DCM Modeling

DCM Modeling **Degenerative cervical myelopathy: Treatment implementation through perioperative neurophysiology, simulation and modelling with AI integration**	
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D1.1 SOTA – version 1: State of the Art

Related WP	**WP1 – Research and Analysis. Month 1 – 12.**
Related Task	**Task 1.1 –** To define the state of the art, a literature analysis will be conducted in the different reference areas, namely: currently published FEM spinal cord models (if any), clinical and statistical models of DCM management
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0.1	Table of Contents (ToC)	
0.2	FEM spinal cord models added	
0.3	Clinical and statistical models of DCM management	
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Executive summary

Deliverable D1.1 – SoTA (State of the Art), developed within Task 1.1, presents a comprehensive review of current research related to DCM, focusing on FEM modeling, clinical and statistical approaches, and ML techniques applied to disease assessment, management, and prognosis.

The document is based on a systematic analysis of the scientific literature across multiple relevant domains. It reviews existing FEM models of the cervical spinal cord, highlighting commonly adopted biomechanical assumptions, modeling strategies, and reported limitations. In parallel, the deliverable examines clinical, statistical, and ML-based models used in DCM diagnosis and outcome prediction, as well as neurophysiological prognostic factors associated with cervical myelopathy progression.

Additionally, the role of medical imaging modalities in the evaluation and modeling of DCM is discussed, emphasizing their contribution to anatomical characterization, disease assessment, and data-driven modeling frameworks.

This SoTA analysis identifies current challenges and research gaps, particularly regarding the integration of biomechanical modeling with data-driven methods. The insights provided in this deliverable establish a scientific baseline for subsequent project activities and support the development of advanced, patient-specific modeling and decision-support methodologies for degenerative cervical myelopathy.

The deliverable is structured as follows:

Section 1 – Introduction provides an overview of degenerative cervical myelopathy, outlining the clinical background, motivation, and objectives of the SoTA analysis.

Section 2 – AI-based MRI image analysis for DCM reviews current ML approaches applied to cervical spine assessment, with a focus on MRI-based analysis. Subsection 2.1 discusses ML methods used in the analysis of cervical spine structures, while Subsection 2.2 focuses on ML-based techniques for the analysis and interpretation of MR images in the context of DCM.

Section 3 – ML-based analysis of clinical data presents existing machine learning approaches applied to clinical and demographic data for DCM diagnosis, prognosis, and outcome prediction. Subsection 3.1 reviews publicly available spine MRI databases relevant for data-driven modeling and algorithm development.

Section 4 – Finite Element Modeling of the Cervical Spine provides a comprehensive overview of FEM approaches used in cervical spine and spinal cord modeling. This section includes systematic assessments of FEM in cervical spinal cord biomechanics, patient-specific FEM approaches, and applications in modeling disease severity, neurological dysfunction, and surgical planning. Specific surgical evaluation scenarios, including posterior decompression, anterior cervical discectomy and fusion, adjacent segment biomechanics, and motion-preserving alternatives, are also discussed, along with the influence of sagittal alignment.

Section 5 – Research Plan outlines how the identified gaps and limitations in the current SoTA will be addressed in subsequent project activities, providing a methodological roadmap aligned with the project objectives.

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List of Abbreviations

Abbreviation	Explanation
DCM	Degenerative Cervical Myelopathy
PST	PAK Solver Tool
UR	User Requirements
MRI	Magnetic Resonance Imaging
AI	Artificial Intelligence
ML	Machine Learning
CNN	Convolutional Neural Network
ANN	Artificial Neural Network
ACDF	Anterior Cervical Discectomy and Fusion
FEM	Finite Element Modeling
PCLF	Posterior Cervical Laminectomy with Fusion
CT	Computed Tomography

1. Introduction

Degenerative Cervical Myelopathy (DCM) is a prevalent and debilitating neurological condition, representing the most common cause of spinal cord dysfunction in adults. It is characterized by progressive degenerative changes in the cervical spine that lead to spinal canal narrowing and compression of the spinal cord, resulting in a range of neurological symptoms and significant disability. With an estimated prevalence of up to 5% in the general European population, DCM poses a substantial public health challenge.

The diagnosis and management of DCM have traditionally relied on clinical evaluation and medical imaging, primarily Magnetic Resonance Imaging (MRI). While MRI is indispensable for confirming cord compression and structural pathology, it has inherent limitations in quantifying the underlying biomechanical forces, such as stress and strain within the cord tissue, that are critical for symptom development and progression. Furthermore, there is a well-recognized variability in patient outcomes following surgical decompression, highlighting the need for more personalized and predictive tools to guide treatment decisions.

In response to these challenges, two major technological frontiers have emerged. First, advanced computational modeling, particularly Patient-Specific Finite Element Modeling (FEM), has developed as a powerful technique to simulate the biomechanical environment of the spinal cord. These models can quantify the stress and strain resulting from static compression and dynamic neck movements, offering unprecedented insights into the pathomechanics of DCM and allowing for the virtual evaluation of different surgical strategies.

Concurrently, the field of medical artificial intelligence (AI) has seen rapid advancements, especially in the analysis of medical images and clinical data. Machine Learning (ML) and Deep Learning (DL) algorithms are now capable of automating the segmentation of spinal structures from MRI, classifying disease severity, and even predicting surgical outcomes by integrating multimodal data, including clinical scores and neurophysiological parameters.

However, a significant gap remains in the integration of these two powerful approaches. While FEM provides deep biomechanical insight, it often lacks the scalability and automation that AI can offer. Conversely, AI models can identify patterns and make predictions, but typically do not provide the causal, mechanistic understanding that biomechanical modeling affords.

This State-of-the-Art (SOTA) analysis, conducted as part of the bilateral Serbia-Italy project "DCM-modeling," therefore aims to comprehensively review and synthesize the current landscape across these complementary domains. The analysis will cover:

- The current capabilities and limitations of MRI and AI-based image analysis for DCM.
- The evolution and present status of Finite Element Modeling of the cervical spinal cord, with a focus on patient-specific applications.
- The role of neurophysiological data and other clinical biomarkers in prognostic assessment.

By mapping the current frontiers in each of these fields, this report lays the foundational knowledge required to achieve the project's primary objective: the innovative integration of patient-specific FEM, High-Performance Computing (HPC), and AI with perioperative neurophysiology to create a holistic and personalized framework for understanding, diagnosing, and treating Degenerative Cervical Myelopathy.

