Analysis Review of Deep Learning for Lumbar Spine Image based on Computed Tomography and Magnetic Resonance Imaging

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Abstract. Recently, deep learning algorithms have become one of the most popular methods and forms of algorithms used in the medical imaging analysis process. Deep learning tools provide accuracy and speed in the process of diagnosing and classifying lumbar spine problems. Deep learning tools deal with many types of medical images, including computed tomography (CT), X-rays, and magnetic resonance imaging (MRI). MRI is the most common method for diagnosing diseases of the lumbar spine. This paper aims to provide a general overview of how deep learning can be used to analyze lumbar spine images. It focuses on papers, results, and methods used by researchers in recent years. The presented works indicate that deep learning can be highly relied upon in the process of analyzing medical images of the lumbar spine and identifying the correct diagnosis.

Keywords: CT lumbar spine, Deep learning ,MRI lumbar spine, lumbar spine disc classification, lumbar spine.

INTRODUCTION

Since the 1970s, researchers have built systems to analyze medical images and diagnose diseases based on images uploaded to computers. The medical images were analyzed using mathematical design (fitting ellipses, circles, and lines) and low-level pixels (region growing, line detector, and edge filters) [1]. The increase in medical imaging and researchers' interest in their analyses is due to the large number of diseases and their global distribution, especially lower back condition. These can be due to spinal deformity, herniated disc, osteoporosis, and muscle strain resulting from a modern lifestyle of office work and sitting for long periods in front of computers, which have led to an increase in the spread of lower back pain [2][3].

Spinal stenosis is one of the most popular lower back conditions [4]. The process of diagnosing pain in the lower back is achieved by the analysis of medical images by radiologists and doctors. The number of these images, the analysis process that requires expertise, the potential fatigue of experts, differing opinions among doctors, and the financial cost of the process have led researchers to build computer systems that help experts make decisions and speed up the diagnosis process. There are various types of medical imaging techniques that help radiologists to make decisions. The most common of these techniques are computed tomography (CT), X-rays, and magnetic resonance imaging (MRI), which is the most popular technique used to diagnose spinal diseases [5]–[9].

The process of computer-assisted diagnostics and medical imaging analysis mainly relies on machine learning (ML). Following the development of ML techniques and the emergence of the field of deep learning, deep learning has become one of the adopted methods in the diagnostic process. Although there are many ML techniques to analyze medical images in various fields, deep learning has become the trailblazing method for analyzing and diagnosing medical conditions because of its accuracy. Deep learning has become the approved method for many researchers in various fields, including medical imaging [10].

The use of deep learning approaches to analyze medical images has increased significantly. For the purpose of segmentation and classification, deep convolutional networks are often used [11]. The tremendous progress and development in the field of technology that has been witnessed globally has resulted in the emergence of deep learning technologies as a revolution in medical systems. These systems can accurately analyze large amounts of data with high efficiency, and the techniques can be used to analyze and segment the MRI images [3].

Therefore, this paper argues for more detail regarding analyzing medical images of the lumbar spine, using deep learning to ensure better understanding for researchers. The following section focuses on the main types of diagnostic imaging techniques that can be used in analysis tasks; section 3 concentrates on explaining the basic points of convolutional neural networks (CNN); section 4 considers the lumbar spine anatomy and its problems, and section 5 identifies the deep learning studies applied to lumbar spine image analysis. The paper concludes with a summary and an indication for future research.

