ISSN: 2584-0495 Vol. 2, Issue 11, pp. 1329-1330

International Journal of Microsystems and IoT

ISSN: (Online) Journal homepage: https://www.ijmit.org

A Detailed Analysis of Spinal Cord Injury using Deep Learning Techniques in the MRI Scans

Aswathy V K and P. Asha

Cite as: V K, Aswathy, & Asha, P. (2024). A Detailed Analysis of Spinal Cord Injury using Deep Learning Techniques in the MRI Scans. International Journal of Microsystems and IoT, 2(11), 1329–1340. https://doi.org/10.5281/zenodo.14769326

Published online: 29 November 2024

DOI: https://doi.org/10.5281/zenodo.14769326

International Journal of Microsystems and IoT
Vol.2, Issue 11, pp. 1329-1340; DOI: https://doi.org/10.5281/zenodo.14769326

A Detailed Analysis of Spinal Cord Injury using Deep Learning Techniques in the MRI Scans

Aswathy V K and P.Asha

Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai India

ABSTRACT

Medical image segmentation is an important part of medical imaging and has grown in prominence as a result of the rapid development of both computer and medical imaging technologies. Improving the diagnostic approach and decision-making for patients with spinal pain requires an adequate clinical tactic, a thorough knowledge of the pathological manifestations shown by these imaging procedures, and a report based on a universally acknowledged nomenclature. In contrast to Computed Tomography (CT), which can produce ionising radiation that is harmful to humans, magnetic resonance imaging (MRI) can detect changes in water content in tissue components, display changes in lesions. MRI is extensively used for spinal imaging and is often more actual and early in detecting lesions. Various pathologic illnesses affecting the spine, such as congenital, tumour disorders, can be studied in this article, along with the clinical indications and imaging aspects of magnetic resonance imaging (MRI). Its purpose is to serve as a visual aid for medical professionals who diagnose and treat spinal diseases. There is still debate about the clinical indications and additional benefit of using MRI during the acute period of a spinal cord injury (SCI). In this experimental analysis we used python software with artificial intelligence and MRI image to analysis this study. Aiming to disapprovingly assess evidence on the use of MRI to impact decision-making besides outcomes in acute SCI, this review presents the latest research.

Keywords:
Magnetic resonance imaging; Decision Making Process; Medical Imaging Technology; Segmentation. Spina

1. INTRODUCTION

Spinal cord injuries (SCIs) originate from frequent and often catastrophic traumas to the spine. An estimated 750 instances per million people have an acute spinal cord injury each year; this condition disproportionately affects younger people and has far-reaching consequences for both families and society as a whole [1]. The primary emphasis of evidence-based SCI therapy is on the immediate post-injury period, which entails cautious transportation and immobilisation, prevention of hypotension and prompt surgical decompression [2]. Early assessment of spinal injuries relies heavily on imaging, with computed tomography (CT) replacing radiography in most current clinical algorithms [3]. The spinal cord, intervertebral discs, and ligaments are difficult to see on CT scans, despite the fact that the technology is extensively used and can rapidly screen trauma patients for a variety of ailments (thorax, abdomen, head, spine, and thorax).

Spinal cord compression, acute epidural haemorrhage can all be detected with the use of (MRI), which offers precise images of these structures [4]. Fears about its availability, discomfort, expense, and time commitment, as well as the claim that MRI results seldom alter clinical decision-making, have prevented MRI from being extensively integrated into trauma procedures. Surprisingly, there is a dearth of high-quality research comparing clinical decision-making with and without MRI, despite the abundance of articles exploring MRI in spinal injuries and SCI [5]. Guidelines for trauma and spinal cord injury (SCI) were published in 2002 and revised in 2013 by the American. However, these guidelines did not provide any recommendations for the use of magnetic resonance imaging (MRI) in adult patients with spinal cord injuries (SCI) clearance [6]. A systematic review conducted by [7] considered multiple indirect lines of evidence to evaluate the clinical utility of magnetic resonance imaging (MRI). The authors, relying on low-quality evidence, made a weak reference that, when possible, all patients with spinal cord injuries (SCI) should undergo MRI to guide their treatment [8].

A multi-disciplinary group that was supported by AOSpine, AANS/CNS, and the Ontario Neurotrauma Foundation recently produced clinical on five contentious issues related to SCI. One of these topics was the utilisation of magnetic resonance imaging (MRI) to guide clinical decision-making in SCI, which was supported by similarly weak evidence [9]. There was a substantial risk of bias owing to methodological flaws in the systematic review that assessed MRI and the fact that it only found one trial meant that this CPG was mostly dependent on expert opinion [10]. Overall, there has not been enough guidance on the regular use of MRI in acute SCI from the efforts to synthesise the data; thus, spinal surgeons and other physicians still practise quite differently.

Spinal image segmentation is difficult in MRI scans due to characteristics including complicated structure, poor tissue contrast, and uneven spinal border morphology. In order to achieve accurate spine segmentation, a reliable algorithm is required [11]. In recent learning has found extensive use in domains including image identification and MRI image segmentation. To address these concerns, researchers have developed a plethora of algorithms for segmenting and recognising spinal images. The primary objective of this research was to ascertain if MRI during the acute phase of spinal cord injury (SCI) provides relevant clinical information that can enhance patient treatment and outcomes.

What follows is an outline of the remaining tasks: Section 2 provides background information on the spine condition, and Section 3 presents the dataset that is currently accessible. While Section 5 provides a basic introduction to artificial intelligence, Section 4 demonstrates the necessity of MRI for SCI identification. In Section 6, we cover the relevant work of current models, and in Section 7, we go into its debate. Section 9 lays out the study's limitations, whereas Section 8 demonstrates the impact of MRI on the decision-making process. Section 10 concludes the whole thing.

2. GENERAL SIGNS FOR MRI OF THE SPINE DISORDERS

When patients present-day with symptoms like cauda equina syndrome, neoplasia, infection, or pain MRI is the preferred technique. This is because it can either confirm a spinal cord injury or compression, identify potential candidates for intervention or surgery, or provide a diagnosis without doubt. Persistent postoperative pain in patients should be investigated with contrast-enhanced magnetic resonance imaging (MRI).