2. AI-based MRI image analysis for DCM

Degenerative cervical myelopathy (DCM) is the leading cause of spinal cord dysfunction in adults, and accurate classification of disease presence and severity on magnetic resonance imaging (MRI) is essential for diagnosis and treatment planning[1]. MRI currently represents the modality of choice for confirming the diagnosis of DCM. It enables detailed assessment of the source and severity of spinal cord compression, the number of affected levels, and the potential need for anterior or posterior decompression based on parameters such as the modified K-line. Furthermore, MRI findings on T1- and T2-weighted sequences provide valuable information, with T2 hyperintensity serving as a more specific indicator of myelopathy than the mere presence of cord compression[2].

2.1 ML in the analysis of the cervical spine

While traditional grading systems such as canal diameter measurements or T2-weighted hyperintensity scoring remain widely used, they suffer from subjectivity and inter-observer variability[3]. There has been a shift toward machine learning and deep learning methods that aim to provide objective and reproducible classification[4].

2.2 ML-based analysis of MR images

Most of the studies have focused on convolutional neural networks (CNNs) and related deep learning architectures. For example, a study on cervical spinal cord compression detection using CNNs demonstrated the ability of deep learning to distinguish compressed from non-compressed cords on MRI[5]. Similarly, CNN-based classification of cervical myelopathy achieved strong performance in differentiating myelopathy from normal cases on axial and sagittal T2-weighted MRI[6]. These works established CNNs as a robust baseline for DCM classification tasks.

This aligns with findings from our earlier work on lumbar spine MRI, where a CNN-based model successfully detected and classified lumbar disc herniations[7]. These results confirm the general applicability of convolutional architectures to spinal imaging and suggest that knowledge transfer from lumbar to cervical applications is feasible. By using transfer learning, cervical classification models may benefit from pretrained lumbar features, by reducing training data requirements and facilitating model development for DCM despite the challenges of limited cervical MRI data. Similar conclusions were reported in a recent chapter, where convolutional neural networks were applied to lumbar MRI for automatic segmentation of vertebrae and discs and for classification of disc herniations, achieving high accuracy on both sagittal and axial views[8]. This further supports the idea that convolutional architectures can generalize across spinal regions and provide a robust baseline for cervical applications.

Alongside CNN-based approaches, other architectures have also been investigated. DCSANet-MD deep learning model, which uses diffusion tensor imaging, achieved 82% accuracy in binary classification (mild and

[1] Tetreault L, Goldstein CL, Arnold P, et al. Degenerative Cervical Myelopathy: A Spectrum of Related Disorders Affecting the Aging Spine. Neurosurgery. 2015;77(suppl_4):S51-S67. doi:10.1227/NEU.0000000000000951

[2] Taniyama T, Hirai T, Yamada T, Yuasa M, Enomoto M, Yoshii T et al (2013) Modified K-line in magnetic resonance imaging predicts insufficient decompression of cervical laminoplasty. Spine 38(6):496–501

[3] Kang, Yusuhn, et al. "New MRI grading system for the cervical canal stenosis." American Journal of Roentgenology 197.1 (2011): W134-W140.

[4] Zhou, S. Kevin, et al. "A review of deep learning in medical imaging: Imaging traits, technology trends, case studies with progress highlights, and future promises." Proceedings of the IEEE 109.5 (2021): 820-838.

[5] Merali, Zamir, et al. "A deep learning model for detection of cervical spinal cord compression in MRI scans." Scientific reports 11.1 (2021): 10473.

[6] Korkmaz, Murat, et al. "Convolutional Neural Networks in the Diagnosis of Cervical Myelopathy." Revista Brasileira de Ortopedia 59 (2025): 689-695.

[7] Šušteršič, Tijana, et al. "A deep learning model for automatic detection and classification of disc herniation in magnetic resonance images." IEEE Journal of Biomedical and Health Informatics 26.12 (2022): 6036-6046.

[8] Sustersic, Tijana, et al. "Computational Modelling and Machine Learning Based Image Processing in Spine Research." (2022).

severe cervical spondylotic myelopathy) and 68% in three-class grading (mild, moderate, severe)[9].

More recent contributions have validated the potential of ensemble learning and hybrid architectures. A recent study applied ResNet, VGG, MobileNet, and EfficientNet models to sagittal T2-weighted MRI, combining them into an ensemble to predict the degree of cervical canal stenosis with an AUC of 0.95 and accuracy of 87.5%[10]. Another study developed model based on a Faster R-CNN architecture, for the automated detection and classification of central canal and neural foraminal stenosis on cervical spine MRI[11]. The model demonstrated comparable diagnostic performance to subspecialist radiologists, achieving an F1 score of 84.8% for the dichotomous classification of central canal stenosis (normal/mild versus moderate/severe), which was better than the radiologists' score (83.8%). Furthermore, this model significantly shortened the diagnosis time, reducing it from an average of 15 seconds to just 0.098 seconds per slice.

Further, Abuhayi et al. proposed Inv-AlxVGGNets, a model that concatenates AlexNet and VGG features augmented with involutional neural networks and residual layers, for four-class cervical spine disease classification on MRI[12]. Their method achieved 98.7% testing accuracy while requiring substantially fewer parameters (<8M) compared to traditional CNNs (>133M), demonstrating both superior diagnostic performance and computational efficiency.

In addition to diagnostic tasks, deep learning has been applied to support clinical decisions, such as surgical planning in cervical spine disorders. A recent study used MRI-based models to guide surgical indications in degenerative cervical spine diseases, achieving Cohen's k of 0.874 for binary classification and up to 0.743 for three-class grading[13]. The developed model demonstrates substantial consistency with experienced spine surgeons and can serve as a tool for clinical decision support.

While these papers highlight the power of deep learning in classification and decision support, it is important to recognize that such tasks often rely on accurate identification of the relevant anatomical structures. In MRI of the cervical spine, this is typically achieved through segmentation, which serves as a fundamental step for reliable classification[14].

Traditional methods for segmenting the cervical spine are performed manually by radiologists or medical experts[15]. This process is time-consuming and creates a critical bottleneck in clinical workflows. Furthermore, manual segmentation is subject to inter-observer variability, which can lead to inconsistencies in diagnosis and planning of the treatment[16]. The challenges are increased by the inherent complexities of the images themselves. Low contrast between vertebrae and surrounding soft tissues, overlapping structures, and various imaging artifacts make it difficult to manually segment boundaries consistently[17]. By automating this process, deep learning models can provide fast and accurate segmentation results, which not only reduces the workload on radiologists but also facilitates the processing of large datasets for both research and clinical applications[18].