DIAGNOSTIC IMAGING TECHNIQUE

Diagnostic imaging techniques are used essentially in identifying places of disease or injury and contribute toward obtaining a high accuracy in diagnosis. There are three main types of diagnostic imaging techniques including X-rays, CT, and MRI. These imaging techniques help in the diagnostic process by creating images of the inside of the body. The first technique is X-rays, which are a popular diagnostic imaging technique that is widely available. Since X-rays are not costly in comparison to other techniques and can be obtained in a short time, they are frequently required before having advanced tests [12]. The second technique is a CT scan, where specific images of the body can be generated by combining X-rays with computer technology. A CT scan works on directing a narrow X-ray beam that is directed to a specific segment of the body. This process generates a collection of images from many various angles. A cross-sectional image can be created by a computer using this information [13], [14]. The third technique is MRI, where it is possible to obtain high-resolution images of the bones and tissues inside the body. Compared to a CT scan, an MRI works through magnetic fields without radiation. Imaging of the lumbar spine is generally done with an MRI. Three levels of width are obtained: coronal (front), sagittal (lateral), and axial (top to bottom)—the last two are normally used in the diagnostic process of the spine. The lumbar spine is shown in a sagittal manner, which is considered the preferable view to determine certain types of pain because it is the easiest to understand. An axial MRI shows more detail of the lumbar spine, making it difficult to comprehend. Clinicians can, therefore, determine the location of any problem in the lumbar spine [15]. MRI is receiving more attention from doctors for several reasons, including the fact that it does not expose people to radiation. Also, the accuracy of diagnosis depends on the precision of the available images—MRI provides high-quality images of the organs inside the body (as shown in FIGURE 1) [16]–[18].

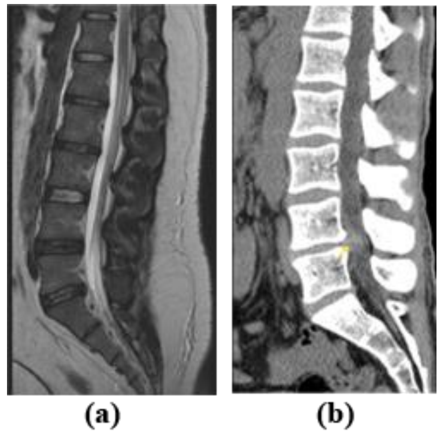

FIGURE 1. Illustrating: (**a**) MRI lumbar spine; (**b**) CT lumbar spine

CONVOLUTIONAL NEURAL NETWORKS (CNNS)

A CNN can be considered a simple version derived from a neocognitron model that was proposed to simulate human vision. This model was first introduced by Fukushima in the 1980s [10]. In the medical image analysis process, CNN is currently one of the best machine learning algorithms, as the spatial relationships are preserved after filtering the input images—in the field of radiology, these relationships are very important [19]–[21].

Features in CNN can be extracted automatically, and the final prediction of CNN can be determined based on the features that were extracted from the input image combined with layers in the CNN, weight factors that changed over the training procedure, and a fully connected layer (FCL) [22]. A CNN has basic components such as convolutional layers, pooling layers, a rectified linear unit (ReLU), and FCLs [23], [24].

The convolution operation in CNN has two main benefits: the first is parameter sharing, which is a feature detector that is useful for one part of the image and may be useful in another part of the image; the second is the sparsity of connections, since any output value builds on a low number of inputs (as shown in FIGURE 2) [23], [25]. The pooling layer is used to capture the main characteristics of the image and to reduce the variance by taking maximum, mean, or other statistics [25]. The task of a fully connected layer is to capture the outputs of the convolution/pooling process and to utilize them to classify the image into a label [26], [27] .

