spine, while also helping doctors reduce diagnosis time and improve diagnosis efficiency. Li et al. [100] used deep learning methods to segment the spine in MRI images, including vertebrae, laminae, and the dural sac. They introduced a multi-scale attention mechanism based on the U-Net model, where the upsampling and downsampling convolutional layer structures were replaced with a convolutional layer and a dual-branch multi-scale attention module, enhancing the model's segmentation efficiency. Masood et al. [44] designed a deep learning model to segment vertebrae in images to further assess spinal spondylolisthesis and lumbar lordosis. They customized an algorithm (VBSeg) in the machine learning field for comparison with deep learning methods, and combined various models in the deep learning approach to configure the encoder-decoder setup for optimal results. Zheng et al. [101] used a deep learning model to segment specific structures according to the Pfirrmann grading, covering 5 types across 14 regions. The proposed BianqueNet architecture, built on DeepLabv3+, incorporated a swin Transformer with skip connection modules. Compared to traditional Transformer modules, this module uses a moving window mechanism, which is more efficient in network computation.

For 3D segmentation of MRI images, Chen et al. [102] used a 3D-UNet model to segment the L4-5 spinal structures to reconstruct a 3D lumbar intervertebral foramen (LIVF) model. After obtaining the measurement results, further calculations were made on the morphological parameters of the LIVF, including the foramen area, height, and width. Experimental results showed that the model could be effectively applied to MRI spinal structure tasks, and based on the segmentation results, it could generate complete and accurate 3D LIVF models. Table 10 summarizes the applications of deep learning models for segmenting lumbar MRI images.

Table 10. Deep Learning in Segmentation of Lumbar MRI Images.

Target Class	Dataset Size	DL Model	Performance (%) MIoU	Performance (%) DSC	Paper List
Vertebrae, and discs	300	U-Net	94.7 (Vertebrae) 92.6 (Discs)	-	[103]
Vertebral body, lamina, and dural sac	1080	CNN	-	92.52	[100]
Vertebrae, and sacrum	22796	U-Net	-	93	[104]
Vertebrae	514	ResNet, UNet	86	97	[44]
Discs	382	VGG 16	93.3	-	[105]
Vertebrae, sacrum, presacral fat area, cerebrospinal fluid area and IVDs	>1000	DeepLabv3+	90.35	94.70	[101]
Vertebrae	1360	U-Net	>74.4	>84.9	[106]
L4-5 spine structures	100	U-Net	-	91.8	[102]
L5/S1 bone structures, and discs	100	U-Net	-	>90.39	[107]

Note: MIoU: mean intersection over union; IVD: intervertebral disc; DSC: dice similarity coefficient.

5.4. Reconstruction

Deep learning techniques for MRI image reconstruction can accelerate imaging speed and enhance image quality. Chazen et al. [108] validated the effectiveness of image reconstruction from image evaluation and statistical analysis. In image evaluation, they graded overall image clarity on a 3-point scale, motion artifacts on a 4-point scale, and used multi-planar reconstruction (MPR) to grade foraminal stenosis. Fujiwara et al. [109] validated the effectiveness of rapid image reconstruction through statistical analysis, including Cohen's kappa statistic, and the interchangeability between the rapid reconstruction protocol and traditional protocols. Han et al. [110] analyzed reconstructed images using deep learning quantitatively. They employed two convolutional neural networks incorporating the 2D V-Net architecture; the first network segmented the intervertebral discs to calculate disc height, while the second network segmented the vertebral bodies to calculate vertebral volume. To validate their effectiveness, Zerunian et al. [111] performed noise analysis on reconstructed images. They measured signal intensity to calculate signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR), and used a five-point Likert scale to assess image quality for qualitative analysis. Gao et al. [112] trained a ResNet model to denoise MRI images to remove Rician noise. They compared the model's denoising results with the weighted stable matching (WSM) algorithm and denoising CNN (DnCNN) algorithm, verifying the model's reliability on MRI lumbar spine images. Table 11 summarizes the applications of deep learning models for reconstructing lumbar MRI images.

Table 11. Deep Learning in Reconstruction of Lumbar MRI Images.

