

Review Article



Determination of Diagnosis and Prognosis in Spinal Cord Injury Using Machine Learning

Seonghoon Jeong ¹, Suk Hyung Kang ², Myeong Jin Ko ³, Subum Lee ⁴,
Woo-Keun Kwon ⁵, and Byung-Jou Lee ¹

¹Department of Neurosurgery, Ilsan Paik Hospital, Inje University College of Medicine, Goyang, Korea

²Department of Neurosurgery, School of Medicine, Kyung Hee University, Seoul, Korea

³Department of Neurosurgery, Chung-Ang University Hospital, Chung-Ang University College of Medicine, Seoul, Korea

⁴Department of Neurosurgery, Korea University Anam Hospital, Korea University College of Medicine, Seoul, Korea

⁵Department of Neurosurgery, Korea University Guro Hospital, Korea University College of Medicine, Seoul, Korea



Received: Sep 25, 2025

Revised: Oct 14, 2025

Accepted: Oct 18, 2025

Published online: Oct 24, 2025

Address for correspondence:

Byung-Jou Lee

Department of Neurosurgery, Ilsan Paik Hospital, Inje University College of Medicine, 170 Juhwa-ro, Ilsanseo-gu, Goyang 10380, Korea.

Email: lbjguni@hanmail.net

Copyright © 2025 Korean Neurotraumatology Society

This is an Open Access article distributed under the terms of the Creative Commons Attribution Non-Commercial License (<https://creativecommons.org/licenses/by-nc/4.0/>) which permits unrestricted non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