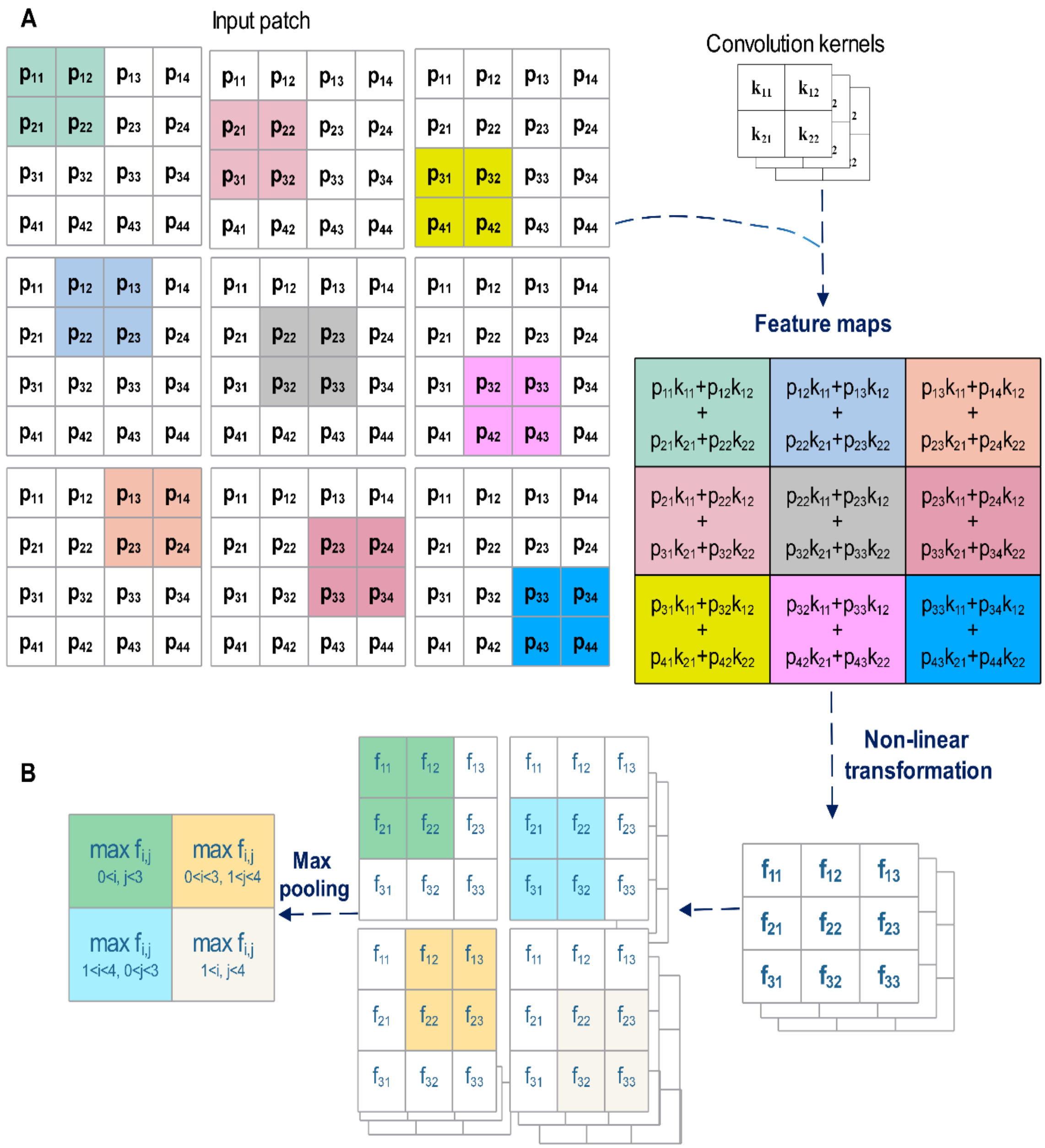

FIGURE 2. shows a CNN (A: In the convolution layer, each element in matrix f is calculated by multiplying the color blocks in the matrix p by a kernel denoted by k. B: The pooling layer summed up the output of the convolution layer. The max pooling is stated as a sample.)[25]

LUMBAR SPINE LESIONS

Lower back pain is considered the main cause for the loss of years of productive life due to disability, and its percentage increases among the elderly [28], [29]. Neuritis that is because of either mechanical pressure or chemical irritation leads to pain [2], whereas spinal stenosis and disc herniation are major factors in lower back pain [30]. The lumbar spine consists of five vertebrae, labelled L1 to L5, and these vertebrae progressively increase in size downward. Each vertebra is connected with the other vertebrae by intervertebral discs. The intervertebral discs help stabilize the spine and act as shock absorbers, in addition to protecting the bones from friction and interference. These discs are filled with a gel-like fluid, and if they dry out it is an indication of some problem. FIGURE 3 shows the most significant problems with intervertebral discs [31].