MRI in congenital conditions of the spine

There are two types of congenital spinal abnormalities: simple, which include no spinal deformity or minimal clinical relevance, and complicated, which involve significant deformities. Alterations to the spine at birth can be categorised morphologically according to whether they are a result of problems with vertebral development, vertebral segmentation, or both.

The pattern of curvature is another way congenital abnormalities can be diagnosed. Scoliosis was seen in 80% of individuals with congenital spinal abnormalities, kyphoscoliosis in 14%, and pure kyphosis in 6%. The most frequent kind of congenital scoliosis is hemovertebra, whereas unilateral unsegmented bar is the second most common. The most common and deadly kind is segmented hemivertebra, which develops while growing in isolation from its neighboring vertebrae, creating a wedge that widens and eventually causes scoliosis. The risk of further deformity development is often reduced in cases with semi-segmented hemivertebrae since they are synostosis to one of the neighbouring vertebrae. Lastly, since they are placed in a location of the spine where there are no big voids between the vertebrae, imprisoned hemivertebrae have less room to grow and exhibit some deformities.

Common causes include segmentation failure, mixed anomalies, and anterior failure of vertebral body development. One third of the vertebrae are located in the posterolateral quadrant, while 7% are in the posterior hemivertebra, 13% are in the butterfly vertebra, and 5% are in the anterior wedge vertebrae.

Embryopathy is another criterion for categorising vertebral abnormalities. In the first two or three weeks of embryonic development, during the gastrulation phase, defects can arise in the notochord and potentially impact the neuroaxis and axial skeleton, which are components of the three germinal cell layers. Primary or secondary neurulation abnormalities (3-6 weeks) can also play a role in these deformities. Spinal dysraphism is the aggregate name for certain birth defects affecting the spinal cord and spine. There are two kinds of spinal dysraphism, called "open" and "closed," which are distinguished by the presence or lack of the covering skin. In myelomeningocele, through a midline bone and cutaneous defect, making up 98% of all cases of open dysraphism.

The existence or absence of a subcutaneous lump allows for further classification of closed spinal dysraphism. There are two primary types of closed dysraphism that may be distinguished when a subcutaneous tumour is present: lipomyelocele and lip myelomeningocele. Differentiation is possible according to whether the neural placode lipoma contact is located within or outside the spinal canal. Intradural lipoma, filar conditions that can be differentiated when there is no subcutaneous mass. As a last point, further complicated dysraphic conditions include neuroenteric cyst, syndrome, segmental spinal dysgenesis, split cord/diastematomyelia, dorsal enteric fistula, and split syndrome.

Traumatic pathologies

According to morphological criteria, there are three distinct kinds of spinal injuries: compression injuries, translational injuries. These three primary types are further subdivided into nine subcategories.

While most assessments of neurological state rely on clinical examinations, magnetic resonance imaging (MRI) enables the correlation of neurological results with the degree and severity of spinal cord injury. In this way, MRI can help pinpoint the precise area of injury and quantify its severity.

According to T2-weighted and/or T2-*-gradient echo pictures, there are three distinct kinds of spinal cord injuries: (I) denotes cord haemorrhage; (II) denotes cord edoema; (III) denotes a contusion or small central haemorrhage surrounded by edoema; (IV) displays a mixed pattern; and (IV) carries an intermediate prognosis; (I) shows initial hypo-intensity on MRI; (II) bears the best prognosis; and (III) shows cord edoema. The example picture for this illness is shown in Figure 1.

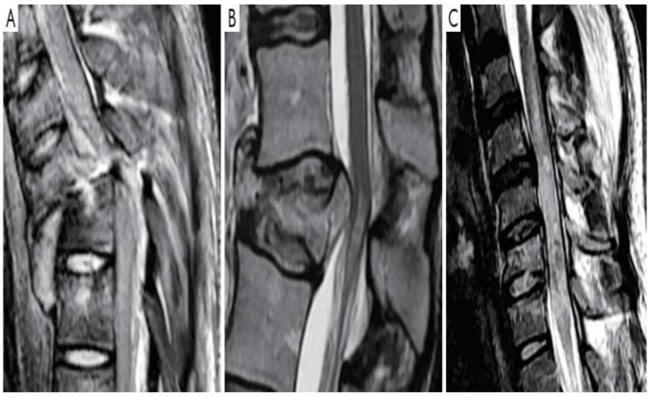

Fig 1: Traumatic spinal cord injury. (A) Kind I, hemorrhagic lesion; (B) Kind II, edematous injury; (C) Kind III, mixed injury.

Low energy vertebral fractures

Osteoporosis manifests as when a vertebral fracture develops after relatively moderate trauma. While CT and radiography may characterize and quantify these fractures, MRI is the gold standard for identifying edoema, a marker of acute or unstable chronic fracture. Furthermore, it may take some time for the morphological changes to emerge that enable the diagnosis of osteoporotic fractures. Consequently, it is not necessarily the case that a vertebral fracture cannot be seen on conventional radiography in a patient with osteoporosis. If there is no spinal deformity, MRI can identify fractures. It is important to check for the attendance of additional chronic osteoporotic vertebral fractures.

Degenerative pathologies

Anatomical sites that can be impacted by degenerative disease in the spine include synovial joints, spinous processes, intervertebral discs, ligaments, and the places where they attach to the bone.

Spinal stenosis

Anatomical sites that can be impacted by degenerative disease in the spine include synovial joints, spinous processes, intervertebral discs, ligaments, and the places where they attach to the bone.

Alignment abnormalities

Congenital or dysplastic, isthmic, traumatic, degenerative spondylolistheses are the six kinds that have been characterised.

3. ALTERATIONS IN THE SPINAL CURVATURE

Roughly 90% of kyphoses in children and adolescents are caused by Scheuermann's illness or idiopathic kyphosis. Kyphosis more than 45 degrees and wedging of more than 5 degrees in at least one vertebra are diagnostic criteria for this disorder. There is a correlation between Schmorl's nodes and irregular endplates. A standing radiograph with a Cobb measurement of a spine curvature more than 10 degrees is considered scoliosis (128). The four main types of scoliosis are inherited, neuromuscular, degenerative, and idiopathic. The latter is the most common kind, often causes no discomfort, and is identified after other possible causes have been ruled out.

