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Machine learning Techniques for Spondylolisthesis diagnosis: a review

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A B S T R A C T

Spondylolisthesis, a condition marked by vertebral slippage, presents a challenge in medical diagnosis and grading. This study examines previous research on image processing for spondylolisthesis severity evaluation. Methodologies, sample sizes, algorithms, and measurement accuracy are the main topics of interest. The study shows the potential of computer-assisted methods for diagnosing spondylolisthesis, particularly in situations where qualified medical personnel are scarce. Machine learning techniques and deep learning models, including convolutional neural networks (CNNs), are utilised to accurately detect and assess spondylolisthesis. Notably, these findings address a gap in previous research by measuring spondylolisthesis severity and distinguishing between normal and abnormal spines. The analysis emphasises the significance of selecting the appropriate modality and data quality, with X-rays predominating as the preferred imaging technique. This review highlights how deep learning and machine learning models can improve spondylolisthesis diagnosis, enabling enhanced diagnosis and treatment methods.

Introduction

The Greek word "olisthanein" which means "to slip," is where the word "spondylolisthesis" originates. As a result, it broadly refers to the instability of the segment caused by the translation of one vertebral body over the other [1]. It has been categorised into six major categories: isthmic, traumatic, degenerative, pathologic, dysplastic, and postsurgical; among these, degenerative spondylolisthesis (DS), which affects the elderly population, is the most frequently documented [2][3].

Since spondylolisthesis generally does not exhibit any symptoms, there may be variations in how it presents and during the physical examination. Although the examination is not a valid method for identifying spondylolisthesis, it can help in evaluating the condition [4].

The physical examination reveals lumbar spine flatness, discomfort during flexion and extension, and muscular spasm. The symptoms of spondylolisthesis are influenced by various circumstances, but the degree of translation is particularly significant in determining the appropriate therapy approach. Therefore, it is crucial to establish a uniform classification system in order to accurately measure the extent of displacement and track the advancement of slip. The Meyerding classification system was created to fulfil this requirement and is assessed on a scale from I to V based on the extent of the spondylolisthesis, as evaluated by the use of plain radiographs [4,5].

Spondylolisthesis primarily affects the lower lumbar spine, however it can also occur in the cervical spine and, less commonly, in the thoracic spine, unless caused by trauma. In adulthood, degenerative spondylolisthesis is more common in women than in men, and obese individuals are at higher risk. The L5-S1 level is where spondylolisthesis most frequently occurs, where the anterior translation of the L5 vertebral body onto the S1 vertebral body occurs. The second typically occurring site of spondylolisthesis is the L4-5 level [6].

The typically utilized grading system for anterior spondylolisthesis is Meyerding's classification (as illustrated in FIGURE 1). It's based on the anterior translation percentage in relation to the adjacent level. Grade I spondylolisthesis is defined as slippage of 1 to 25%, grade II as slippage of up to 50%, grade III as slippage of up to 75%, and grade IV as slippage of 76 to 100%. Spondyloptosis or grade V spondylolisthesis is the term for spondylolisthesis when there is more than 100% slippage[7]. While The term "retrolisthesis" refers to the posterior slippage of one vertebral body relative to the adjacent vertebra[8]. Grade I spondylolisthesis accounts for 75% of all cases[7].

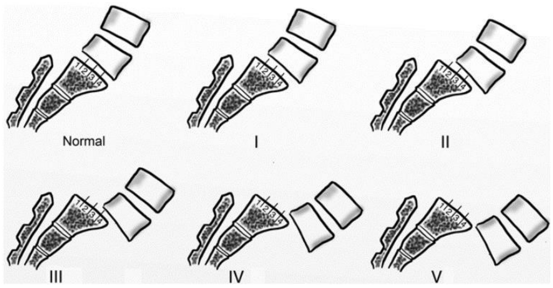

Figure 1. The Meyerding System's five grades for anterior spondylolisthesis [7]

This review study seeks to showcase and evaluate the many methods that have been employed to assess the severity of spondylolisthesis using image processing algorithms. It also aims to compare the methodologies, sample sizes, algorithms, and measurement quality of the previous related studies, since that computer-assisted systems for spondylolisthesis diagnosis can be extremely helpful when qualified doctors are difficult to find.