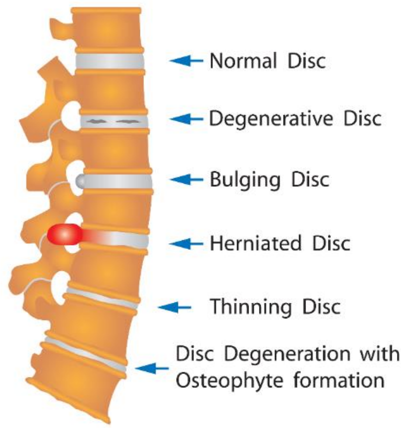

FIGURE 3. Disc degeneration

Several characteristics distinguish lumbar discs, including size, height, and shape. Lumbar discs are characterized by being thicker when compared to other areas of the spine; however, they become shorter during the day as the form of the lumbar discs changes with movement [32].

Lumbar discs may have lesions such as degeneration, bulging, and herniation. Disc degeneration can be distinguished by loss of fluid (seen only on an MRI), loss of height (seen on an MRI, CT, or X-ray), or intradiscal gas (seen on CT) [33]. In a bulging disc, the inner part of the intervertebral disc remains within the framework of the fibrous ring, unlike a herniated disc, where the nucleus leaks out of the disc. There may be pain spreading to the lower back and/or other areas of the body because the bulging disc compresses the surrounding nerve roots [26].

A herniated disc may occur gradually as a result of general wear and tear, heavy lifting, or an injury resulting from a specific accident. The nucleus pulposus (the soft inner core of the disc) is pushed into the annulus fibrosus (the outer shell). In severe cases, the fibrous layers of the annulus rupture and cause the nucleus pulposus to leak. Herniated discs are one of the most common problems of the lumbar spine because they can inflame or compress the nearby nerve root. Disc herniation in the L4–L5 and L5–S1 levels are the most common problem areas in the lumbar spine [6]. There are many challenges that a radiologist faces in diagnosing a herniated disc, including blurry images, complex background, and noise. The process of segmentation and localization of different discs in the lumbar spine is an important part of computer-aided diagnosis of herniation [34].

DEEP LEARNING STUDIES APPLIED TO LUMBAR SPINE IMAGE ANALYSIS

Deep learning has become the trailblazing method for analyzing and diagnosing medical conditions, because of its accuracy.There have been many previous studies on computer-aided techniques (see TABLE 1). **Sa et al.** [35] proposed a method of disc detection through X-Ray images by using Faster R-CNN. Due to the lack of medical images, they fine-tuned a pre-trained deep network on a small medical dataset and obtained satisfactory results. The method achieved an average accuracy of 0.905 with an average computation time per image of three seconds. **Kuok et al.** [12] proposed a hybrid approach using image processing for the detection process of the vertebrae and using CNN in the segmentation task of the vertebrae. They used a private dataset from the National Cheng Kung University Hospital in Taiwan for 60 X-ray imaging. The segmentation efficiency using the proposed method was significantly elevated with a DSC value of 0.941.

Some studies using CT images, such as **Navab et al.** [36] worked on CT scans where the proposed approach was the automatic detection and localization of vertebrae in volumetric CT. The location of each part was predicted by the contextual information in the image by using deep feed-forward neural networks. A public data set of 224 arbitrary field-of-view CT scans of the pathological cases was used to evaluate the method. The detection rate was 96% and the total operating time was less than three seconds. In contrast, **Zaho et al.** [37] proposed a technique to perform the localization and segmentation of the vertebra applied on CT imaging using transfer learning—500 spine CT images were used from a SpineWeb public dataset. The results displayed that the proposed approach could indicate considerable properties of the spinal vertebrae as well as provide useful localization and segmentation performance.