Due to its common relationship with neural magnetic resonance imaging (MRI) is suggested in infantile and juvenile scoliosis in 10 years old. Unless there are unpleasant or atypical symptoms, including headache or neurological involvement, tomographic imaging methods are usually not recommended for the most prevalent kind of scoliosis in adolescents (11 to 17 years old). Neurological axis anomalies are 7.9-12.6% common in these individuals, according to presurgical screening. Bony tumours like osteoid osteoma or osteoblastoma are among the benign causes of scoliosis.

Inflammatory pathologies

To rule out spinal structural damage in cases of suspected inflammatory spondylarthrosis, radiography is still a good first line of investigation. One major issue with radiography is that it doesn't pick up on early non-structural changes that might be signs of active inflammation, such effusion. In order to show active changes in their early stages, MRI is the method of choice.

Infectious pathologies

Magnetic resonance imaging (MRI) has shown to be more sensitive and specific than radiography and bone scans in cases of suspected spinal infection. In addition, it is able to identify subchondral endplate edoema alterations, the first indication of spondylodiscitis.

Tumor pathologies

There are three main types of spinal tumours: primary benign, metastatic, and primary malignant. Around 90% of these cases have spread to other parts of the body, and 20% of those cases had canal invasionand/or cord compression. Since MRI provides better contrast to identify illness in several compartments (intramedullary, intradural-extramedullary, extradural, intraosseous, and paravertebral), it is often the best tool for assessing spinal tumours.

4. AVAILABLE DATASETS FOR SPINE DISORDER

Since most current models rely on datasets obtained from healthcare facilities, there are insufficient datasets available for categorization purposes.

4.1 Classification of the endplate lesions

Here is a brief summary of the grading method given in reference (12) for identifying intervertebral spaces based on endplate lesions: (i) If the sagittal MRI slices covering the intervertebral space do not visually reveal any abnormalities, the categorization is designated as "normal." If one or more endplates have changed shape relative to the normal curvature of the space, the classification is "wavy/irregular," even though the endplates themselves seem structurally normal. A wavy or otherwise irregular endplate form is possible; (iii) a minor lesion seen in at least one sagittal MRI slice is used to classify the image as "notched." On one or both endplates, you can see the lesion, which can look either round or V-shaped. These grooves could be signs of minor endplate defects or indentations; (iv) when a deep focal defect is found in the vertebral endplate, the "Schmorl's node" classification is applied. There is no rough edge to the lesion, and it seems rounded overall. Disc material that extends over the endplate and into the spinal marrow is a hallmark of Schmorl's nodes.

Note that the present work did not include the extra class "fracture" from the reference study since it did not have a large enough sample to be meaningful. Thus, the primary objective of the study was to categorise intervertebral spaces according to the lesions found in the MRI scans:. Please see the primary source (12) for further information on the score methodology and its validation.

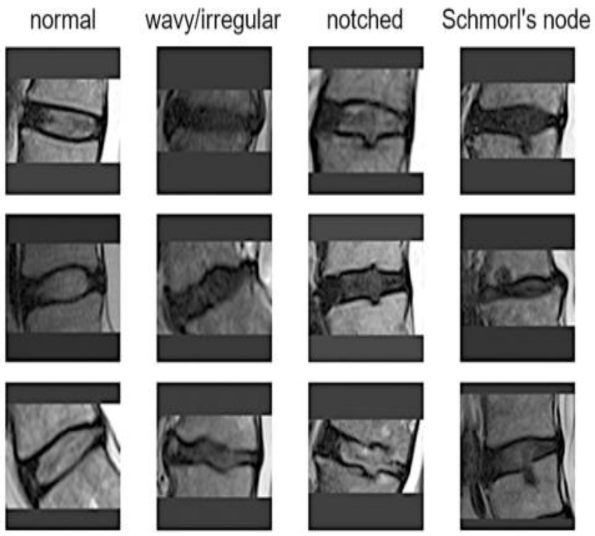

Fig 2: Classification arrangement with instances for the endplate lesion kinds.

Anonymized participants who underwent lumbosacral MRI scans among June 2016 and January 2018 were identified using a retrospective search utilising the Picture Archiving and Communication System (PACS). The study was done at the IRCCS Istituto Ortopedico Galeazzi in Milan, Italy.

Study design and population

As previously mentioned, the inquiry was structured which comprised a sizable representative sample of individuals from the general population ranging in age from 25 to 74 years. All individuals had a thorough evaluation of their health. Also, 400 individuals met the inclusion and exclusion criteria for whole-body MRI that were previously outlined. There was a median of 33 days (IQR 24-45) between the first consultation and the MRI scan. Both local institutional review board and the Bavarian Chamber of Physicians' ethics council in Munich, Germany, gave their stamp of approval to the study. All participants provided written informed permission, as required by the Declaration of Helsinki.

Deep Learning Techniques

Among the many branches of machine learning, "deep learning" refers to methods that use multi-layer neural networks. When contrasted with machine learning, deep learning offers greater benefits [14]. Using a data-driven approach, deep learning can automatically retrieve the information. These characteristics outperform the conventional, hand-made ones in terms of discrimination. These models undergo end-to-end training using interactive supervised learning to enhance feature extraction, selection, and classification. Therefore, deep learning is applicable to many different sectors and domains. It improves the accuracy of diagnoses in cases when subtle pathologic alterations are not apparent to the naked eye [15]. I have compiled a list of few of the best deep learning techniques:

[1] Autoencoder
[2] Deep belief network
[3] Long Short-Term Memory
[4] Deep Neural Network

Convolution Neural Network (CNN):

CNNs are an updated kind of deep neural networks that are associated with the correlation of nearby pixels. The three neural networks that make it up are the pooling layer, the convolutional layer, and the other one. Many convolutional filters make up the convolutional layer. The training data's features are extracted and mapped out by this layer. By reducing the dimensionality of the network parameters and feature maps, the pooling layer helps to reduce overfitting. The feature map is integrated as a feature vector using the fully linked layer. During training, adjustments are made based on the randomly determined patches. Once training is complete, the network uses the updated patches to make predictions and validate the findings. The CNN employs two distinct transformations; the first, known as convolution, involves filtering the pixels via a series of convolutions. Subsampling would be the second one.