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[9] Yang, Shuoheng, et al. "A Deep-Learning-Based Diffusion Tensor Imaging Pathological Auto-Analysis Method for Cervical Spondylotic Myelopathy." *Bioengineering* 12.8 (2025): 806.

[10] Rhee, Wounsuk, et al. "Deep learning-based prediction of cervical canal stenosis from mid-sagittal T2-weighted MRI." Skeletal Radiology (2025): 1-10.

[11] Zhang, Enlong, et al. "Deep learning model for the automated detection and classification of central canal and neural foraminal stenosis upon cervical spine magnetic resonance imaging." BMC Medical Imaging 24.1 (2024): 320.

[12] Abuhayi, Biniyam Mulugeta, Yohannes Agegnehu Bezabh, and Aleka Melese Ayalew. "Inv-AlxVGGNets: Cervical Spine disease Classification using concatenated involutional neural networks with Residual net." IEEE Access (2024).

[13] Li, Kai-Yu, et al. "Deep learning models for MRI-based clinical decision support in cervical spine degenerative diseases." Frontiers in Neuroscience 18 (2024): 1501972.

[14] Q. Zhang et al., "Pathology-Guided AI System for Accurate Segmentation and Diagnosis of Cervical Spondylosis," in IEEE Journal of Biomedical and Health Informatics,

[15] Wang, Zhi, Pingsen Xiao, and Hao Tan. "Spinal magnetic resonance image segmentation based on U-net." Journal of Radiation Research and Applied Sciences 16.3 (2023): 100627.

[16] Nozawa, Kyohei, et al. "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 (2023): 45-54.

[17] A. Suzani, A. Rasoulian, A. Seitel, S. Fels, R. N. Rohling, and P. Abolmaesumi, "Deep learning for automatic localization, identification, and segmentation of vertebral bodies in volumetric mr images," in Medical Imaging 2015: Image-Guided Procedures, Robotic Interventions, and Modeling, vol. 9415. International Society for Optics and Photonics, 2015, p. 941514

[18] Li, Yilin, et al. "Large scale models in radiology: revolutionizing the future of medical imaging." Radiology Science 3.01 (2024): 15-24.

The U-Net architecture remains a backbone of medical image segmentation because of its U-shaped design, which combines a contracting path for context capture and an expansive path for precise localization[19]. The crucial element of its design is the inclusion of skip connections, which pass high-resolution features from the encoder to the decoder, enabling accurate pixel-wise classification even when the anatomical structures are small relative to the image background. This architecture has become a standard baseline for comparison in the field[15].

A recent study demonstrated the successful segmentation of compressed spinal cords in patients with DCM using a model based on U-Net and DeepLabv3+ architectures[20]. The best performance was achieved with a U-Net model combined with an EfficientNet-b7 backbone, which achieved a Dice coefficient of approximately 0.91, showing high concordance with expert manual segmentation. In addition, a 3D MRI segmentation model based on U-net has been developed specifically for cervical spinal stenosis, demonstrating high diagnostic accuracy and objective classification of stenotic regions, further highlighting the potential of deep learning models to optimize cervical spine analysis[21]. While the original U-Net architecture has established itself as a reliable baseline, numerous extensions have been proposed to enhance its performance in complex tasks such as spinal image segmentation. For instance, Zhang et al. introduced SeUneter, a channel-attentive U-Net variant specifically designed for cervical spine MRI segmentation[22]. The model extends the original U-Net structure and incorporates a channel attention mechanism to emphasize informative feature channels while reducing the impact of irrelevant ones. SeUneter achieved state-of-the-art performance on a newly collected dataset of 600 T2-weighted cervical spine MRI images, outperforming baseline U-Net, AttU-Net, UNet++, DeepLab-v3+, TransUNet, and Swin-Unet. With a mean Dice similarity coefficient of 90.67% and a mean Intersection over Union of 82.73%, SeUneter demonstrated the potential of adapted deep learning models to significantly improve the accuracy and robustness of cervical spine segmentation.

Similarly, FractalSpiNet, a recently proposed model, integrates fractal convolutional blocks into the U-Net framework to enable multi-scale feature extraction[23]. This approach was specifically developed for automatic segmentation of the cervical spinal cord and detection of multiple sclerosis (MS) lesions, addressing challenges such as subtle lesions and image artifacts. In a dataset of 87 MS patients, FractalSpiNet achieved a Dice similarity coefficient of 98.88% for CSA segmentation and 90.90% for MS lesion detection.

In addition to methodological advances, the clinical feasibility of U-Net-based models has been demonstrated in a recent study. Zhu et al. quantitatively evaluated a 3D U-Net for automatic segmentation and measurement of cervical spine MRI in 160 patients[24]. Their results showed that approximately 90% of the segmentations required no further correction by radiologists, significantly reducing the time and effort of manual analysis. Beyond accurate segmentation of the spinal cord, the authors introduced novel quantitative indicators, such as anterior and posterior extraspinal spaces.

More recently, researchers have begun to explore more advanced architectures beyond U-Net to address challenges such as low contrast, overlapping structures, and blurred boundaries in cervical imaging. Liu et al. proposed a Transformer-based diffusion model for cervical vertebra segmentation by integrating a diffusion process with Transformer modules to enhance fine structural and boundary features[25]. Their method achieved a Dice score of 93.3% and IoU of 87.5%, outperforming U-Net and SOLOv2. Although the approach required

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[19] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." International Conference on Medical image computing and computer-assisted intervention. Cham: Springer international publishing, 2015.

[20] Nozawa, K., Maki, S., Furuya, T. et al. Magnetic resonance image segmentation of the compressed spinal cord in patients with degenerative cervical myelopathy using convolutional neural networks. Int J CARS 18, 45–54 (2023).

[21] Hohenhaus, Marc, et al. "Quantification of cervical spinal stenosis by automated 3D MRI segmentation of spinal cord and cerebrospinal fluid space." Spinal Cord 62.7 (2024): 371-377.

[22] Zhang, Xiang, et al. "SeUneter: Channel attentive U-Net for instance segmentation of the cervical spine MRI medical image." Frontiers in Physiology 13 (2022): 1081441.

