Artificial Intelligent Approach for Spinal Cord Diseases: A Comprehensive Review

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Abstract

Spinal cord diseases, which include traumatic injuries, degenerative disorders, tumors, congenital anomalies, and infections, have significant challenges to healthcare owing to their complex nature and varying degrees of severity. In recent years, the integration of Artificial Intelligence (AI) techniques such as machine learning (ML), deep learning (DL), and natural language processing (NLP) has shown great potential in enhancing the accuracy of early diagnosis, personalized treatment plans, and predicting disease progression. The paper systematically reviews the existing literature, highlighting AI-driven diagnostic tools, image analysis techniques, and AI-supported rehabilitation strategies. This review can provide a comprehensive understanding of the current AI advancements in spinal cord diseases, identifying gaps and offering insights for future research to improve patient outcomes.

1. INTRODUCTION:

Spinal cord diseases, encompassing traumatic spinal cord injuries (SCIs), degenerative spinal disorders, neoplasms, and infections, become a significant challenge to global healthcare systems due to their complex diagnosis, often irreversible neurological damage, and long-term disability outcomes. According to the World Health Organization, every year, between 250,000 and 500,000 people suffer a spinal cord injury worldwide, with many experiencing chronic pain, paralysis, and reduced quality of life [1]. Traditional diagnostic and treatment approaches, relying heavily on clinical assessment, radiological imaging, and subjective interpretation, often lead to delayed diagnoses and suboptimal therapeutic strategies [2]. The heterogeneity in presentation and progression of spinal cord diseases further complicates early intervention and rehabilitation planning.

In recent years, Artificial Intelligence (AI) has emerged as a transformative force in modern medicine, offering new solutions to longstanding challenges in spinal cord care. Machine learning (ML) and deep learning (DL) models, particularly convolutional neural networks (CNNs), have demonstrated promising results in analyzing magnetic resonance imaging (MRI) and computed tomography (CT) scans, allowing for more accurate identification of spinal pathologies and lesion segmentation [3,4]. Natural Language Processing (NLP) has also been applied to electronic health records to extract meaningful insights for patient stratification and clinical decision support [5]. Moreover, predictive models have been developed to forecast disease progression, rehabilitation outcomes, and treatment responses, facilitating personalized and proactive medical care [6].

AI-based tools have shown efficacy in automating routine diagnostic tasks, reducing inter-observer variability, and assisting clinicians in complex decision-making scenarios. For instance, automated image analysis can help detect early signs of myelopathy or disc degeneration, which might be missed in conventional assessments [7]. Additionally, AI-powered rehabilitation platforms offer adaptive and personalized therapy, enhancing recovery trajectories in patients with spinal cord dysfunction [8].

Despite the promising developments, the integration of AI into spinal cord disease management is still in its infancy. Several challenges remain, including data quality, ethical concerns, model generalizability, and regulatory issues [9,10]. The objective of this review is to provide a comprehensive overview of AI applications in spinal cord diseases, including imaging analysis, clinical decision-making, rehabilitation, and prognosis prediction. The review also identifies research gaps and discusses opportunities to enhance the effectiveness of AI in spinal care.

Following figure1 shows the Block diagram of process flow of AI used in Spinal cord disease detection and recovery.