Previous Studies

In 2013, Ansari *et al.* suggested an approach for diagnosing and categorising illnesses of the vertebral column using machine learning classifiers such as feed forward back propagation neural network, generalized regression neural network, and support vector machine. They also assessed the effectiveness of these classifiers. The dataset is obtained by extracting information from magnetic resonance imaging (MRI) and is categorised into three distinct classes: disc hernia, spondylolisthesis, and normal. The classifiers are trained using a 50% ratio and 10-fold cross-validation techniques and are thoroughly assessed with various architectures, activation functions, and kernel functions.

The empirical findings indicate that the feed forward back propagation neural network achieves an accuracy of 93.87% on unfamiliar test subjects, surpassing the performance of other approaches[9].

In 2014, Karabulut *et al.* suggested an automated system based on a logistic model tree is developed for precise disagnosis of the vertebral column disorders. Pelvic incidence, pelvic tilt, lumbar lordosis angle, sacral slope, pelvic radius, and degree of spondylolisthesis were the six biomechanical measurements employed. The data; which included the medical records of 310 individuals, of whom 60 had disk hernias, 150 had spondylolisthesis, and 100 had normal conditions. It was preprocessed using the Synthetic Minority

Over-sampling Technique (SMOTE) in the first phase, and the preprocessed data were then fed into the Logistic Model Tree (LMT) classifier in the second phase. The computer-based automatic detection of the pathology was able to reach an accuracy of 89.73% and 0.964 Area Under Curve (AUC)[10].

In 2016, Liao *et al.* proposed an auto measuring framework as a means of addressing issues with spinal analysis. The framework presents a learning-based technique for classifying lumbar vertebrae in photos that takes into account both geometrical information and appearance. Additionally, it suggests a hierarchical method for positioning important locations in the spine by fusing population data with particular image information. The framework is tested on 258 individuals with CT spondylolisthesis and achieved an accuracy of 94.51% [11].

In 2017, Cai *et al*. introduced a spondylolisthesis detection technique that can precisely pinpoint the abnormal spine section and produce the associated grading. This study introduced a brand-new spondylolisthesis detection technique that can precisely pinpoint the abnormal spine section and produce the associated grading. A group of learning-based detectors that have been specifically trained using samples of synthetic spondylolisthesis images to perform the detection process. Three publicly available datasets were utilised for this task: the SpineWeb multi- modal (MR+CT) lumbar spondylolisthesis dataset (http://spineweb.digitalimaginggroup.ca), the xVertSeg CT dataset from the University of Ljubljana, and the MR segmentation dataset from the University of Siegen. The SpineWeb dataset included 15 pairs of lumbar spine scans with varying spondylolisthesis grades (primarily Grades I and II). The xVertSeg CT dataset comprised 15 lumbar and/or chest scans, while the Siegen MR dataset included 17 MR images. Notably, the xVertSeg and Siegen datasets lacked any spondylolisthesis cases.

This technique correctly recognised 34 out of 39 (MR+CT) actual spondylolisthesis patients and 9 out of 9 synthesised validation instances. The specificity for genuine cases was 90.0%, while the sensitivity was 91.8%. For both MR and CT scans, the estimated spondylolisthesis grading in genuine patients (Grade 0, 1, 2) had an 85.3% success rate. The specificity for genuine cases was 90.0%, while the sensitivity was 91.8%. For both MR and CT scans, the estimated spondylolisthesis grading in genuine patients (Grade 0, 1, 2) had an 85.3% success rate [12].

In 2018, Hasan *et al*. proposed a study that attempts to help experts identify the type of orthopaedic disease by using a variety of machine learning algorithms to examine how well each system identified and categorises orthopaedic patients. Six biomechanical variables, obtained from the configuration of the pelvis and lumbar spine, are used to describe each patient in the dataset. The majority of the tested algorithms provided an average accuracy of more than 90% during our two-stage operation, but the Decision Tree (DT) method stood out from the competition by achieving 99% accuracy [13] .