[23] Polattimur, Rukiye, et al. "FractalSpiNet: fractal-based u-net for automatic segmentation of cervical spinal cord and MS Lesions in MRI." IEEE Access (2024)a .

[24] Zhu, Yifeng, et al. "A quantitative evaluation of the deep learning model of segmentation and measurement of cervical spine MRI in healthy adults." Journal of Applied Clinical Medical Physics 25.3 (2024): e14282.

[25] Yang, L. I. U., et al. "Preliminary application of a cervical vertebra segmentation method based on Transformer and diffusion model for lateral cephalometric radiographs in orthodontic clinical practice." Journal of Shanghai Jiao Tong University (Medical Science) 44.12 (2024): 1579.

longer inference time, it exhibited higher robustness and stability in handling noisy, low-quality images, providing accurate and reliable segmentation results.

Furthermore, a transformer-based model known as the Segment Anything Model (SAM) has been introduced, representing a new paradigm for medical image segmentation[26]. Unlike traditional task specific architectures, SAM is trained on billions of images with diverse prompts, enabling it to generalize across different segmentation tasks without requiring large, domain-specific datasets. However, directly applying SAM to medical images, especially high-dimensional MRI data of the spine, remains challenging because of anatomical complexity and the need for accurate prompt generation. To address these limitations, Fan et al. developed MA-SAM, a multi-atlas guided SAM framework that generates pseudo mask prompts without manual annotations, improving segmentation performance on both CT and MRI spine datasets[27].

[26] Kirillov, Alexander, et al. "Segment anything." Proceedings of the IEEE/CVF international conference on computer vision. 2023.

[27] Fan, Dingwei, et al. "Ma-sam: A multi-atlas guided sam using pseudo mask prompts without manual annotation for spine image segmentation." IEEE Transactions on Medical Imaging (2025).

3. ML-based analysis of Clinical data

While MRI remains the gold standard for the diagnosis and grading of DCM, it has notable limitations, particularly regarding subjectivity, inter-observer variability, and limited ability to predict clinical outcomes[28]. This has motivated researchers to focus on blood biomarkers as a complementary or alternative approach for diagnosis, prognosis, and treatment guidance. Biomarkers derived from serum, plasma, and peripheral blood transcriptomes offer the promise of objective, minimally invasive, and reproducible measures of disease activity.

One line of investigation has examined serum protein markers. A prospective study measured a panel of proteins, including neurofilament light chain (NfL), IL-6, BDNF, TNF-α, and Aβ-42 in patients with DCM and healthy controls[29]. NfL and IL-6 were significantly elevated in patients, and preoperative NfL levels correlated with postoperative improvement in hand function, suggesting their dual role as diagnostic and prognostic indicators.

Further, recent studies have used transcriptomic analyses. Peripheral blood RNA expression profiling identified several differentially expressed genes, such as TBCD, TPM2, PNKD, EIF4G2, and AP5Z1 that allowed accurate prediction of lesion severity. In particular, Zheng et al. developed a model using LASSO regression on RNA biomarkers to classify disease severity[30]. Their five-gene model achieved ~93.5% diagnostic accuracy, while single-gene models distinguished mild from severe DCM with accuracies ranging from 76.7% to 83.3%. Further, immune cell populations such as memory B cells and activated CD4+ T lymphocytes were found to support lesion level prediction highlighting the potential of combining transcriptomics with computational modeling.

Inflammatory markers have also been extensively studied. Serum cytokine analysis revealed that IL-6, but not IL-1β, INF-γ, or TNF-α, was significantly elevated in patients with DCM compared with healthy controls. Importantly, IL-6 levels showed a strong correlation with clinical severity, reinforcing the view that inflammation is a central driver of disease progression and positioning IL-6 as a promising biomarker for monitoring disease burden[31].

Finally, work on circulating microRNAs (miRNAs) suggests a novel class of minimally invasive biomarkers. Divi et al. investigated serum profiles of circulating miRNAs in patients with DCM and demonstrated that specific miRNAs were differentially expressed compared with healthy controls[32]. Several of these miRNAs were linked to inflammatory and neurodegenerative pathways, highlighting their potential role in disease pathophysiology. Although still at an exploratory stage, these findings highlight the promise of miRNAs as non-coding RNA signatures that could complement existing protein- and transcriptome-based biomarkers in the diagnosis of DCM.

Beyond imaging and blood biomarker-based models, clinical data have also been used for machine learning applications in DCM. Merali et al. developed and validated random forest models using data from the AOSpine North America and International studies to predict surgical outcomes in DCM patients[33]. The models achieved accuracies up to 77% and an AUC of 0.73 on independent validation, with key predictors including older age,

[28] Wu, Huachuan, et al. "Comparative intra-and inter-observer reliability of two methods for evaluating intraoperative ultrasonography-based spinal cord hyperechogenicity intensity in degenerative cervical myelopathy." BMC musculoskeletal disorders 23.1 (2022): 630.

[29] Kim, Hyun Woo, Hu Yong, and Graham Ka Hon Shea. "Blood-spinal cord barrier disruption in degenerative cervical myelopathy." *Fluids and Barriers of the CNS* 20.1 (2023): 68.

[30] Zheng, Zhenzhong, et al. "Peripheral blood RNA biomarkers can predict lesion severity in degenerative cervical myelopathy." Neural Regeneration Research 20.6 (2025): 1764-1775.

[31] Du, Shengchao, Yuan Sun, and Bizeng Zhao. "Interleukin-6 serum levels are elevated in individuals with degenerative cervical myelopathy and are correlated with symptom severity." *Medical Science Monitor: International Medical Journal of Experimental and Clinical Research* 24 (2018): 7405.

[32] Divi, Srikanth N., et al. "Circulating microRNAs may be predictive of degenerative cervical myelopathy." *Spine* 49.20 (2024): 1393-1400.

[33] Merali, Zamir G., et al. "Using a machine learning approach to predict outcome after surgery for degenerative cervical myelopathy." PloS one 14.4 (2019): e0215133

longer symptom duration, worse baseline disease severity, higher body weight, and smoking status.