Some studies using MRI images as in **Xing Ji et al.**[38] presented a method to solve a problem segmentation of the challenging intervertebral disc (IVD) by using deep CNNs, where they studied the effect of four different correction sampling strategies for deep CNNs. They used the MICCAI 2015 IVD dataset to evaluate the method and this method achieved a mean average absolute surface distance of 1.3 mm and an average Dice overlap coefficient of 89.2%. **Jamaludin et al.** [39] proposed an approach to automatically predict radiological scores in spinal MRIs. They also determined diseases based on radiation scores. They worked on a two-fold approach: (i) architecture and training of CNN, and (ii) the prediction of a heat-map of evidence hotspots for each score. The results show that the hotspots of pathology and radiological scores can be projected at an excellent level. **Davies et al.** [40] proposed a method that uses magnetic resonance of the cervical and lumbar spine to classify disc degeneration. The goal of this method was to explore the association between histological grading and magnetic resonance of IVD degeneration in the lumbar spine and the cervical spine for patients undergoing discectomy. **Heinrich and Oktay** [38] presented a method for finding anatomical landmarks in spine MRI scans by using Vantage Point Hough Forests and multi-atlas fusion. The proposed method achieved Dice segmentation overlaps of almost 90%, sub-voxel localization accuracy of 0.61 mm, as well as a processing time of approximately ten minutes per scan. **Hetherington et al.** [41] proposed a method of vertebral level labeling and identification without the use of an outer chase device. The suggested CNN successfully distinguished ultrasound images of the sacrum, intervertebral spaces, and vertebral bones with a 20-fold cross-validation precision of 88 percent. Seventeen of 20 test ultrasounds provided a wealthy recognition of all vertebral levels and processed a real-time speed of 40 frames per second. **Kim et al.** [42] proposed a new deep learning network to divide intervertebral discs from MRI spine images. The traditional method (U-net) is known to work well for medical image segmentation. However, its performance in terms of segmentation details, such as boundaries, is limited by structural limitations of the maximum clustering layers. The proposed network achieved 54.62% compared with 44.16% for convolutional U-net. In contrast, **Zhou et al.** [43] suggested a deep learning-based detection algorithm. The data hail from Hong Kong University's Department of Orthopedics and Traumatology. The MRI dataset consisted of samples from various age groups and used 2739 unhealthy and 1318 healthy samples. To train the CNN to detect the lumbar spine they worked on a similarity function, and the proposed method compared similarities between vertebrae using an earlier lumbar image instead of distinguishing vertebrae using annotated lumbar images. S1 was identified due to its unique shape, and a rough area around it was removed in order to look for L1–L5. The accuracy, precision, mean, and standard deviation (STD) of the results were calculated, and this detection algorithm had an accuracy of 98.6 percent and precision of 98.9 percent. The majority of the failed findings were due to misplaced S1 vertebrae or undetected L5 vertebrae. **Whitehead et al.** [44] worked on spine segmentation by proposing a technique that was not model-based. They proposed a technique established on a string of four pixel-wise division networks. They used a dataset from UCLA Radiology, and each network chunk MR imaged at several scales. The input to the network in the chain was fed by the output from the previous network. Each sequential network produced an increasingly filtered segmentation outcome by using both the original image and the output from the last network as input. In comparison to the U-net segmentation method, the proposed approach led to improving the segmentation task in the vertebrae and discs at the rate of 1.3% and 4.9%, respectively. In addition, **Hu et al.** [45] used deep learning to distinguish patients with low back pain from healthy persons in static standing. They used 44 chronic Low back pain (LBP) and healthy individuals and the spine kinematics and pressure points were listed. The outcomes showed that deep neural networks could identify low back pain persons with a precision of up to 97.2%. The study showed the classification task with precision and recall could be carried out by deep learning networks. **Lu et al.