Deep Neural Network (DNN)

The DNN is an evolution of the first artificial neural network. The main distinction between the CNN and DNN is that the former makes use of several hidden layers while the latter makes use of just two. A variety of models are available on the DNN, such as CNN, RNN, and LSTM. When the network is multi-layered, training the data is more difficult and time-consuming. In contrast, training a complex network using DNN is significantly faster. It is a technique for machine learning that aims to learn complex nonlinear functions. Using DNN to remove ambient noise from audio is a typical use case.

Recurrent Neural Network (RNN):

A feedforward neural network extension is RNN, a deep learning approach. Although it can handle text, its primary usage is in processing sequential and time-series data. As a result, it finds use in branches of text analysis such speech recognition, prediction control, text prediction, and time series prediction. An alternative ANN that takes neuronal data as input is the recurrent neural network (RNN). In order to respond to the layers that came before it, the processed neurons' output is used. The input of the subsequent layer in a flat RNN is the output of the previous layer. RNN is able to handle time-series data because it has a recurrent hidden state. Consequently, an issue with memory capacity develops. Connecting different gates and memory cells fixes these issues.

Autoencoder (AE):

Autoencoder is a kind of deep learning that doesn't rely on labelled data to analyse the input data's attributes. From the input data, it extracts code, which is then used to generate the output. Both the input data set and the structure of the autoencoder (AE) are comparable to those of the feedforward neural network. Hence, it endeavours to provide an original illustration for the input of the concealed layer. The AE's training data is not need to be labelled. The data used for training is used to create the output. Denoising, stacked, variational, and sparse autoencoders are among the many varieties of AE.

Deep Belief Network (DBN):

Here, two layers are used for feature identification in the Deep Belief Network, which is built based on the structure of multiple Restricted Boltzmann Machines (RBMs). Problems with sluggish learning, local minima, and parameter searches in deep layer networks may be effectively addressed with RBM, a unique kind of Markov random field. It analyses the input dataset's probability distribution as a generative random artificial neural network. In order to construct different single-layer networks, each layer in the stack communicates with the layers below and above it. All of the DBN's layers, with the exception of the first and last, serve as both input and concealed layers. Clustering, picture creation, motion capture, and video sequencing are all tasks it can do. DBN investigates the overarching characteristic of the time-domain ultrasound data. The change detection map is a byproduct of the change detection procedure.

Long Short-Term Memory (LSTM):

One subset of RNNs, often known as cell states, is a Long Short-Term Memory network. It is used to analyse complex human activities since it can recall patterns for lengthy periods of time. The previous data is stored in the cell and cannot be disregarded due to the recursive nature. Underneath the cell state lies the forget gate, which is utilised to change the cell state. The data is stored in the cell if the forget gate's output is 1, and they are forgotten if it's 0. The information fed into the cell state is handled by the input gate, while the data is sent to the subsequent hidden layer by the output gate. Deep Long Short-Term Memory (DLSTM) and Contextual Long Short-Term Memory (CLSTM) are two variants of the LSTM concept. The several layers that make up DLSTM set it apart from the standard LSTM. Compared to the one-layered LSTM, the multi-layered LSTM is better able to deliver a temporal characteristic. In contrast, CLSTM uses an LSTM to collect temporal characteristics and a convolutional layer to gain spatial features. Sequential time series data is the primary application of the LSTM.

5. Novel MR Imaging Apparatuses for Intervertebral Disc Degeneration

Noninvasive and accurate diagnostic tools for early phases of spinal cord injury (SCI) have been developed in the last decade through the use of various quantitative magnetic resonance imaging (QMRI) techniques.

Table 1. Table summarising recent MRI findings in both healthy and diseased discs.

Technique	Degenerated IVD Signal Intensity	Biochemical Changes Evaluated	Normal IVD Intensity
dGEMRIC	Low or high	Diffusion rate, GAG content incidentally	High or low
MT and MTR	MT high	Exchange process among free and macromolecule-	
T1ρ relaxation mapping	Low	PG besides water count, collagen anisotropy	High
T2 relaxation mapping	Low	PG besides water content	High
Quantitative T2* mapping	Low	Macromolecule architecture and water mobility	High
DWI with ADC and DTI with FA	Low ADC High FA	Topics covered include water movement, tissue make-up, and structure	High ADC Low FA
[1]Na-MRI	Low	Na^+ concentration, GAG/PG content indirectly	High
GagCEST	Low	Hyperhydroproton exchange among glycogen and water in bulk, glycogen content	High
Ultrashort TE (and zero-TE sequences)	Low Low GAG/collagen	Tissue arrangement and organization	Intermediate/from top to bottom High collagen
MRS	Low GAG/collagen Low GAG/lactate High lactate/collagen ratio	Stages of metabolites: lactate, alanine, GAG	High levels of glycogen and collagen Acute glycosaminoglycan spike Decreased collagen-to-lactate ratio

Preliminary biochemical and architectural alterations inside the disc can be investigated using these functional MRI methods; these changes occur before structural changes and functional impairment. So, before invasive surgical procedures are necessary, QMRI may be able to start the IVD degenerative process and guide patients to regeneration therapy. But there are a number of reasons why these methods aren't employed frequently: they're hard to come by, they take longer to acquire than what's clinically feasible, and there isn't enough standardisation and validation.

6. NEW DIAGNOSTIC PERSPECTIVE: ARTIFICIAL INTELLIGENCE

Several areas of healthcare are seeing rapid use of artificial intelligence (AI). Right now, artificial intelligence is finding a lot of use in medical image analysis. It was proposed that artificial intelligence (AI) applied to MR pictures can provide a rapid and reliable diagnostic as well as prognosis prediction for spinal illnesses. Radiologists often use their subjective and time-consuming knowledge to analyse the intensity, form, and other properties of intravascular discovascular defects (IVDs) in MRI of the spine. This includes disc localization, segmentation, and other similar tasks. Over the past ten years, a number of research have looked into the possibility of using AI to evaluate DDD in MR images. Indeed, developing and testing algorithms that mechanically analyse MR scans to objectively measure DDD is very desirable. For example, it has been shown how AI integrated with ML can reliably and accurately grade IVD degeneration in MRI images. Research on the subject has utilised MRI knowledge to accomplish feature tasks, with the majority of research achieving accuracy rates and Sørensen-Dice coefficients over 85%.