DL Model/Software	Patient Number	Quantitative Analysis Indicators	Paper List
AIR Recon DL	35	Cohen's kappa statistic	[108]
Advanced Intelligent Clear-IQ Engine	58	Cohen's kappa statistic	[109]
AIR Recon DL	18	Disc heights and vertebral body volumes	[110]
AIR Recon DL	35	Conger's kappa statistic	[113]
AIR Recon DL	80	Quantitative image noise analysis	[111]
ResNet	127	Quantitative image noise analysis	[112]

6. Discussions

From the papers reviewed, we can find that deep learning has been extensively used across various fields of lumbar spine image analysis, including the diversity of image modalities and the variety of processing methods, with some research results already reliably applied in clinical applications. Compared to traditional algorithms, deep learning stands out with its robust feature extraction capabilities, multi-level abstraction, and excellent flexibility and universality in image analysis tasks. A wide range of image preprocessing methods have significantly contributed, including data augmentation [54, 75, 96], and image quality enhancement [53]. Tsai et al. [96] employed image rotation and adjusted brightness and contrast to enhance MRI images, achieving an 86.2% accuracy in LHD detection with just 350 original images. Transfer learning offers another effective way to enhance performance by using pre-trained models on other datasets as a starting point and further fine-tuning them to align closely with specific task requirements, thus addressing tasks with fewer samples. In Al-kubaisi et al.'s research [42], the fine-tuned VGG16 model's classification performance on an MRI dataset increased from 78.2% to 87.91%. Additionally, appropriate modifying network structures [70,100,101], improving activation functions [90,97], and post-processing of model results [68,75] can all effectively enhance the overall performance of tasks.

Different deep learning models exhibit various strengths and weaknesses across different imaging modalities and tasks. CNNs, such as LeNet, AlexNet, VGG, and ResNet, are widely used in classification, detection, and segmentation tasks for X-ray, CT, and MRI images due to their powerful feature extraction capabilities, although they require significant computational resources. R-CNNs and its variants excel in object detection tasks in CT and MRI images with high accuracy but at the cost of higher computational demands. Single-stage detectors like YOLO and SSD are favored for real-time applications in X-ray and CT images, offering faster detection speeds with slightly lower accuracy. FCN and U-Net are highly effective for segmentation tasks, particularly in MRI images, but depend heavily on high-quality annotated data. GANs are useful for data augmentation and image reconstruction, producing high-quality synthetic images, though their training can be unstable and complex to tune.

Deep learning in lumbar spine image processing still faces shortcomings and challenges. First, compared to other body parts like the breast [114] and heart [115], lumbar spine images lack sufficient public datasets. Although data augmentation can somewhat mitigate this issu, there is still a gap between the training performance of models and their potential maximum performance. Therefore, establishing high-quality public datasets is necessary. Secondly, deep learning has poor generalization ability. Models trained solely on data from a single field often fail to generalize when applied to other fields [116], and lumbar spine images often show significant variation across different modalities or even within the same modality under different acquisition devices. With the continuous development of large-scale pre-trained models [117] in recent years, this issue might be addressed. Moreover, the substantial computational resources required for processing and analyzing lumbar images also hinder the widespread application of deep learning in practical settings. Although deep learning models have shown potential in diagnosing and predicting lumbar diseases, the ability to process large volumes of patient data in real-time, and the demand for computational resources by these models, remain practical challenges that need to be overcome. In some studies [54,62], the application of compact networks like MobileNet [118] has been able to mitigate the impact of these issues.

With the advancement of data sharing and privacy protection technologies, public datasets of lumbar spine images are expected to become more abundant. This will help enhance the training effectiveness and generalizability of deep learning models. Additionally, developing techniques such as transfer learning and self-supervised learning will further improve model performance in data-scarce situations. In clinical applications, deep learning is expected to further improve doctors' work efficiency and diagnostic accuracy by integrating with other technologies such as augmented reality (AR) and virtual reality (VR). For example, real-time image analysis based on deep learning can provide more precise guidance for surgical navigation, thereby increasing surgical success rates and reducing postoperative complications. Moreover, with the continuous improvement in the performance of computing devices, the inference speed and processing power of deep learning models will also be significantly enhanced. This will enable deep learning technologies to be more widely applied in real clinical settings, achieving real-time, accurate diagnosis and treatment of lumbar spine diseases.

7. Conclusion

We have summarized the latest applications of deep learning in various modalities of lumbar spine imaging while also compiling a list of available public datasets and discussing common models used in different tasks. Deep learning has now become one of the mainstream directions in the field of lumbar spine image analysis. The rapid and accurate performance demonstrated by deep learning in image classification, detection, segmentation, and reconstruction can be reliably applied to the diagnosis, treatment, and prognosis of lumbar spine diseases, effectively enhancing doctors' work efficiency. Although some problems and challenges exist, with the future emphasis on privacy protection, the improvements in model interpretability and generalization abilities, as well as the continuous development of computing devices, deep learning is expected to become an important tool for managing spinal diseases.

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