Similarly, Park et al. applied ensemble machine learning algorithms (random forest and XGBoost) to classify expert-level therapeutic decisions in DCM, achieving AUC-ROC values above 0.9 across multiclass and binary models[34]. Their analysis identified clinical and electrophysiological factors such as the mJOA score, central motor conduction time, age, and BMI as key determinants in distinguishing between conservative and surgical treatments, as well as between anterior and posterior approaches. These findings demonstrate the feasibility of ML not only for outcome prediction but also for supporting surgical decision-making in DCM. More recently, researchers have also employed ensemble learning strategies to improve predictive performance[35]. A large cohort study of 672 patients with DCM developed stacking-based ensemble classifiers to predict the JOA recovery rate at one year follow-up, achieving superior accuracy compared with individual models. This approach highlights the added value of ensemble methods for prognostic modeling and further supports the integration of ML into clinical management of DCM.

3.1 Publicly available spine MRI databases

As spinal imaging datasets are often limited in size, the inclusion of publicly available datasets should be considered. These publicly available datasets provide valuable resources to complement local data and support the development of more robust models. Table 1 presents an overview of publicly available spinal MRI datasets.

[34] Park, Dougho, et al. "Classification of expert-level therapeutic decisions for degenerative cervical myelopathy using ensemble machine learning algorithms." Frontiers in Surgery 9 (2022): 1010420.

[35] Cai, Zhiwei, et al. "Machine-learning-based prediction by stacking ensemble strategy for surgical outcomes in patients with degenerative cervical myelopathy." Journal of Orthopaedic Surgery and Research 19.1 (2024): 539.

Table 1. Summary of publicly available datasets of spine MRI.

Dataset	Region	Number of images/patients	View	Sequence	Diseases	Download link
MMCSD dataset[36]	Cervical spine	250 patients	Sagittal/Axial	T1/T2	Cervical spondylosis	https://github.com/sjyzy/CSMD
Spine generic[37]	Cervical spine	260 participants	Sagittal/Axial	T1w, T2w, T2*	Healthy controls (normative dataset, no pathology)	https://spine-generic.readthedocs.io/
Dataset of Instrumented Spinal Cord T1/T2-weighted MRI Scans[38]	Spinal cord	About 100 studies with different modalities	Axial	T1w, T2w	Cervical Spondylotic Myelopath, Spinal Cord Injury	https://data.mendeley.com/datasets/sjpx7md7cf/1
Spinal Cord Images - Spine MRI Dataset[39]	Spine	9 studies made from different angles	Sagittal/Axial	/	Osteochondrosis, Spondyloarthrosis, Hemangioma, Physiological lordosis smoothed, Osteophytes	https://www.kaggle.com/datasets/trainingdatapro/spinal-cord-dataset?resource=download
Spine MRI dataset[40]	Lumbar spine	2.4 million spine MRI studies (full access requires licensing and payment)	Sagittal/Axial	/	/	https://unidata.pro/datasets/spine-mri-image-dicom/
Spider Lumbar MRI[41]	Lumbar spine	447 MRI series from 218 patients	Sagittal	T1/T2	Low back pain	https://zenodo.org/records/10159290
Lumbosacral	Lumbar	MRI images of	Sagittal/Axial	T2	Healthy participants	https://doi.org/10.6084/m9.figshare.c.7372564

[36] Yu, Qi-Shuai, et al. "Multi-modal and Multi-view Cervical Spondylosis Imaging Dataset." Scientific Data 12.1 (2025): 1080.
[37] Cohen-Adad, Julien, et al. "Open-access quantitative MRI data of the spinal cord and reproducibility across participants, sites and manufacturers." Scientific data 8.1 (2021): 219.
[38] Sharafi, Azadeh; Koch, Kevin (2024), "Dataset of Instrumented Spinal Cord T1/T2-weighted MRI Scans", Mendeley Data, V1, doi: 10.17632/sjpx7md7cf.1
[39] Spinal Cord Images - Spine MRI Dataset https://www.kaggle.com/datasets/trainingdatapro/spinal-cord-dataset?resource=download accessed 29 Sept 2025
[40] Unidata: Spine MRI dataset https://unidata.pro/datasets/spine-mri-image-dicom/ accessed 29 Sept 2025
[41] van der Graaf, Jasper W., et al. "Lumbar spine segmentation in MR images: a dataset and a public benchmark." Scientific Data 11.1 (2024): 264.

spine MRI dataset[42]	spine	14 participants				
The MS-Multi-Spine Miccai 2025 Challenge	Spinal cord	90 pairs of T2–STIR, 45 pairs of T2–PSIR, 45 pairs of T2–MP2RAGE, and 20 triplets of T2–STIR–MP2RAGE data	Sagittal	T2-STIR, T2–PSIR, T2–MP2RAGE	Multiple Sclerosis	https://portal.fli-iam.irisa.fr/ms-multi-spine/

[42] Liu, Jionghui, et al. "An open-access lumbosacral spine MRI dataset with enhanced spinal nerve root structure resolution." Scientific Data 11.1 (2024): 1131.

4. Finite Element Modeling of Cervical Spine

4.1 Introduction

Degenerative cervical myelopathy (DCM) is widely recognized as the most common cause of spinal cord dysfunction in adults. The disease arises from progressive degenerative changes in the cervical spine, leading to narrowing of the spinal canal, direct compression of the cord, and adverse mechanical loading during physiological motion. Clinical imaging modalities such as MRI and CT can depict the degree of cord compression and structural deformity, but they cannot quantify the internal biomechanical environment of the spinal cord. Yet, it is increasingly understood that static compression and dynamic stress and strain during neck motion contribute significantly to disease progression and neurological outcomes.

Finite element modeling (FEM) has emerged as a powerful computational technique to address this challenge by discretizing patient-derived anatomy into computational meshes with defined material properties. This allows for the simulation of stress and strain under various loading and surgical conditions, offering a window into the otherwise inaccessible internal biomechanical environment of the cord. The evolution of this technology has progressed from simplified, generic models to sophisticated, patient-specific simulations that hold immense promise for clinical translation. In the context of DCM, FEM provides insights into the mechanical consequences of different spinal alignments, degrees of stenosis, and surgical interventions.

This review will outline the current state of the art by first examining the systematic findings that have highlighted the need for standardization and patient-specificity. It will then delve into the latest advances in patient-specific FEM, showcasing its application in correlating biomechanics with disease severity and neurological dysfunction, as well as its groundbreaking potential in pre-surgical planning. Finally, the review will explore the specific insights gained from FEM in evaluating a range of surgical interventions for DCM, culminating in a discussion of emerging directions and remaining challenges in the field.