** [4] worked to classify MRI lumbar spinal stenosis using CNN, the natural language processing used to extract the labels for different types and degrees of spinal stenosis from radiology diagnoses. They used U-Net architecture for the segmentation of the lumbar spine vertebrae and localization of the disc level. Data from the Department of Radiology of Massachusetts General Hospital during the period from April 2016 to October 2017 was used. In the segmentation task of the vertebral body, the standard guaranteed that all lumbar intervertebral discs could be taken away with the algorithm. The pass rate for the test group according to these criteria was 94%. **Palkar and Mishra** [46] proposed a method to generate a single image containing all the important features from MR and CT images of the lumbar spine by using CNN and wavelet-based fusion. First, using wavelets, both MR and CT images were analyzed into detail and approximation coefficients. Then, using a CNN framework, approximation coefficients were fused with the corresponding detail. Finally, the fused image was generated using inverse wavelet transform. A SpineWeb public dataset was used. Experimental results indicated that the proposed method had performed well when compared to conventional methods. In digitalized video fluoroscopic imaging (DVFI) sequences, **Liu et al**. [47] proposed a method for automatically tracking lumbar vertebras with bounding boxes that have been rotated. Instead of using lumbar pictures or sequences that have been annotated to distinguish vertebrae, they used transfer learning to train a full-convolutional Siamese neural network offline to memorize non-specific image characteristics. The Siamese network learned a similarity task that distinguished candidate patches from the current frame from the marked target from the beginning frame. If the two images represented the same thing, the similarity task gave a high score. Without any online alteration, the learned similarity task was used to monitor an early invisible entity. The tracker worked by evaluating candidate revolve patches collected from all over the previous target's locations and presenting revolve bounding boxes for lumbar spine positions L1 to L4. The results showed that the proposed tracking method could reliably and consistently track the lumbar vertebrae. According to this analysis, the lumbar tracker based on the Siamese convolutional network could be trained successfully without annotated lumbar sequences. **Mbarki et al.** [34] studied identifying a herniated lumbar disc by working on MRI, using CNN, based on the VGG16 geometry. A special data set was used from Sahloul University Hospital in Sousse, Tunisia. U-net was used with an axial view MRI to locate and detail the location of the herniated lumbar disc. The accuracy of the proposed model was 94%. **Won et al.** [48] validated the utility of the computer-assisted spinal stenosis classification system by comparing agreement between experts trained in CNN classifications and a diagnostic agreement between two experts. For the detection process, they used Faster R-CNN, and for the classification process, they used VGG network. After the grading agreement was completed, the differences in the results between each expert and the trained models were not considerable, while the final agreement between the trained model and the expert was 74.9% and 77.9%, respectively. **Lakshminarayanan and Yuvaraj** [26] proposed a method for analyzing and classifying spinal vertebrae images. After scanning the spinal vertebrae, the images were analyzed and classified into different disc types using the CNN ConvNet algorithm. In their proposed model, they showed the CNN system was better than the SVM system. However, the precision of the SVM was 90%, while the CNN was 96.9%. The results stated that the proposed method provided speed and accuracy compared to traditional algorithms. **Zhang et al.** [31] developed a deep convolutional neural network (DCNN) model to classify osteopenia by the use of X-ray images of the lumbar spine, as a reference standard, it was used DXA-derived bone mineral density (BMDs). According to DXA BMD T-score the patients were classified into three groups: osteopenia ($-2.5 < T < -1.0$), normal ($T \geq -1.0$), and osteoporosis ($T \leq -2.5$). **Kónya et al.** [49] proposed a method to explore the accuracies of segmentation of various hand-trained segmentation networks on 730 hand-annotated lateral lumbar spine X-rays. segmentation networks of Instance were compared to segmentation networks of semantic. Postoperative images with metallic implants, and comprised diseased, within the cohort study. **Buerger et al.** [50] proposed a new method to segment and label all vertebrae using combined deep learning and model-based segmentation. To create 24 instance segmentations per vertebra, they applied four steps. The first step to segment the spine applied a single-class U-Net. Samples were then taken from the coarse segmentation to create fine segmentation including vertebral body landmarks as well as individual labeling of some key vertebrae. Thereafter, the coordinates of the features from the classes estimated in the previous step were detected and labeled. Finally, all the MBS vertebrae models were initialized. The segmentation results on 147 patient images were tested to validate the method. The root mean squared distances of RMSDist = 0.90 mm were achieved through computed surface distances between segmentation and ground truth meshes over all cases and vertebrae.