Validation and refinement of results generally need user supervision, despite the high reliability of these procedures. Further research into the usage of AI to analyse IVD degeneration in MR images is anticipated to be undertaken in the near future. This technology has the potential to alleviate work stress for radiologists, aid in clinical decision making, and ultimately lower expenses associated with spinal illnesses by enhancing the indications for medicinal or surgical therapy.

6. RELATED WORKS

Table 2: Survey of existing models for spinal cord injury

Author with reference	**Methodology**	**Advantage**	**Dataset**	**Performance Metrics**	**Limitation**
Raju, P. V., et al., [16] (2023)	Predicting outcomes in traumatic and non-traumatic SCI using a correlated graph model (CGM) that uses correlated learning	For the purpose of predicting differences from other locations, the suggested CGM builds the connectivity pattern among the wounded region.	This research makes use of the publicly available Cancer Imaging Archive dataset.	Accuracy: 99.5%; RMSE: 3.12±0.03	The time complexity of the CGM model is high.
Kalyani, P., et al., [17] (2023)	Extreme gradient boosting (XGBoost)	Medical expenses can be effectively reduced and the efficacy of personalised neurotherapeutics for SCI patients can be predicted with this methodology, which enables clinicians to treat alterations.	ASIA Impairment Scale [AIS] D and E	Accuracy: 81.1%; AUC: 0.867	Overfitting presents in this research work.
Blanc, C., et al., [18] (2023)	Innovative automatic segmentation solution that leverages neural network power and deterministic approach flexibility	The technique begins by repeatedly running the PropSeg algorithm on tiny MRI spinal cord with different starting values.	The adult dataset from the spine generic project	Dice score = 0.88	CNN requires large amount of dataset, but only few samples are used for this work.
Bao, X. X., et al., [19] (2024)	Features such as intensity statistics, grey level co-occurrence matrices, Gabor textures, local binary patterns, and superpixel areas yielded by a simple linear iterative clustering method were used to construct the feature sets. Also, support vector machines really come into their own when it comes to classification.	The recognition method based on the combination of superpixel and SVM technology is insensitive to the shape and size of the spinal necrosis area.	T1- and T2-weighted MRI spinal cord images	With respect to ACC, the recognition results were 1.00±0.00, PPV was 0.89±0.09, SE was 0.88±0.12, SP was 1.00±0.00, and dice was 0.88±0.07.	In cases where there is a lot of noise in the dataset, such as when the target classes overlap, poorly.
Fei, N., et al., [20] (2023)	A suggested heatmap distance loss for auto-segmentation was used to train the UNet model.	The projected segmentation perfect has the conceivable to offer a more cord enumerating a more thorough status of the cervical spinal cord.	An complete sample size of 89 patients with CSM was recruited for this study. All of the CSM patients are examination	The fractions of the error among the two standards of manifold ROIs were 0.07, 0.07, 0.11, and 0.08 on the left side	Dissimilar categories of input images possibly affect the performance of segmentation, and many factors of MRI sequences can affect the diffusion tensor imaging (DTI) images.
Hallinan, J. T. P. D., et al., [21] (2023)	Convolutional Neural Network is used	Delays in therapy are linked to worse results, higher expenses, and shorter survival rates; earlier CT identification of ESCC may alleviate these problems.	The DL model was trained and validated using data from 183 patients in total. For the purpose of DL perfect evaluation, a	The DL model demonstrated acceptable sensitivity (91.82), specificity (92.01), and area under the curve (0.919), with a high kappa (κ = 0.879).	Overfitting issues is not addressed.

			distinct group of 40 patients underwent 60 matched MRI and staging CT images spaced no more than 2 months apart.		
Nozawa, K., et al., [22] (2023)	Utilising U-Net, DeepLabv3+, and PyTorch, the CNN architecture was constructed.	We successfully segmented patients using deep learning using MRI of deformed cords as training material. The results were highly concordant with expert manual segmentation.	There were a total of 27,62 axial slices taken from 174 patients; 32 individuals had an extra 517 slices held for validation; and 46 patients had 777 slices for testing.	Spearman's rank correlation coefficient = 0.38 ($p = 0.007$),	Segmentation only carried out in this work, classification of injury is not mentioned.
Wang, Z., et al., [23] (2023)	U-Net CNN is used for segmentation	We suggest using networks for accurate segmentation of spinal MRI images based on their features and the strong contrast among the grey levels of vertebrae in these images. This approach is based on cross-validation.	From 2013 through 2023, our institution collected 210 MRI pictures of the spinal cord in people; 195 of these images served as the training set, while 15 served as the test set.	average segmentation accuracy of over 88%.	One disadvantage of this technique is that it is time consuming a precisely.
Harris, R. J., et al., [24] (2023)	A model was industrialized to screen for critical epidural lesions	This perfect has value for together worklist prioritization of emergent studies and recognizing missed findings.	Training with epidural lesions was possible in 153 trials. trained using these segmented lesions. We also used epidural lesions that had been overlooked in the past to generate a test data set.	In terms of specificity, the ideal detected epidural lesions in 50% of cases. With a 98.9 percent specificity rate, the algorithm prioritised 18 out of 18 epidurals for prospective data correctly on the first read.	Memory requirement is high in this work.
Mohanty, R., et al., [25] (2023)	Multiple Mask Regional were trained on countless datasets for district segmentation	The model is very adaptable for a broad range of spinal cord tumour categorization scenarios due to its consistent performance across various tumour kinds and areas of the cord.	Mendeley datasets	On average, the suggested model outperformed the state-of-the-art models in terms of speed (15.6% improvement), accuracy (98.9% for tumour classification), and segmentation efficiency (14.5%) across the board.	The spreads of tumor was not identified by the model.