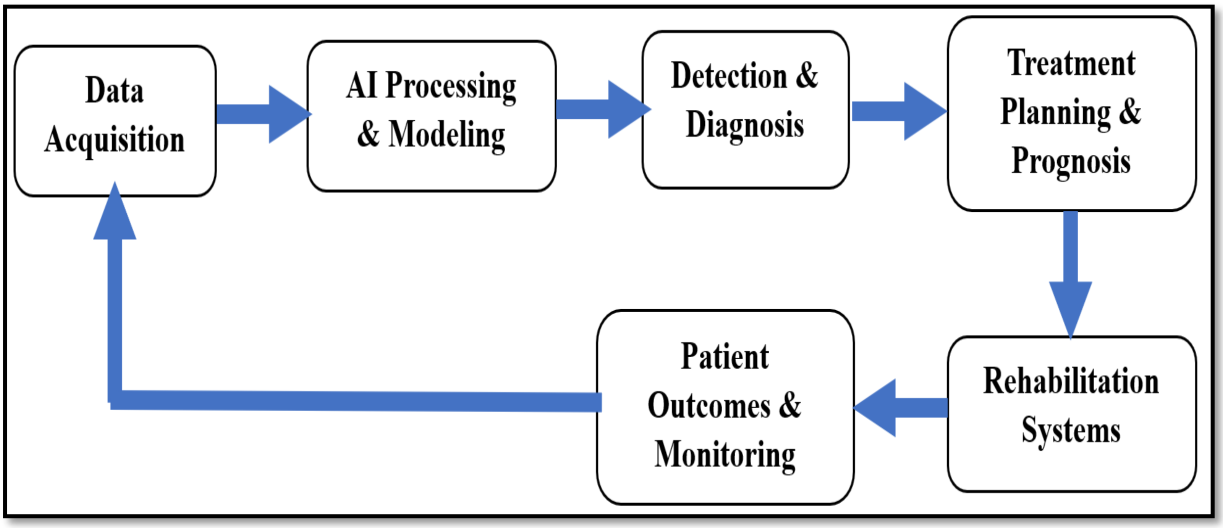

Figure1: Block diagram of process flow of AI used in Spinal cord disease detection and recovery.

Figure 1 shows the basic process used in designing AI model for spinal cord disease detection and recovery. The initial stage is Data Acquisition system. It collects the diverse patient data, including MRI/CT images, clinical records, patient-reported outcomes, and real-time sensor data during rehabilitation. At second stage different AI algorithms, machine learning (ML) and deep learning (DL) algorithms (e.g., CNN, SVM, Random Forests) were used to process data for analysis. This stage involves training and validating AI models. The detection and diagnosis stage AI models analyze data to identify diseases or injuries, their location, and severity. By using this data AI model assists in creating personalized treatment paths and predicting patient recovery or outcomes. In rehabilitation system AI is integrated into physical therapy and assistive technologies to personalize and enhance recovery. The continuous monitoring of patient recovery progress and outcomes will be made to assess the effectiveness of treatment. Then the outcomes data are fed back to into the data acquisition retrain and improve the initial AI models, ensuring continuous refinement of the entire process stage to

2. AI APPLICATIONS IN SPINAL CORD DISEASES

Artificial Intelligence has emerged as a essential technology in advancing diagnostic accuracy, optimizing clinical decision-making, and supporting rehabilitation in patients with spinal cord diseases. AI applications in this domain can be broadly categorized into imaging-based diagnostics, clinical decision support systems, predictive modeling, and rehabilitation technologies. Each category leverages distinct methodologies within machine learning, deep learning, and natural language processing to address existing limitations in spinal cord disease management [11, 12]. These categories are briefly discussed below.

2.1 AI in Imaging-Based Diagnostics:

Radiological evaluation primarily using Magnetic Resonance Imaging (MRI) and Computed Tomography (CT scan) is essential for diagnosing spinal cord injuries, degenerative conditions, tumors, and infections. Conventional imaging interpretation, however, is limited by inter-observer variability and the complexity of spinal anatomy. AI-driven imaging approaches significantly enhance diagnostic performance [13].

A) Lesion Detection and Segmentation: Deep learning, especially convolutional neural networks (CNNs), has excelled in segmenting the spinal cord, intervertebral discs, vertebrae, and intramedullary lesions [14]. U-Net, V-Net, and attention-based segmentation models can delineate subtle abnormalities such as myelomalacia, syringomyelia, and cord edema with high precision [15]. Automated segmentation not only accelerates workflow but also provides quantitative biomarkers critical for clinical assessments.

B) Automated Classification of Spinal Pathologies: AI models have demonstrated high accuracy in classifying spinal conditions including disc degeneration, stenosis severity, tumorous lesions, and traumatic injury grades. Transfer learning models using pre-trained CNNs such as ResNet, DenseNet, EfficientNet enable classification even with limited training data. These models support rapid, particularly in emergency trauma settings where timely diagnosis is crucial [16,17].