TABLE 1. Deep learning studies applied to lumbar spine image analysis

Reference	Dataset	Data-set type	Objective	Methods	Result
[34]	Private Dataset: Sahloul University Hospital of Sousse	MRI	Worked on the classification of the lumbar herniated disc.	CCN based on VGG16 architecture and U-net based on axial view MRI.	The proposed model had a 94 percent accuracy rate.
[4]	Data used from Massachusetts General Hospital (MGR) during the period from April 2016 to October 2017.	MRI	Lumbar vertebral segmentation and lumbar spinal stenosis classification.	CNN U-net.	The pass rate for the test group was 94%.
[48]	542 L4-5 axial MR images	MRI	They compared agreement between experts qualified CNN classifications and a diagnostic agreement between two experts to verify the usefulness of the computer-assisted spinal stenosis classification system.	R-CNN and VGG network.	The differences in results between each expert and the trained models were not considerable, while the final agreement between the trained model and the expert was 74.9% and 77.9%.
[44]	Private Dataset: UCLA	MRI	Spine segmentation.	U-net and string of four pixel-wise division networks.	The proposed approach led to improve the segmentation task in vertebrae and disk at the rate of 1.3% and 4.9%.
[45]	44 chronic LBP and healthy individuals.	MRI	They used deep learning to recognize LBP patients from well persons in static standing.	Deep neural networks.	Outcomes showed that deep neural networks could recognize low back pain persons with precision up to 97.2%.
[46]	SpineWeb	MR and CT	They proposed a method to produce one image containing whole significant features from MR and CT images of lumbar spine by using CNN and wavelet-based fusion.	Wavelets and VGG-19 convolutional neural network.	The results state that the proposed method provides speed and accuracy compared to traditional algorithms.
[42]	Twenty patients from SpineWeb dataset 10.	MRI	They proposed new deep learning network to divide intervertebral discs.	BSU-Net	The proposed network achieved 54.62% compared with 44.16% for conventional U-net.
[38]	MICCAI 2015 IVD	MRI	To solve a problem segmentation of the challenging Intervertebral Disc (IVD).	CNN	The suggested procedure yielded an average absolute surface gap of 1.3 mm and an 89.2 percent mean overlap coefficient.
[43]	The data comes from Hong Kong University's Department of Orthopedics and Traumatology.	MRI	Detection and identification lumbar vertebrae.	A deep learning-based detection algorithm was proposed.	The suggested detection algorithm achieves a precision of 98.9% and an accuracy of 98.6 percent.
[37]	SpineWeb: 500 spine images	CT	Localization and segmentation of the vertebrae.	Transfer learning	The proposed approach was capable to hold considerable properties of the spinal vertebrae as well as provide useful localization and segmentation performance.
[36]	SpineWeb: 224 CT images	CT	to the automated identification and localization of vertebrae.	Deep feed-forward neural networks.	Detection rate was 96% and the total operating time was less than three seconds.
[35]	Private dataset: 974 for training images as well as 108 testing images.	X-ray	Intervertebral disc detection.	Faster-RCNN	The system had an average accuracy of 0.905 and a three-second average computation time per picture.
[12]	Private dataset from National Cheng Kung University Hospital, Taiwan for 60 X-ray imaging.	x-ray	Vertebrae detection and segmentation.	Hybrid method: image processing and CNN.	The segmentation efficiency using the proposed method was significantly elevated with DSC value of 0.941.
[50]	Private dataset: 147 patients.	CT	Segmentation of vertebrae.	- Segment the spine using U-Net. - Create fine segmentation using another U-Net model. – Recognize and label the vertebrae.	Squared distance of RMSDist = 0.90 mm.

CONCLUSION

To conclude, it appears that deep learning has a prominent role in the diagnosis of the lumbar spine as an analysis tool. This is mainly because they are highly effective in the identification and classification of medical images. In addition, recent advances in deep learning have shed light on analyzing medical images by discovering structural patterns in images. Due to the researchers' results, deep learning has achieved good performance in the process of analyzing medical images for a lumbar herniated disc, as well as in various medical applications. However, there is still a need for diagnostic evaluation by specialized doctors, so there is room for improvement and development using large numbers of training data to reach the required accuracy. There are some challenges to using deep learning in analyzing images of the lumbar spine. The most important of these challenges is the size of the database, as a large database is required for the purpose of training, and is directly proportional to the size of the data. The larger the data size, the higher the accuracy of the analysis and vice versa. The training process is time-consuming because it deals with data that has high dimensionality. In addition to choosing the right deep learning structure to solve the problem, each structure has its positive and negative points. However, deep learning remains the important and trailblazing method for analyzing and diagnosing medical images of the lumbar spine.

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