4.2 Systematic Assessments of FEM in the Cervical Spinal Cord

The work of Singhal et al. (2023) provides the most comprehensive overview of FEM applications in cervical spinal cord biomechanics to date[43]. Reviewing 23 studies, the authors identified that FEM has been employed across three broad domains: injury biomechanics, the study of pathological processes such as myelopathy, and the evaluation of surgical interventions. A major finding of the review was the wide heterogeneity in modeling strategies. Some models represented only the spinal cord, while others included varying combinations of dura mater, cerebrospinal fluid, pia mater, nerve roots, or ligaments. Stress and strain outputs were inconsistently reported, and there was no standardization of loading or boundary conditions. Moreover, dynamic simulations—which are essential for modeling neck flexion, extension, and rotation—were used only in a minority of studies. The review concluded that without standardization and greater use of patient-specific data, FEM would remain confined to the research domain and could not yet inform clinical practice.

This systematic perspective sets the stage for more recent efforts that have sought to move beyond generic or simplified models toward clinically meaningful, patient-specific FEM.

[43] Singhal, I., Harinathan, B., Warraich, A., Purushothaman, Y., Budde, M. D., Yoganandan, N., & Vedantam, A. (2023). Finite element modeling of the human cervical spinal cord and its applications: A systematic review. North American Spine Society Journal (NASSJ), 15, 100246. https://doi.org/10.1016/j.xnsj.2023.100246

4.3 Patient-Specific FEM Approaches

The most significant paradigm shift in cervical spinal cord FEM has been the move towards patient-specific modeling. By constructing computational models directly from individual patient MRI and CT data, researchers have begun to bridge the gap between abstract biomechanical principles and clinical reality. The following subsections detail how this approach is being used to: establish a direct link between mechanical factors and clinical disease severity; correlate computed stress and strain with specific neurological deficits; and simulate surgical procedures to predict their biomechanical outcomes prior to intervention.

4.3.1 Modeling Biomechanical Correlates of Disease Severity

A key methodological advance has been the development of FEM models derived directly from individual patient imaging. Vedantam et al. (2023) applied such patient-specific FEMs to six individuals spanning mild, moderate, and severe DCM[44]. Using MRI-derived geometries, the models incorporated vertebrae, discs, ligaments, dura, pia, cerebrospinal fluid, and spinal cord. The study simulated physiological neck motions to quantify intramedullary stress and strain. A central finding was that segmental range of motion (ROM), particularly during flexion–extension and axial rotation, was more predictive of cord stress and strain than static compression severity alone. This result challenges the prevailing reliance on compression metrics from MRI as the sole indicator of disease severity and suggests that dynamic biomechanical factors may explain why some patients with similar imaging findings experience divergent symptoms.

4.3.2 Linking Biomechanics with Neurological Dysfunction

One of the more significant steps toward clinical translation was achieved by Rahman et al. (2025), who investigated twenty DCM patients with patient-specific FEM simulations[45]. By correlating FEM-derived stress and strain with clinical measures of neurological dysfunction, they provided the first evidence that computational biomechanics aligns with patient symptoms. Increased intramedullary strain correlated strongly with reduced hand sensation and dexterity, and stress values differentiated between mild-to-moderate and severe disease. These findings suggest that FEM outputs could serve as objective, biomechanically grounded biomarkers of neurological impairment, moving beyond purely structural imaging.

4.3.3 Patient-Specific FEM in Surgical Planning

Another line of work has focused on simulating surgical interventions. The study[46] represents a methodological milestone, in which MRI-derived three-dimensional geometries of the cervical cord and surrounding structures were used to construct detailed finite element models in which anterior cervical discectomy and fusion (ACDF) procedures were simulated, complete with bone grafts and instrumentation. This workflow is illustrated in Figure 1, which shows pre-surgical MRI data, segmentation into patient-specific FEM, and the corresponding 1-, 2-, and 3-level ACDF models. The authors found that while spinal cord stress was reduced by approximately 60% at decompressed levels, stress increased substantially at the superior adjacent levels, reaching 160% above baseline in three-level ACDF. Figure 2 demonstrates these differences, showing the distribution of stress across the spinal cord during flexion and extension for single- and multi-level ACDF models. This provides a mechanistic explanation for the phenomenon of adjacent segment degeneration observed clinically after fusion surgery. The study demonstrates the unique ability of patient-specific FEM to reproduce the local

[44] Vedantam, A., Harinathan, B., Purushothaman, Y., Scripp, S., Banerjee, A., Warraich, A., Budde, M. D., & Yoganandan, N. (2023). Determinants of spinal cord stress and strain in degenerative cervical myelopathy: a patient-specific finite element study. Biomechanics and Modeling in Mechanobiology, 22(6), 1789–1799. https://doi.org/10.1007/s10237-023-01732-3

[45] Rahman, M., Banurekha Devaraj, K., Chauhan, O., Harinathan, B., Yoganandan, N., & Vedantam, A. (2025). Intramedullary Stress and Strain Correlate with Neurological Dysfunction in Degenerative Cervical Myelopathy. Applied Sciences, 15(2), 886. https://doi.org/10.3390/app15020886

[46] Vedantam, A., Purushothaman, Y., Harinathan, B., Scripp, S., Budde, M. D., & Yoganandan, N. (2022). Spinal Cord Stress After Anterior Cervical Diskectomy and Fusion: Results from a Patient-Specific Finite Element Model. Annals of Biomedical Engineering, 51(5), 1040–1051. https://doi.org/10.1007/s10439-022-03118-5

benefits of decompression and also to predict adverse biomechanical consequences elsewhere in the spine.