C) Extraction of Quantitative Imaging Biomarkers: AI systems are increasingly used to extract high-dimensional features from MRI and CT scans using radiomics. These features—such as texture, shape, and intensity patterns—are associated with disease severity, surgical risk, and neurological prognosis [18]. ML-based radiomic models have shown promise in identifying early degenerative changes and predicting postoperative outcomes [19].

Following table 1 represent results of some researchers that uses AI techniques in Imaging-Based Diagnostics of spinal cord diseases

Table 1: AI techniques in Imaging-Based Diagnostics of spinal cord diseases

Sr. No.	Spinal Cord disease	AI Technique / Model Used	Performance (Accuracy / Metric)	Ref.
1	Spinal Cord Injury (SCI) lesion & cord segmentation	Deep Learning: SCIseg (CNN-based)	Dice: 0.92 (cord), 0.61 (lesion)	[20]
2	Intramedullary spinal cord tumors	Cascaded U-Net / CNN segmentation	Dice: 76.7% (tumor+edema), 61.8% (tumor-only)	[21]
3	Tumor vs. demyelinating lesions (MS/NMOSD)	MultiResUNet + DenseNet121	Classification accuracy: 96%; segmentation Dice varies by lesion	[22]
4	Cervical spondylotic myelopathy (DTI-based segmentation)	Deep Learning: SCS-Net (DTI segmentation)	Improved segmentation reliability over manual (exact Dice not in abstract)	[23]
5	Cervical spondylotic myelopathy (CSM) prediction using MRI-radiomic features	Machine Learning : Random Forest, SVM, Logistic Regression	Random Forest accuracy: 87%; SVM accuracy: 85%	[24]

2.2 AI for Clinical Decision Support:

Clinical decision-making in spinal disorders often involves integrating complex, multidimensional data, including symptoms, imaging, comorbidities, and electrophysiological findings. AI-based decision-support systems provide objective, data-driven insights to assist clinicians.

A) **Use of NLP for Electronic Health Records (EHRs):** Natural Language Processing enables efficient extraction of structured clinical data from unstructured physician

notes, radiology reports, and operative summaries. NLP models support tasks such as automated disease coding, prediction of complications, and identification of prognostic indicators. These systems reduce documentation burden and enhance real-time decision-making [25].

B) **B) Predictive Modeling for Disease Progression:** Machine learning models are widely used to predict neurological improvement, risk of deterioration, and long-term disability. Features commonly incorporated include initial motor scores, lesion characteristics, inflammatory markers, and demographic data. Random forests, support vector machines (SVMs), gradient boosting, and recurrent neural networks (RNNs) are frequently employed to generate reliable prognostic insights [26,27].

C) **Treatment Response Prediction:** AI enables personalized medical care by predicting which patients are most likely to benefit from surgical interventions, pharmacological treatments, or rehabilitation therapies. Models analyzing imaging biomarkers, electrophysiology, and genetic factors can estimate treatment efficacy and guide individualized therapeutic planning [28].

Following table 2 represent use of AI for clinical decision-making in spinal cord disorders.

Table 2: Use of AI for clinical decision-making in spinal cord disorders

Sr. No.	AI technique / model	Spinal cord disease	Reported performance (as reported)	Ref.
1	NLP (Bidirectional LSTM) + XGBoost	Automated detection of Cervical Spondylotic Myelopathy (CSM) from unstructured clinical notes	LSTM: AUC 0.9025, Accuracy 0.8740, F1 0.9122; XGBoost: AUC 0.8292, Accuracy 0.8247.	[29]
2	Convolutional Neural Network (CNN)	Cervical spondylotic myelopathy detection from lateral cervical radiographs	Accuracy 87.1%; AUC ≈ 0.864	[30]
3	Random Forest (and other ML ensembles)	Predicting spinal cord injury (SCI) risk in patients with cervical spondylosis	Random Forest reported best performance among tested models (highest AUC 0.80)	[31]
4	Ensemble ML (Ridge classifier best in ensemble)	Predicting AIS grade at discharge after acute traumatic SCI	Best model (Ridge) test accuracy ≈ 73.6%	[32]
5	XGBoost	Predicting neurological recovery after cervical SCI (clinical dataset)	Reported accuracy ~81.1% XGBoost best among tested models; logistic regression (80.6%) and decision tree (78.8%), AUC reported	[33]