In 2018, Abdullah *et al.* proposed an approach for identifying the key physical factors that contribute to spinal abnormalities and predicting such abnormalities based on collected spine data. The most significant variable found to contribute to spinal abnormalities is the degree of spondylolisthesis. This was achieved by employing unsupervised machine learning methods like Principal Component Analysis (PCA), as well as supervised machine learning methods such as K-Nearest Neighbours (KNN) and Random Forest (RF). The dataset contains 310 subjects in total records that are classified into two distinct classes, consisting of 100 normal subjects and 210 abnormal spines. All attributes are contained within the numerical attribute. Each patient is depicted as a pattern consisting of 12 biomechanical attributes. When comparing the results of the RF classifier with the KNN classifier, it was found that the KNN classifier outperformed the RF classifier. This is because the accuracy percentage of the KNN method (85.32%) is higher than that of the RF classifier (79.57%) [14].

In 2019, Varçin *et al.* discussed the diagnosis of spondylolisthesis via convolutional neural networks. In this study, a dataset of 272 X-ray images, including 136 images from patients with spondylolisthesis and 136 images of normal subjects, was analysed using two renowned artificial neural networks, AlexNet and GoogleLeNet. The results indicate that GoogleLeNet achieved an accuracy rate of 93.87%, outperforming AlexNet, which achieved an accuracy of 91.67% [15].

In 2019, Zhao *et al*. suggested the Faster Adversarial Recognition (FAR) network, which uses an adversarial module as the discriminator and a multi-task recognition network as the generator, to grade spondylolisthesis. Using the high-order statistics of the distribution of the detected bounding box coordinates as inputs, the adversarial module (discriminator) controls the generative network. 150 MRI scans from various medical facilities, including T1, T2, PD, and TSE, were included in the dataset. For spondylolisthesis grading on MRI images from various modalities, the FAR network is judged to be reliable and accurate (training accuracy: 98.83 ± 9.4%, testing accuracy: 89.33 ±2.76%) [16].

In 2019, Handayani employed the Vertebral Column dataset, which consists of three distinct classes: disc hernia, spondylolisthesis, normal and instances in UCI machine learning. The data set consisted of 100 normal subjects, 60 disc hernia patients, and 150 spondylolisthesis patients, which were organised into two classes: 100 normal individuals and 210 abnormal individuals. This study applied the K-NN algorithm to classify disc hernia and spondylolisthesis in the vertebral column. The data was subsequently categorised into two classification tasks: "normal" and "abnormal". The findings indicated that the K-NN classifier achieved an accuracy of 83% [17].

Varçin *et al*. also discussed the diagnosis of spondylolisthesis in 2021. A dataset of 2109 X-ray images was used for training the model, of which 187 images reserved for validation. The model was then tested on 598 images. Yolov3 model was utilised to extract regions of interest (ROIs) during training, which were subsequently split into training and validation sets. Afterwards, a MobileNet Convolutional Neural Network (CNN) was adjusted for training using the ROIs. Images were fed to the model during the testing phase, which classified them as either normal or indicative of spondylolisthesis. The end-to-end transfer learning-based CNN model performed remarkably well, as evidenced by the findings, which showed 99% test accuracy, 98% test sensitivity, and 99% test specificity. These results are quite encouraging and show that the model may be used successfully [18].

In 2021, Nguyen *et al.* introduced a deep learning system supported by a CNN on 1000 X-ray images. The CNN model corrects critical vertebral corner points to precisely assess required characteristics. The range of lateral bending views that this approach may measure includes flexion and extension postures. The results are accurate, with a mean deviation of 1.76° and a short processing time of 0.12 seconds for a single X-ray image, when validated against standard references [19].

In 2022, Savargi *et al.* presented a study for an optimised deep learning model for spondylolisthesis detection in X-ray radiographs. The dataset consisted of 299 X-ray images, with 156 showing spondylolisthesis and 143 of normal spines. The dataset was expanded by 701 further images using image augmentation techniques. The study utilised TFLite model optimisation to improve the VGG16 and InceptionV3 image classification models. The VGG16 model outperformed the InceptionV3 model in terms of accuracy, scoring 98% versus 96%, according to the results. The model's size is reduced by up to four times to make it suitable for small devices. The accuracy rates for the compressed VGG16 and InceptionV3 models are 100% and 96%, respectively [20].