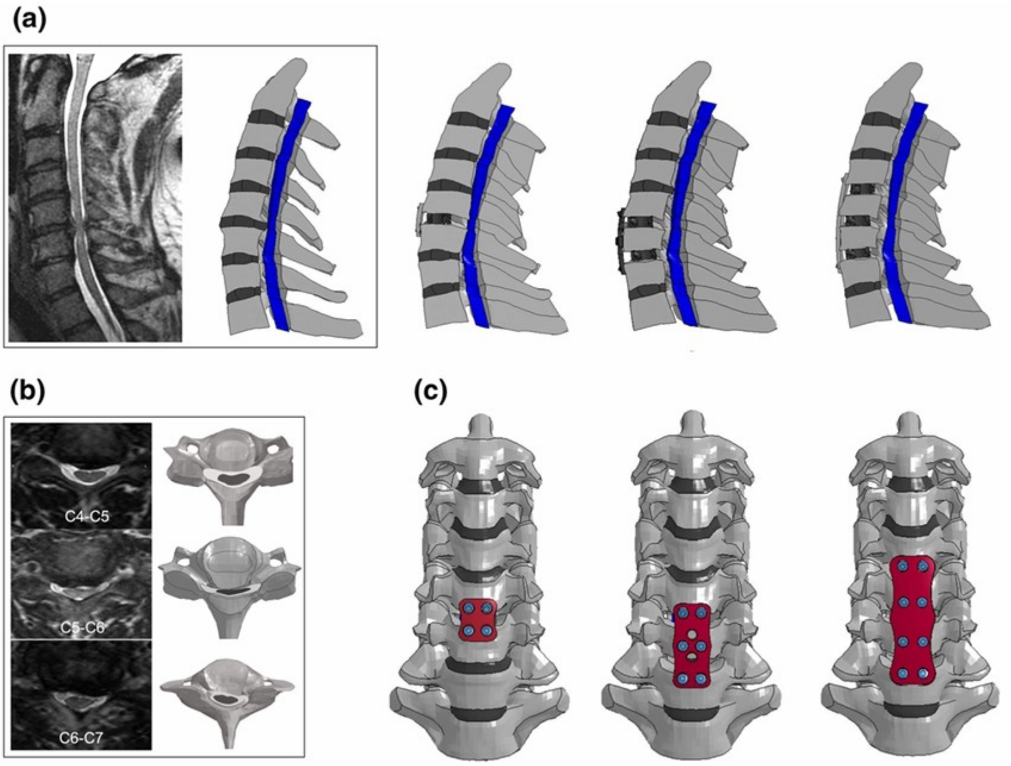

Figure 1. (a, b) Pre-surgical T2-weighted sagittal MRI and pre-surgical patient-specific FE model for DCM patient with multi-level stenosis (axial MRI and FE model at C4–5, C5–6 and C6–7); and (c) 1-, 2- and 3-level ACDF FE models showing osteoligamentous spine and spinal cord shown. (taken from Vedantam et al (2022)[4])

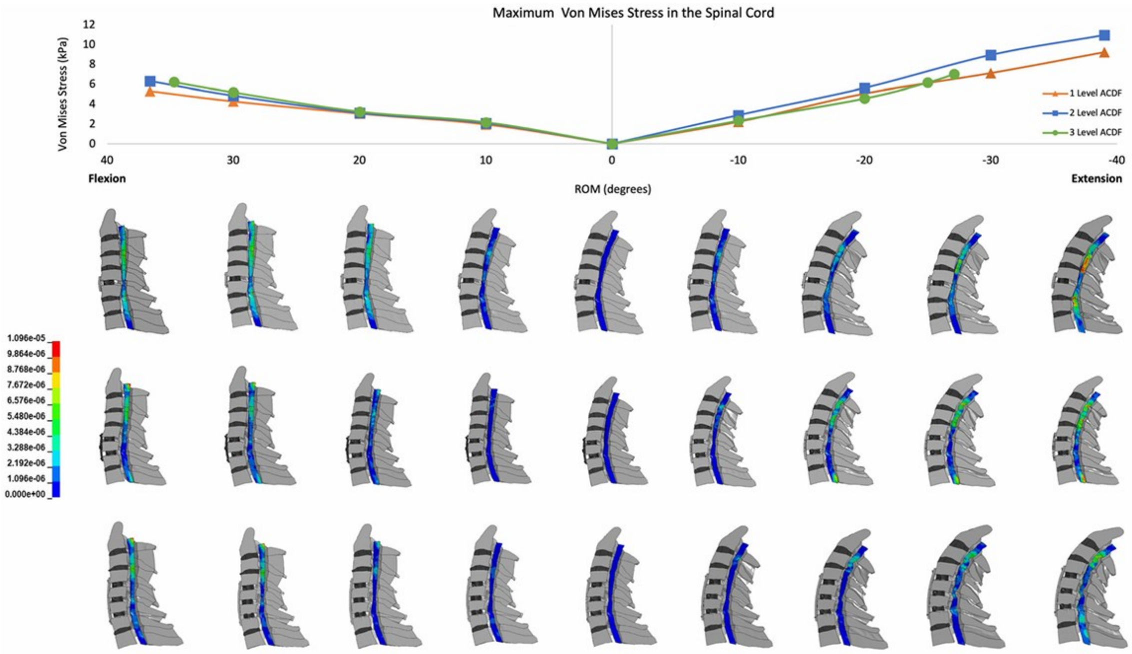

Figure 2. Patterns of spinal cord stress during flexion and extension for 1-, 2-, and 3-level ACDF FE models. (taken from Vedantam et al (2022)[4])

4.4 FEM Applications in Surgical Evaluation

A critical application of patient-specific FEM is the quantitative evaluation and comparison of surgical strategies for DCM. By creating a "digital twin" of a patient's spine, surgeons and engineers can virtually test different decompressive and stabilizing procedures, observing their impact on spinal cord stress and strain in a risk-free environment. This capability provides a mechanistic understanding of why certain procedures succeed or fail and allows for the exploration of inherent surgical trade-offs, such as stability versus mobility. The following sections synthesize findings from recent studies that have employed FEM to analyze the biomechanical consequences of four key surgical approaches: posterior decompression techniques, anterior cervical discectomy and fusion, the comparative effects of anterior versus posterior surgery on adjacent segments, and motion-preserving alternatives like foraminotomy.

4.4.1 Posterior Decompression

Vedantam et al. (2023) compared posterior decompression strategies—laminectomy, laminoplasty, and laminectomy with fusion—using patient-specific FEM[47]. Both laminectomy and laminoplasty increased cord strain during motion, with a 118% increase in extension after laminectomy. By contrast, laminectomy with fusion reduced stress and strain but at the expense of restricted mobility. These results highlight the clinical trade-off between preserving motion and reducing biomechanical loads on the spinal cord.

4.4.2 Anterior Cervical Discectomy and Fusion

In a complementary study, Vedantam et al. (2023) simulated one-, two-, and three-level ACDF procedures[48]. While decompression consistently lowered stress at the surgical levels, it induced marked increases at adjacent segments, particularly in multi-level constructs. Importantly, the increase in stress correlated with greater ROM and intradiscal pressure at adjacent levels. These results demonstrate that while ACDF addresses focal compression, it simultaneously introduces biomechanical risks elsewhere in the cervical spine.