			~0.867–0.877 depending on comparator.	
6	Deep learning based prediction model RNN, linear regression (LR), Ridge, and Lasso models	Gait recovery, functional ambulation prediction after SCI (clinical + neurophysiology)	RNN was better than LR, Ridge, and Lasso. RMSE = 0.3738 and excellent predictive performance for discharge gait.	[34]
7	CNN for classification (radiograph)	Detection of ossification of the posterior longitudinal ligament (OPLL) and differentiation from other cervical pathology on radiographs	The convolutional neural network achieved strong and consistent performance in classifying lateral cervical spine radiographs, with an accuracy of 0.86, recall of 0.86, precision of 0.87, and F1-score of 0.87. The accuracy was higher for CNN compared to any expert spine surgeon,	[35]
8	MRI radiomics + ML (LinearSVC, Random Forest Classifier, Extra Trees, KNN, Decision Trees, Gbdt, AdaBoost, MLP , and XGBoost algorit hms used)	Pre-operative stenosis severity / spinal cord function prediction; biomarker extraction for prognosis	The study prospectively enrolled patients with mild cervical spondylotic myelopathy and developed a radiomics-based machine learning model to automatically detect compressed spinal segments and predict SUVmax reduction in those segments. The model performed strongly, achieving AUCs of 0.981 and 0.830 in training and 0.962 and 0.812 in testing for the two tasks, respectively.	[36]
9	Systematic review / meta-analysis (various AI methods: CNN, RF, XGBoost, RNN, radiomics)	Overall diagnostic and prognostic capabilities of AI in spinal cord disease	AI systems show high diagnostic accuracy (mean accuracy 0.898) and moderate prognostic performance (mean AUC 0.770) in traumatic spinal cord injury. Their clinical use remains limited by inconsistent methods and insufficient external validation. Future development should emphasize multimodal models that combine imaging, clinical features, and	[37]

			clinician input to better reflect real-world decision-making.	

2.3 AI-Enhanced Rehabilitation and Recovery

Rehabilitation is critical for functional recovery following spinal cord injury or degenerative disease progression. AI technologies improve therapy personalization, enhance engagement, and monitor real-time progress. It includes following aspects

A) Robotic and Exoskeleton-Assisted Rehabilitation:

A recent meta-analysis (2025) of 13 trials involving 247 patients with spinal cord injury (SCI) found that exoskeleton-robotic training significantly improved multiple motor function measures: 6-minute walk test (6-MWT), 10-m walk test (10-MWT), ambulatory index (WISCI-II), timed up-and-go (TUG), and lower extremity motor score (LEMS). Improvements were seen both in early (< 6 months) and chronic phases [38]. For patients with motor-complete SCI using wearable powered exoskeletons (e.g., "ReWalk"), improved over-ground walking has been documented; smoother exoskeleton control algorithms (software) correlated with better gait performance irrespective of anthropometric differences [39]. Beyond motor gains, robotic rehabilitation appears to confer psychological benefits: increased motivation, self-confidence, improved mood, greater sense of normalcy, and possibly reduced anxiety/depression, which may support long-term therapy adherence [40].

AI-driven exoskeleton and robotic rehabilitation have matured to provide measurable gains in mobility, functional independence, and psychological well-being in SCI patients often outperforming or enhancing conventional rehabilitation, especially for gait recovery and lower-limb function.

B) Intelligent Virtual Reality (VR) and Gamified Therapy

A systematic review concluded that VR or with other non-invasive treatments has potential to improve motor and cognitive outcomes better than traditional therapy in SCI, though variability remains in protocols, session durations, and immersion levels [41]. Hybrid systems combining VR with robotics or brain/machine-interface (BMI) have been explored: a small study demonstrated that a VR-trained motor imagery-based brain-computer interface (BCI) could control a lower-limb exoskeleton; preliminary feedback from SCI patients was positive, suggesting feasibility and tolerability [42]. A 2024 meta-analysis of VR-based rehabilitation in SCI patients found mostly positive results: out of 46 selected studies (652 patients), VR (or mixed reality) interventions compared either with baseline or conventional rehab showed functional benefits and overall favourable trends [43].