In 2022, Fraiwan *et al.* employed deep transfer learning to detect spondylolisthesis and scoliosis from X-ray images, eliminating the need for any manual measurements. The dataset consisted of 338 subjects‘ X-ray images, of which188 were scoliosis patients, 79 were spondylolisthesis patients, and 71 were healthy individuals. Deep transfer learning models were created to do three-class classification and pairwise binary classifications within the three classes. The mean accuracy and maximum accuracy for three-class classification were 96.73% and 98.02%, respectively [21].

In 2022, Saravagi *et al*. suggested another method for CNN model optimisation for small-device lumbar spondylolisthesis diagnosis. Their approach involves weight and unit pruning strategies to reduce the model's complexity. The dataset consisted of 337 X-ray images, 156 of which were spondylolisthesis diagnosed patients, while the remaining 181 were normal subjects.

According to experimental results, the unit pruning technique surpasses weight pruning with a remarkable 94.12% accuracy, even after 90% of the network load has been reduced. This indicates that just a small subset of parameters (about 30% for weight pruning and 10% for neuron pruning) in each layer affect the final outcome. The trimmed model's accuracy outperforms the previous model created for lumbar spondylolisthesis diagnosis, making it more effective for devices with limited resources [22].

In 2022, Trinh *et al*. introduced the LumbarNet CADx algorithm for spotting spinal slippage in clinical X-ray images. LumbarNet includes three key components: a piecewise slope detection (PSD) technique, a dynamic shift (DS) detection routine, and a P-grade approach. Thus, LumbarNet was specialised to analyse complex structural patterns in lumbar spine X-ray images. LumbarNet outperformed other U-Net based techniques in comparative testing. LumbarNet demonstrated its effectiveness in identifying vertebral regions on conventional clinical lumbar spine X-ray images, with an accuracy rate of 88.83%. Additionally, it successfully detected vertebral slippage, as indicated by a mean intersection over union (mIOU) value of 0.88 [23].

Moreover, in 2022, Trinh *et al.* developed LumbarNet, a computer-aided diagnostic (CADx) algorithm, and assessed its effectiveness in automatically detecting spondylolisthesis from lumbar X-ray images. The feature fusion module (FFM) of LumbarNet, which is based on the U-Net architecture together with a P-grade approach, a piecewise slope detection (PSD) scheme, and a dynamic shift (DS) mechanism. This enabled LumbarNet to analyse complex structural patterns visible in a variety of lumbar X-ray images, including true lateral, flexion, and extension lateral views. The data set consisted of 706 X-ray images and 312 cases with 312 X-rays of abnormal lumbar vertebrae. The evaluation findings showed LumbarNet's potential, reaching a mean intersection over union (mIOU) value of 0.88 in vertebral area segmentation and an accuracy rate of 88.83% in vertebral slip detection [24].

In 2022, Lee *et al*. suggested an approach to assess cervical spondylotic myelopathy. The dataset included 207 individuals. 96 of them were affected by cervical spondylotic myelopathy. The CNN algorithm was employed. To evaluate the effectiveness of the model, 70% of the included patients (145 photos) were randomly assigned to the training set, while the remaining 30% (62 images) were assigned to the test set. The area under the curve was 0.864, and the detection accuracy was 87.1% [25].

In 2023, Xuan *et.al*. also utilised YOLOv3, YOLOv5, and PP-YOLOv2 deep transfer learning models to build and train the Baidu PaddlePaddle framework. According to the experimental findings after testing 604 patients, the PP-YOLOv2 model had a diagnosis accuracy for normal, IVD bulges, and spondylolisthesis of 90.08% overall, which was 27.5 and 3.9% higher than YOLOv3 and YOLOv5, respectively. Finally, a visualisation of the PP-YOLOv2 model-based intelligent spine assistant diagnostic program was produced. With a 98% accuracy rate, this software automatically generates supplemental diagnoses [26].

In 2023, Zhang *et al*. also presented a detection algorithm for lumbar spondylolisthesis clinical auxiliary diagnosis and compared it to physicians' assessments to confirm its effectiveness and viability. To create the dataset, lumbar lateral radiographs from 1,596 patients with lumbar spondylolisthesis were gathered. The Faster Region-based Convolutional Neural Network (R-CNN) outperformed the doctor group in identifying spondylolisthesis, achieving higher precision (0.935), recall (0.935), and F1-score (0.935) compared to the doctor group's precision (0.927), recall (0.892), and F1-score (0.910 Moreover, the implementation of the DL model resulted in a 4.8% gain in precision, an 8.2% increase in recall, a 6.4% rise in F1-score, and a reduction of 7.139 seconds in the average diagnostic time for plain X-rays by the doctor group [27].