7. DISCUSSION

7.1.1. Main Findings

An independent predictor of adverse outcomes is the change in SC signal on the preliminary MRI following traumatic SCI, according to the data. Patients experiencing a change in their SC signal had a 109% increased risk of experiencing an adverse event, and this risk persisted even after accounting for age and baseline AIS weakening. The fact that 55% of patients were ambulatory at the beginning of the study and were 64% less likely to be ambulatory at the end of the study is indicative of a shift in SC signals that is consistent with severe neurological impairment. Patients experiencing a SC signal shift also tended to have longer hospital stays, however this was not associated with any different fatality rates. The SC signal intensity is a quick and accurate way to evaluate the expected result, modify the treatment options and inform the patient in order to perhaps change the real result.

The main harm occurs when the first mechanical force acts on the SC. These injuries can be caused by either impact with brief compression (like a hyperextension injury) or impact with chronic compression, scarring, cause subsequent injuries when these pressures harm the SC routes and blood vessels. In order to brand broad predictions about the patient's short- and long-term prognosis following severe SCI, the authors believe that first MRIs should be obtained and evaluated with great care.

7.2.1. Frequency of Abnormal Findings

Ligamentous Injury

The incidence of ligamentous damage varied from zero to one hundred percent in the ten investigations that concentrated on individuals with SCIWORA. The overall incidence of ligamentous damage in SCIWORA was 36% (145 out of 404 studies were excluded because their cohorts overlapped), nevertheless, there was a substantial level. Similarly, across all patients with SCI (190/483 over 12 trials), the combined occurrence of ligamentous damage was 39%, and there was a significant amount of heterogeneity $(I2 = 0.93, p < 0.01)$.

7.2.2. Disc Injury/Herniation

Studies include cervical SCIWORA found a disc damage rate of 4% to 42%, but other SCI studies found a rate of 40% to 88%. While 37% to 100% of individuals with SCIWORA had disc herniation, 24% to 100% of those with SCI had the condition. Two compression in 3% to 83% of cases. There was a high level of variability among studies in SCIWORA, with an damage of 20% (46/230) and disc of 45% (102/229); both results were statistically significant (p < 0.001). All studies (SCIWORA and SCI) showed a pooled frequency of 26% (71/278), 43% (159/370), and 16% (12/74) of disc herniation causing cord compression, disc injury, respectively. Heterogeneity was high across all examines $(I2 = 0.95, 0.83, and\ 0.98, respectively, with\ all\ p <$ 0.001).

7.2.3. Cord Compression

The cord density frequency was 89% (63/71) in a cohort study of sub axial SCI patients with a T1w sagittal sequence, 92% (65/71) with a $T2w$ sagittal sequence, and 96% (68/71) when both results were positive. Five investigations in SCIWORA found evidence of cord compression in patients ranging from 0% to 100%. Two investigations found that between 65 and 83 percent of patients with cervical dislocations had cord compression. One research found that the frequency of cord compression decreased from 65% (11/17) before traction to 12% (2/17) after traction for patients with fracture-dislocation. Cord density occurred in 41% of patients with SCIWORA (47 out of 116) and in 70% of all instances of SCI (413 out of 589). There was a substantial level of heterogeneity in both categories (I2 = 0.94 and 0.95, respectively, with both p < 0.001).

7.2.4. Epidural Hematoma

The data demonstrated significant heterogeneity (I2 = 0.92, p < 0.01), with three studies on cervical SCI reporting patients, for a combined pooled incidence of 10% (20/198).

7.2.5. Fracture

The investigations reported a frequency of 15% (6/41), with a range of 10% to 20%; the results were consistent across the two studies, with $0, p = 0.2$, regarding the identification of fractures in individuals with SCI.

7.2.6. Intramedullary Lesions in SCIWORA

There were 44 thoracic damages included in the research that revealed how often intramedullary signal changes in individuals with SCIWORA. A total of 40% (74/187) of cases were simple edoema, and 77% (291/380) were any intramedullary lesion (including edoema, contusion, haemorrhage, or cavitation) [19,24,32-38,40-42,45]. There was a significant level of heterogeneity amongst the studies, with I2 values of 0.90 and 0.91 respectively, and both p < 0.001.

8. INFLUENCE OF MRI ON CLINICAL DECISION-MAKING

Based on MRI results in acute SCI, several studies have provided data on whether surgery is necessary, the best surgical technique, the optimal operating time, if instrumentation is necessary, which levels to decompress, and whether reoperation is necessary following surgery.

8.1. If Surgery Is Required

Disc herniation, instability, ligamentous damage, cord compression, and intramedullary edoema (together with cord compression were among the specific MRI results that allegedly prompted the decision to undergo surgical therapy. There was a noteworthy level studies (I2 = 0.96, p < 0.001) and the reported incidence of MRI results foremost to an operating decision varied from 3% to 100% among studies, with a pooled regular of 36% (223/611).

8.2. Surgical Approach

From 3% to 83% of instances, seven studies justified anterior surgery by stating that the patient had an acute disc herniation with cord compression. According to two further SCIWORA investigations, MRI dictated the surgical tactic in all patients who needed surgery. The reasons given for choosing anterior surgery were kyphosis, anterior compression restricted to 1-3 segments, and anterior compression in general. In the included trials, 143 out of 500 patients, or 29% of the total, had their surgical approach impacted by MRI, and there was a lot of heterogeneousness ($I2 = 0.97, p < 0.01$).

8.3. When to Function

Emergency surgery was necessary for 49% to 52% of patients in two linked investigations with overlapping datasets because of cord compression shown by magnetic resonance imaging (MRI). Between one-third and eighty-two percent of patients had satisfactory decompression following traction/closed reduction, allowing them to postpone surgery for permanent fixation, according to two studies. There was a lot of heterogeneity in the meta-analysis, with 78% (65/83) of patients having their surgery scheduling impacted by MRI ($I2 = 0.84, p = 0.1$).

8.4. Essential for Instrumentation

Instrumented fusion was shown to be necessary in one investigation because of the presence of segmental instability. Severe edoema on magnetic resonance imaging (MRI) and any degrees of ligamentous damage (19 out of 23 patients) or segmental instability during surgery (2 out of 23 patients) were found to be amenable to decompression and fusion, according to this study.