AI-driven VR and gamified rehabilitation hold promise for enhancing engagement, motivation, and functional recovery in spinal cord disease. VR-based protocols possibly combined with robotics or BMI may reinforce neuroplasticity and improve adherence.

C) Remote Monitoring and Tele-Rehabilitation

Wearable sensors combined with machine learning have been increasingly validated as tools for remote monitoring and tele-rehabilitation in spinal-cord injury (SCI) patients. For example, a wrist-worn accelerometer study demonstrated that a machine-learning pipeline could recognize different rehabilitation movements (shoulder/elbow flexion/extension, internal/external rotation, etc.) with 96.86% overall accuracy, providing an objective method

to monitor activity and adherence outside clinic walls [44]. Similarly, a wearable physiological telemetry system pairing ECG, skin-nerve-activity (skNA) sensors and ML classification was able to detect symptomatic autonomic dysreflexia (AD) in real time with ~94 % accuracy and a false-negative rate below 5%, offering a non-invasive way to track dangerous autonomic events remotely [45]. To realizing the full promise of wearable devices (WD) + ML for SCI care requires careful alignment of device capabilities, physiological relevance, analytic rigor, and clinical context especially given the complexity of autonomic and motor dysfunction in SCI [46].

Wearable sensors integrated with ML algorithms allow continuous monitoring of mobility, autonomic function, and activity levels in home environments. Tele-rehabilitation systems use predictive analytics to detect early decline, guide remote therapeutic adjustments, and reduce hospital readmissions.

3. CHALLENGES AND LIMITATIONS:

Despite promising advances, several challenges limiting AI deployment in healthcare. AI systems depend on high-quality, labeled datasets; however, spinal cord imaging and clinical datasets often suffer from heterogeneity, limited sample sizes, hence generalization of AI model is difficult.

Many AI systems operate as black boxes, offering high predictive accuracy but limited interpretability, which reduces clinician trust and complicates clinical decision-making, it requires algorithm transparency. Efforts such as saliency maps, explainable AI frameworks, and rule-based hybrid models are emerging but remain insufficient for widespread clinical integration.

Issues related to data privacy, algorithmic bias, consent, and cross-border data governance remain major obstacles. Regulatory frameworks for AI-based medical devices require continuous validation, raising concerns regarding clinical safety and accountability.

Despite technological advancements, incorporating AI tools into daily clinical workflows remains difficult. Challenges include lack of interoperability with hospital information systems, clinician hesitation, cost constraints, and the need for continuous re-training of models [47, 48].

FUTURE SCOPE:

Future developments in healthcare AI are expected to focus on creating large multimodal databases that integrate imaging, clinical narratives, genomic profiles, and electrophysiological signals to significantly enhance model robustness and predictive capability. Parallel advancements in explainable AI aim to improve algorithmic transparency, thereby facilitating clinician trust and clinical adoption. Real-time AI systems are anticipated to play a transformative role in emergency and critical care by enabling rapid diagnostic support and continuous monitoring. Additionally, AI-guided personalized medicine will leverage patient-specific data to generate individualized treatment strategies, ultimately improving therapeutic precision and clinical outcomes.

CONCLUSION

Artificial Intelligence offers transformative potential for improving the diagnosis, treatment, and management of spinal cord diseases. From advanced imaging analysis and predictive modeling to intelligent rehabilitation systems, AI tools demonstrate significant advantages over traditional methods by providing accuracy, efficiency, and personalization. However, challenges such as data quality, ethical considerations, model interpretability, and integration barriers must be addressed to ensure responsible and effective implementation. While current systems offer promising results, further research, larger datasets, and interdisciplinary collaboration are needed to translate AI innovations into routine clinical practice. Ultimately, AI-enhanced medicine could lead to earlier diagnoses, improved treatment personalization, and better outcomes for patients with spinal cord diseases.

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