4.4.3 Adjacent Segment Biomechanics

Harinathan et al. (2024) extended this work by comparing anterior (ACDF) and posterior cervical laminectomy with fusion (PCLF)[49]. Their patient-specific FEM simulations showed that ACDF increased stress during flexion at the superior adjacent segment, whereas PCLF increased stress during extension. Both procedures altered intradiscal pressure and ligament strain patterns. This suggests that surgical choice differentially redistributes biomechanical loads and may account for varying patterns of adjacent segment degeneration observed clinically.

4.4.4 Motion-Preserving Alternatives

Yoganandan et al. (2024) modeled posterior foraminotomy as a motion-preserving alternative to fusion[50].

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[47] Vedantam, A., Harinathan, B., Warraich, A., Budde, M. D., & Yoganandan, N. (2023). Differences in spinal cord biomechanics after laminectomy, laminoplasty, and laminectomy with fusion for degenerative cervical myelopathy. Journal of Neurosurgery: Spine, 39(1), 28–39. https://doi.org/10.3171/2023.3.spine2340

[48] Vedantam, A., Purushothaman, Y., Harinathan, B., Scripp, S., Budde, M. D., & Yoganandan, N. (2022). Spinal Cord Stress After Anterior Cervical Diskectomy and Fusion: Results from a Patient-Specific Finite Element Model. Annals of Biomedical Engineering, 51(5), 1040–1051. https://doi.org/10.1007/s10439-022-03118-5

[49] Harinathan, B., Jebaseelan, D., Yoganandan, N., & Vedantam, A. (2024). Comparing adjacent segment biomechanics between anterior and posterior cervical fusion using patient-specific finite element modeling. Asian Spine Journal, 18(6), 777–793. https://doi.org/10.31616/asj.2024.0179

[50] Yoganandan, N., Choi, H., Purushothaman, Y., Vedantam, A., Harinathan, B., & Banerjee, A. (2023). Comparison of Load-Sharing Responses Between Graded Posterior Cervical Foraminotomy and Conventional Fusion Using Finite Element Modeling. Journal of Engineering and Science in Medical Diagnostics and Therapy, 7(2). https://doi.org/10.1115/1.4063465

While foraminotomy preserved motion and reduced adjacent segment overload, excessive facet resection introduced instability. This underscores the delicate balance between achieving decompression and maintaining long-term biomechanical stability.

4.5 Influence of Sagittal Alignment

Sagittal alignment is another major determinant of spinal cord biomechanics. Gundamraj et al. (2024) demonstrated that kyphotic alignment produces significantly higher stress and strain than neutral or lordotic configurations, with baseline stresses reaching 7.53 kPa and strains 5.4% [51]. Rahman et al. (2024) further showed that laminoplasty in kyphotic spines resulted in more than a doubling of stress and strain compared to lordotic spines[52]. These findings provide a biomechanical explanation for the inferior clinical outcomes observed in kyphotic patients undergoing motion-preserving surgery and underscore the importance of incorporating alignment into surgical planning.

4.6 Conclusions

Taken together, the literature demonstrates clear progress but also persistent limitations. Generic FEM studies provided foundational insights but lacked anatomical detail and clinical relevance. Patient-specific FEM now incorporates individualized geometries and has shown correlations with both disease severity and surgical outcomes. However, limitations remain: most models do not differentiate between white and gray matter, tissue properties are still largely cadaveric rather than patient-derived, and sample sizes are small. Moreover, there is no consensus on modeling parameters, leading to variable results across studies.

The central advance of recent years is the demonstration that patient-specific FEM predicts mechanical stress and strain and also correlates with clinical neurological function[3]. This finding, combined with evidence that surgical interventions redistribute stress in complex ways[4–7], establishes patient-specific FEM as the most promising approach for clinical translation.

Future efforts to overcome these limitations should focus on the integration of artificial intelligence (AI) and automated modeling pipelines. For instance, leveraging AI to automatically generate and refine finite element meshes from clinical MRI and CT scans could dramatically increase the speed, reproducibility, and clinical feasibility of patient-specific simulations, ultimately paving the way for their use in routine preoperative planning and personalized intervention strategies."

[51] Gundamraj, S., Devaraj, K. B., Harinathan, B., Banerjee, A., Yoganandan, N., & Vedantam, A. (2024). Effect of sagittal alignment on spinal cord biomechanics in the stenotic cervical spine during neck flexion and extension. Biomechanics and Modeling in Mechanobiology, 23(5), 1757–1764. https://doi.org/10.1007/s10237-024-01866-y

[52] Rahman, M., Palmer, P., Harinathan, B., Banurekha Devaraj, K., Yoganandan, N., & Vedantam, A. (2024). Using Finite Element Models to Assess Spinal Cord Biomechanics after Cervical Laminoplasty for Degenerative Cervical Myelopathy. Diagnostics, 14(14), 1497. https://doi.org/10.3390/diagnostics14141497

5. Research Plan

Based on the comprehensive State-of-the-Art analysis presented, a focused action plan has been formulated to guide the subsequent phases of the DCM Modeling project. The project will concentrate exclusively on DCM, leveraging the insights gained from the review of Finite Element Modeling (FEM) and AI-based medical image analysis. Key FEM objectives have been identified, including the assessment of pressure on the spinal cord, interdiscal pressure, and stress on neighboring spinal levels both before and after simulated surgical interventions. Additionally, the potential of FEM to evaluate the biomechanical impact of flexion/extension dynamics will be explored, as these dynamic factors have been shown to significantly influence cord stress and strain, offering a more complete understanding of DCM pathophysiology beyond static imaging.

To ensure feasibility and depth of analysis, the project will initially forgo a fully parametric 3D FEM approach and instead focus on generating detailed, patient-specific 3D reconstructions for a cohort of 2-3 representative cases. This targeted strategy allows for the development and validation of an integrated modeling pipeline without the prohibitive computational and data requirements of larger parametric studies. The crucial tasks of MRI segmentation and 3D reconstruction will be undertaken by the machine learning team, utilizing advanced deep learning architectures reviewed in this document to ensure accurate delineation of anatomical structures from clinical imaging data.

The execution of this plan will be facilitated by the provision of necessary DICOM files, ensuring that the ML team has direct access to the primary imaging data required for model development. This collaborative workflow between clinical data provision, AI-driven image processing, and patient-specific biomechanical simulation establishes a clear pathway for achieving the project's goal of creating a holistic and personalized framework for understanding and treating DCM, effectively bridging the gap between advanced computational modeling and clinical application.