8.5. Which Levels to Decompress

According to one research, the decision of which level(s) to decompress and fuse was based on intraoperative instability results and magnetic resonance imaging (MRI) findings of edoema and ligamentous damage.

8.6. Need for Re-Operation after Surgical procedure

There were 2-studies that used MRI following spinal cord injury (SCI) surgery to check for sufficient cord compression. Additional posterior surgical decompression was performed after one research discovered that 11 out of 28 individuals who underwent anterior compression. Inadequate decompression was observed in 63 out of 184 patients who underwent surgery for acute SCI; this finding emphasises the significance of potential necessity of expansile duraplasty and multi-level laminectomy.

9. LIMITATIONS

Spine MRIs were acquired according to clinical indications and using diverse imaging methods, rather than as part of a formal research methodology. This is an inherent drawback of the study. However, the study was able to do thorough and consistent analysis on scans that mirrored the actual experience, which might make our findings more applicable to a broader context. We may have underestimated the proportion of silent lesions discovered in our analysis since spinal cord MRI was conducted based on clinical indication, which meant that it was more commonly sought for children with clinical indications of myelitis. While studies employing images taken during acute myelitis had a higher incidence of gadolinium-enhancing lesions, our study did not need clinical myelitis at the time of MRI collection, therefore we can safely assume that this is not the case. Because of the extended interval between clinical attack and spine MRI acquisition in the MS group compared to other groups, this is of special relevance to them.

10. CONCLUSIONS

When possible, MRI must use in patients with acute SCI of any manifestation since it is safe and often finds critical abnormalities with strong diagnostic accuracy that change therapeutic care. Hence, it seems that the scepticism that some surgeons have regarding using MRI to influence decisions in cases with acute SCI is unwarranted. There is some indirect evidence that supports the former CPG advice "that MRI be performed in adult patients with acute SCI prior to surgical intervention, when feasible, to facilitate improved clinical decision-making," although it is not conclusive. To better understand the value and ROI of MRI for particular SCI types, further prospective studies are required. This will enable for more robust suggestions to be made to enhance and standardise clinical practice.

REFERENCES

1. Pfyffer, D., & Freund, P. (2021). Spinal cord pathology revealed by MRI in traumatic spinal cord injury. *Current Opinion in Neurology, 34*(6), 789-795. https://doi.org/10.1097/WCO.0000000000000985
2. Jin, C., Zhao, L., Wu, J., Jia, L., Cheng, L., & Xie, N. (2021). Traumatic cervical spinal cord injury: relationship of MRI findings to initial neurological impairment. *European Spine Journal, 30*, 3666-3675. https://doi.org/10.1007/s00586-021-07048-8
3. Smith, A. C., Albin, S. R., O'Dell, D. R., Berliner, J. C., Dungan, D., Sevigny, M., ... & Weber II, K. A. (2021). Axial MRI biomarkers of spinal cord damage to predict future walking and motor function: a retrospective study. *Spinal Cord, 59*(6), 693-699. https://doi.org/10.1038/s41393-021-00633-1
4. Jahanian, O., Van Straaten, M. G., Goodwin, B. M., Lennon, R. J., Barlow, J. D., Murthy, N. S., & Morrow, M. M. (2022). Shoulder magnetic resonance imaging findings in manual wheelchair users with spinal cord injury. *The Journal of Spinal Cord Medicine, 45*(4), 564-574. https://doi.org/10.1080/10790268.2021.1887692
5. Arnet, U., de Vries, W. H., Eriks-Hoogland, I., Wisianowsky, C., van der Woude, L. H., Veeger, D. H., ... & SwiSCI Study Group. (2022). MRI evaluation of shoulder pathologies in wheelchair users with spinal cord injury and the relation to shoulder pain. *The Journal of Spinal Cord Medicine, 45*(6), 916-929.