Methodology

Dataets

The aforementioned studies primarily concentrated on utilising machine learning techniques to diagnose and evaluate the severity of spondylolisthesis. They employed diverse datasets to train and assess their algorithms. The datasets include medical records and imaging data of patients diagnosed with vertebral column-related conditions.

Typically, two categories of datasets were employed: numeric datasets containing data measured by doctors using different imaging techniques, or image datasets derived from image modality scans.The number of samples, dataset sizes, and specific details varied among the studies.

Machine Learning (ML) Studies:

Multiple studies in this review employed machine learning techniques for the diagnosis and evaluation of spondylolisthesis. Machine learning algorithms, such as feed forward back propagation neural networks, logistic model trees, and support vector machines, were used. The algorithms underwent training using datasets that included features derived from MRI scans and biomechanical measurements. The ML models successfully achieved accurate classification and categorization of various conditions associated with spondylolisthesis using these features. Machine learning techniques utilise statistical and mathematical models to acquire knowledge of patterns and generate predictions [9,10,12–14,17].

Deep Learning (DL) Studies:

Several studies have investigated the application of deep learning methods for diagnosing spondylolisthesis [15,16,18–27].

Deep learning in medical imaging involves the utilisation of deep neural networks, such as Convolutional Neural Networks (CNNs), for the analysis of medical images. The process entails training these networks using large data sets to automatically acquire and extract intricate characteristics. Deep learning has demonstrated superior predictive performance when compared to conventional machine learning algorithms in the classification of medical images, particularly in intricate situations. An advantage of deep learning models is their ability to automatically extract pertinent features from images, thereby eliminating the need for manual feature extraction [28,29].

RESULTS AND DISCUSSIONS

The reviewed studies demonstrate the potential of computer-aided approaches in the diagnosis and grading of spondylolisthesis. Several machine learning techniques and deep learning models, particularly CNNs, have been utilized with promising findings. These approaches have demonstrated a notable level of accuracy in the identification and evaluation of spondylolisthesis, while also effectively differentiating between spines that are considered normal and those that exhibit abnormalities. The results demonstrate how important it is to use machine learning and deep learning models to increase spondylolisthesis diagnosis accuracy (see Table1).

Table 1. a summery of earlier studies in terms of dataset. Imaging modality, machine learning algorithms and results' accuracy

Ref.	year	Dataset Size (No. of subjects)	Modality	Machine learning algorithm	Limitations	Accuracy (%)

[9]	2013	310	MRI	feed forward back propagation neural network	1. T Only distiguishes between normal and abnormal spines without specifying the cause of abnormality. 1. The dataset was manually constructed as a record of measurement of features	93.87
[10]	2014	310	N/A	Logistic Model Tree (LMT)	2. Only distiguishes between normal and abnormal spines without specifying the cause of abnormality. 3. The dataset was manually constructed as a record of measurement of features. 4. Accuracy 89.73	89.73
[11]	2016	258 (validation)	CT	N/A	The study compares automated and manual radiologists' measurements, highlighting the potential for variability and subjectivity in hand measurements, which can affect assessment precision.	94.51
[12]	2017	39 MR/CT pairs (test)	MR+CT	Restricted Boltzmann Machine (RBM) and Convolutional Restricted Boltzmann Machine (CRBM) based network	minimal sized testing dataset Accuracy 85.3	85.3
[13]	2018	N/A	N/A	Decision Tree (DT)	1. The dataset was manually constructed as a record of measurement of features. 2. The classes were normal , disc hernia and spondylolisthesis without considering the severity of the injury	99
[14]	2018	310	N/A	KNN & RF	1. The dataset was manually constructed as a record of measurement of features. 2. The acquired accurecies are 85.32 & 79.57	85.32 79.57
[15]	2019	272	X-ray	AlexNet & GoogleLeNet	The classes were normal and spondylolisthesis without considering the severity of the injury	91.67 & 93.87
[16]	2019	150	MRI	FAR network	1. Accuracy 89.33 2. Limited sample size dataset	89.33
[17]	2019	310	N/A	KNN	1. The dataset was manually constructed as a record of measurement of features. 2. although there were initially three classes in the dataset: normal, disc hernia, and spondylolisthesis, this study provides less information regarding the cause of abnormality because disc hernia and spondylolisthesis were combined into one class (abnormal). 3. The acquired accurecies are 83	83
[18]	2021	2109	X-ray	MobileNet CNN	The dataset only considered normal and spondylolisthesis pathients with no regards for the gradings.	99
[19]	2021	1000	X-ray	CNN	Does not include information regarding the validation of the proposed deep learning system on an external dataset or in a distinct clinical setting.	N/A