https://doi.org/10.1080/10790268.2021.1941981
6. David, G., Pfyffer, D., Vallotton, K., Pfender, N., Thompson, A., Weiskopf, N., ... & Freund, P. (2021). Longitudinal changes of spinal cord grey and white matter following spinal cord injury. *Journal of Neurology, Neurosurgery & Psychiatry, 92*(11), 1222-1230. https://doi.org/10.1136/jnnp-2020-325910
7. Lee, S. Y., Schmit, B. D., Kurpad, S. N., & Budde, M. D. (2022). Acute magnetic resonance imaging predictors of chronic motor function and tissue sparing in rat cervical spinal cord injury. *Journal of Neurotrauma, 39*(23-24), 1727-1740. https://doi.org/10.1089/neu.2021.0438
8. Leguy, S., Combès, B., Bannier, E., & Kerbrat, A. (2021). Prognostic value of spinal cord MRI in multiple sclerosis patients. *Revue Neurologique, 177*(5), 571-581. https://doi.org/10.1016/j.neurol.2020.12.006
9. [9] Murphy, S. A., Furger, R., Kurpad, S. N., Arpinar, V. E., Nencka, A., Koch, K., & Budde, M. D. (2021). Filtered diffusion-weighted MRI of the human cervical spinal cord: feasibility and application to traumatic spinal cord injury. *American Journal of Neuroradiology, 42*(11), 2101-2106. https://doi.org/10.3174/ajnr.A7287
10. Cohen-Adad, J., Alonso-Ortiz, E., Abramovic, M., Arneitz, C., Atcheson, N., Barlow, L., ... & Xu, J. (2021). Generic acquisition protocol for quantitative MRI of the spinal cord. *Nature Protocols, 16*(10), 4611-4632. https://doi.org/10.1038/s41596-021-00580-6
11. Costanzo, R., Brunasso, L., Paolini, F., Benigno, U. E., Porzio, M., Giammalva, G. R., ... & Maugeri, R. (2022). Spinal tractography as a potential prognostic tool in spinal cord injury: a systematic review. World Neurosurgery, 164, 25-32.
12. **[12]** Brayda-Bruno, M., Albano, D., Cannella, G., Galbusera, F., & Zerbi, A. (2018). Endplate lesions in the lumbar spine: A novel MRI-based classification scheme and epidemiology in low back pain patients. *European Spine Journal*, 27(11), 2854-2861. DOI: [10.1007/s00586-018-5787-6](https://doi.org/10.1007/s00586-018-5787-6)
13. Bamberg, F., Hetterich, H., Rospleszcz, S., Lorbeer, R., Auweter, S. D., Schlett, C. L., ... & Peters, A. (2017). Subclinical disease burden as assessed by whole-body MRI in subjects with prediabetes, subjects with diabetes, and normal control subjects from the general population: The KORA-MRI study. *Diabetes*, 66(1), 158-169. DOI: [10.2337/db16-0734](https://doi.org/10.2337/db16-0734)
14. **[14]** Yu, A. C., Mohajer, B., & Eng, J. (2022). External validation of deep learning algorithms for radiologic diagnosis: A systematic review. *Radiology: Artificial Intelligence*, 4(3), e210064. DOI: [10.1148/ryai.210064](https://doi.org/10.1148/ryai.210064)
15. Liu, B., Yu, L., Che, C., Lin, Q., Hu, H., & Zhao, X. (2023). Integration and performance analysis of artificial intelligence and computer vision based on deep learning algorithms. *arXiv preprint arXiv:2312.12872*. DOI: [10.48550/arXiv.2312.12872](https://doi.org/10.48550/arXiv.2312.12872)
16. **[16]** Raju, P. V., Asanambigai, V., & Mudunuri, S. B. (2023). A learning-based correlated graph model for spinal cord injury prediction from magnetic resonance spinal images. *International Journal of Advanced Computer Science and Applications*, 14(1). DOI: [10.14569/IJACSA.2023.0140127](https://doi.org/10.14569/IJACSA.2023.0140127)
17. Kalyani, P., Manasa, Y., Ahammad, S. H., Suman, M., Anwer, T. M. K., Hossain, M. A., & Rashed, A. N. Z. (2023). Prediction of patient's neurological recovery from cervical spinal cord injury through XGBoost learning approach. *European Spine Journal*, 1-9. DOI: [10.1007/s00586-023-07551-y](https://doi.org/10.1007/s00586-023-07551-y)
18. **[18]** Blanc, C., Shahrampour, S., Mohamed, F. B., & De Leener, B. (2023). Combining PropSeg and a convolutional neural network for automatic spinal cord segmentation in pediatric populations and patients with spinal cord injury. *International Journal of Imaging Systems and Technology*. DOI: [10.1002/ima.22779](https://doi.org/10.1002/ima.22779)
19. Bao, X. X., Zhao, C., Bao, S. S., Rao, J. S., Yang, Z. Y., & Li, X. G. (2023). Recognition of necrotic regions in MRI images of chronic spinal cord injury based on superpixel. *Computer Methods and Programs in Biomedicine*, 228, 107252. DOI: [10.1016/j.cmpb.2023.107252](https://doi.org/10.1016/j.cmpb.2023.107252)
20. Fei, N., Li, G., Wang, X., Li, J., Hu, X., & Hu, Y. (2023). Deep learning-based auto-segmentation of spinal cord internal structure of diffusion tensor imaging in cervical spondylotic myelopathy. *Diagnostics*, 13(5), 817. DOI: [10.3390/diagnostics13050817](https://doi.org/10.3390/diagnostics13050817)
21. Hallinan, J. T. P. D., Zhu, L., Tan, H. W. N., Hui, S. J., Lim, X., Ong, B. W. L., ... & Tan, J. H. (2023). A deep learning-based technique for the diagnosis of epidural spinal cord compression on thoracolumbar CT. *European Spine Journal*, 1-10. DOI: [10.1007/s00586-023-07495-3](https://doi.org/10.1007/s00586-023-07495-3)
22. **[22]** Nozawa, K., Maki, S., Furuya, T., Okimatsu, S., Inoue, T., Yunde, A., ... & Orita, S. (2023). Magnetic resonance image segmentation of the compressed spinal cord in patients with degenerative cervical myelopathy using convolutional neural networks. *International Journal of Computer Assisted Radiology and Surgery*, 18(1), 45-54. DOI: [10.1007/s11548-022-02668-8](https://doi.org/10.1007/s11548-022-02668-8)
23. Wang, Z., Xiao, P., & Tan, H. (2023). Spinal magnetic resonance image segmentation based on U-net. *Journal of Radiation Research and Applied Sciences*, 16(3), 100627. DOI: [10.1016/j.jrras.2023.100627](https://doi.org/10.1016/j.jrras.2023.100627)
24. Harris, R. J., Baginski, S. G., Bronstein, Y., Schultze, D., Segel, K., Kim, S., ... & Baker, B. (2023). Detection of critical spinal epidural lesions on CT using machine learning. *Spine*, 48(1), 1-7. DOI: [10.1097/BRS.0000000000004354](https://doi.org/10.1097/BRS.0000000000004354)
25. Mohanty, R., Allabun, S., Solanki, S. S., Pani, S. K., Alqahtani, M. S., Abbas, M., & Soufiene, B. O. (2023). NAMSTCD: A novel augmented model for spinal cord segmentation and tumor classification using deep nets. *Diagnostics*, 13(8). DOI: [10.3390/diagnostics13081234](https://doi.org/10.3390/diagnostics13081234)

AUTHORS

Aswathy V K is a research scholar at the Computer Science and Engineering Department, Sathyabama Institute of Science and Technology, Chennai. Her research interests lie in the realms of Artificial Intelligence and Machine Learning.

Dr. P. Asha is a Professor of Computer Science and Engineering Department, Sathyabama Institute of Science and Technology, Chennai. She has 17 years of working experience in Teaching and Research. Her area of Specialization includes Machine Learning, Internet of Things, Artificial Intelligence, Parallel Computing, Computer Graphics, Visualization and Data Mining. She has 100+ research publications and 60+ in Scopus/ Web of Science Journals and Conferences along with 6 Granted Patents and Copyrights. She serves as a reviewer for many Scopus and Web of Science Journals with High Impact factor. She has also published books on Machine Learning, Web of Things, Data Analytics with Python and Industry 4.0 support by Machine Learning.