[20]	2022	299	X-ray	VGG16 & Inception V3	The dataset only considered normal and spondylolisthesis pathients with no regards for the gradings.	98 & 96
[21]	2022	338	X-ray	Deep transfer learning models	1. The study does not specify if the deep transfer learning models were externally validated on an independent dataset. 2. The classes were normal and spondylolisthesis without considering the severity of the injury	96.73 (mean) 98.02 (max)
[22]	2022	337	X-ray	MobileNet	The dataset only considered normal and spondylolisthesis pathients with no regards for the gradings.	94.12
[23]	2022	NA	X-ray	LumbarNet CADX	Accuracy 89%	89
[24]	2022	706	X-ray	LumbarNet CADX	Accuracy 88.83	88.83
[25]	2022	207	MRI	CNN	1. Accuracy 87.1 2. The dataset only considered normal and spondylolisthesis pathients with no regards for the gradings.	87.1
[26]	2023	604 (test)	MRI	PP-YOLOv2	1. The study lacks information on the dataset used for developing and evaluating a spinal disease diagnosis assistant, which could affect its efficiency and applicability based on its broadness and classification of spinal disorders. 2. The study does not include information regarding the validation of the spinal disease diagnosis assistant in a clinical setting or its testing on real patient data.	98
[27]	2023	1,596	X-ray	Region-based Convolutional Neural Network (R-CNN)	The dataset only considered normal and spondylolisthesis pathients with no regards for the gradings.	N/A

The selection of the appropriate imaging modality and data quality is crucial. FIGURE 2 shows the count of studies against the imaging modality. The majority of the research used X-rays, as can be shown. While some researches only employed records of manually assessed features without using any images as automated input and five studies only used CT and/or MRI scans.

Figure 2. Number of Study Versus Dataset Modality.

Table 1 shows that a number of studies used shallow learning strategies, particularly the ones that used numerical datasets. most of which produced comparatively meagre outcomes and accuracy [9,10,12,14,17].

However, most studies utilised deep learning models such as VGG16, Inception V3, MobileNet, and LumbarNet CADX to analyse image datasets. These models have demonstrated their superior efficiency and accuracy in classifying spondylolisthesis [11,15,16], [18–27].

The primary limitation of state of the art studies is that they can only show normal and abnormal instances without revealing the precise degree of spinal damage [9,10,13,15,18,20].

Additionally, a few studies only used measurements to distinguish between these two classes, thus the diagnosis cannot be made automatically based solely on the patient test images [9,10,13,14,17]. Nevertheless, some of the studies gave relatively low classification accuracy [10,12,14,16,17,23–25]

Additionally, real data quality is a crucial consideration, especially when the size of the accessible dataset is limited; depending on the scope of data available, noisy real data could result in results that are vague or inaccurate to some extent.

CONCLUSION

In conclusion, this study examined prior relevant works based on their methodology, the number of participants, the image modality, and the classification algorithms. It presented a variety of machine learning algorithms that have been used to measure the incidence of lumbar spondylolisthesis. Convolutional neural networks (CNN) specifically and DL generally were proved to be effective in managing lumbar spondylolisthesis' prognosis and diagnosis. This research provides a method that not only detects normal and abnormal spines but also measures the degree of spondylolisthesis, which can be useful for designing and implementing a new system to address the limitations of prior studies. Additionally, these studies suggest that the creation of more sophisticated systems has the potential to completely change the diagnosis and treatment of spondylolisthesis.

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