ORCID iDs

Seonghoon Jeong

<https://orcid.org/0000-0002-7246-8564>

Suk Hyung Kang

<https://orcid.org/0000-0002-1130-9754>

Myeong Jin Ko

<https://orcid.org/0000-0002-1850-7753>

Subum Lee

<https://orcid.org/0000-0003-4732-8137>

Woo-Keun Kwon

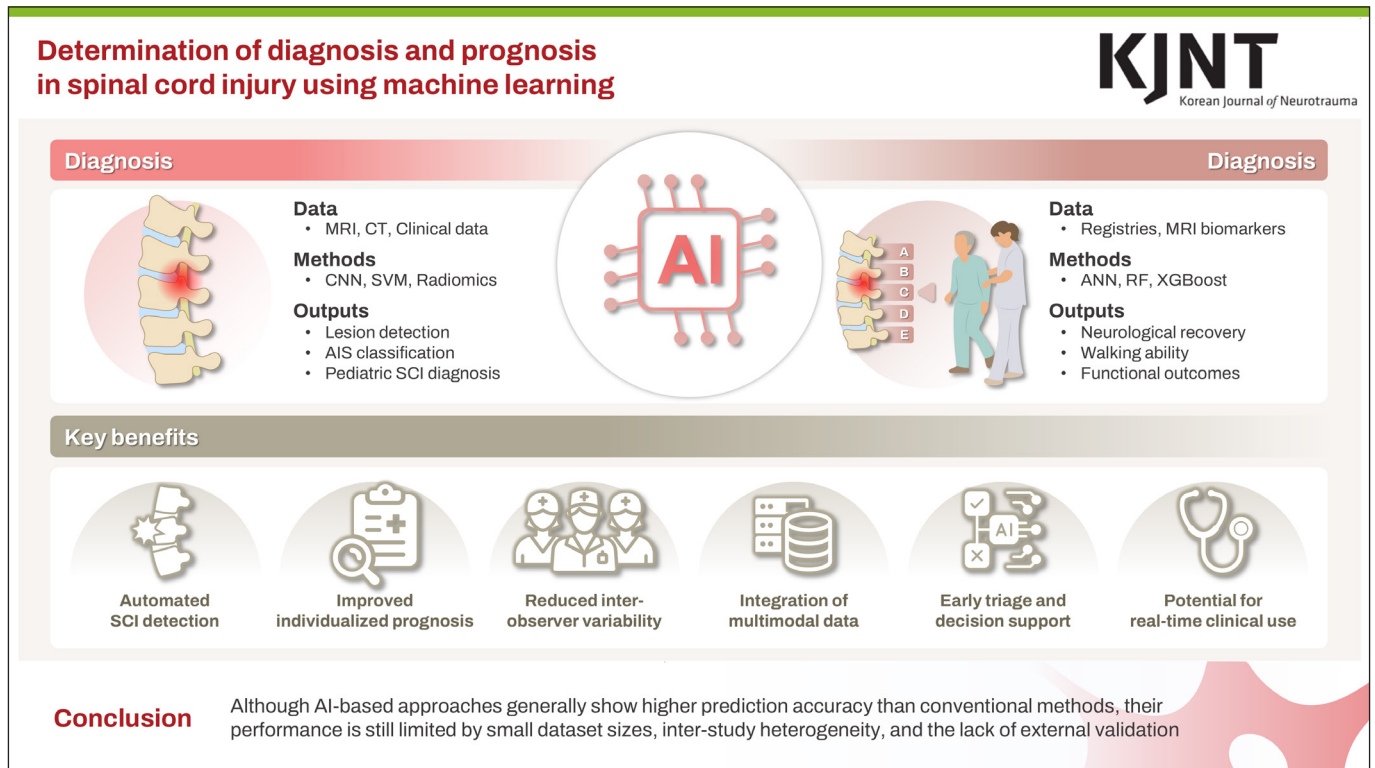
<https://orcid.org/0000-0003-0432-8620>

ABSTRACT

Traumatic spinal cord injury (tSCI) is a neurological disorder that leads to long-term disability, significant economic burden, and limited treatment options. Accurate and timely diagnosis, as well as reliable prognosis, are crucial for acute treatment, rehabilitation, and long-term treatment planning. Recent advances in artificial intelligence (AI) and machine learning have demonstrated significant potential to support the diagnostic workflow and predict clinical outcomes in patients with tSCI. For diagnostic purposes, models based on convolutional neural networks trained using magnetic resonance imaging and diffusion tensor imaging showed high accuracy in detecting cord damage and classifying injury severity. A variety of prognostic models, ranging from traditional logistic regression to advanced neural networks and deep learning-based radiomics, have been applied to predict functional recovery, ambulatory status, and survival. Although AI-based approaches generally have better prediction accuracy than conventional methods, several limitations remain, such as limited dataset sizes, heterogeneity across studies, lack of external validation. Future studies should incorporate multicenter collaborations, standardized reporting frameworks, and integration of multimodal data to enhance clinical generalizability and applicability. With further improvements, AI will play a crucial role in supporting clinicians in making decisions about tSCI and in patient rehabilitation.

Keywords: Spinal cord injuries; Artificial intelligence; Machine learning; Diagnosis; Prognosis

GRAPHICAL ABSTRACT



Byung-Jou Lee 
<https://orcid.org/0000-0002-4030-3618>

Funding

No funding was obtained for this study.

Conflict of Interest

The authors have no financial conflicts of interest.

Informed Consent

This type of study does not require informed consent.

Ethics Approval

This research did not require ethical approval as it does not involve human subjects, their data, or biological samples.

INTRODUCTION

Traumatic spinal cord injury (tSCI) is one of the most severe injuries in neurosurgery and rehabilitation medicine.^{1,12,14,27)} Globally, the incidence rate of tSCI has been estimated at 23 cases per million annually, with regional variations ranging from 15 to 40 per million, and motor vehicle accidents and falls are the main causes.^{3,14,30)} Functional prognosis is difficult to determine during the acute stage because of the variety of injury mechanisms, secondary pathophysiological processes, and variability in rehabilitation responses.¹⁶⁾ Therefore, tools that can improve early diagnosis and enable accurate prognostication with high accuracy would be useful in the management of tSCI.

Conventional diagnostic methods for tSCI include clinical neurological assessments such as the American Spinal Injury Association Impairment Scale (AIS) and imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT).^{8,17,23)} Although these are the main tools to diagnose tSCI in clinical practice, they have limitations such as inter-rater variability, complexity in radiological interpretation, and the dynamic evolution of acute neurological deficits.^{18,22)} Similarly, prognostic assessments which are achieved through large registries and logistic regression models, may have poor individualized precision and perform poorly in predicting long-term recovery.^{20,28)}

Recently, artificial intelligence (AI) models, including machine learning (ML) and deep learning (DL) methodologies, represent promising results in diagnosing and predicting prognosis of tSCI.^{5,16,25,26)} AI models can integrate high-dimensional imaging features,

clinical parameters, and laboratory data to support both diagnosis and outcome prediction. Recent studies have shown that AI-based diagnostic models are as accurate as experts in identifying spinal cord injuries, while prognostic models have shown meaningful results.^{7,15,16)} In particular, convolutional neural networks (CNNs), support vector machines (SVMs), and ensemble learning methods such as random forests have been widely applied to MRI-based evaluation, functional prognostication, and survival prediction.

The purpose of this narrative review is to summarize key findings and trends in studies on AI applications to tSCI. Specifically, this narrative review discuss diagnostic models using imaging and clinical data, prognostic models predicting neurological recovery and functional outcomes, and limitations of AI applications for tSCI. Finally, we suggest future research priorities of AI models for tSCI, including the integration of multimodal data, external validation across diverse populations, and the need for explainable AI to enhance their clinical applicability.

DIAGNOSIS: AI IN THE DETECTION AND CLASSIFICATION OF tSCI

Accurate and early diagnosis of tSCI is essential for timely surgical decision-making, prognosis discussion, and initiating appropriate rehabilitation. Conventional diagnostic approaches rely on neurological examination using the AIS and radiographic modalities such as CT and MRI. However, these methods have limitations, including inter-observer variability, differences in interpretation of radiographic information, and variability in neurological deficits during the acute phase. Recently, AI has emerged as a tool that can improve the diagnostic workflow and consistency of clinical decision-making in tSCI compared to existing methods. **TABLE 1** summarizes AI models developed in recent studies to diagnose tSCI.^{6,9,11,15,21,29)}

MRI is an important imaging tool for evaluating soft tissue integrity, cord compression, and intramedullary pathology. Several studies have proposed AI models to improve the diagnostic accuracy of tSCI using MRI. In particular, CNN-based AI models have demonstrated robust performance in automating lesion segmentation and identifying spinal cord abnormalities, with recent studies reporting accuracies often exceeding 0.94 to 0.96.^{21,29)} Such findings indicate that diagnostic AI models for tSCI are approaching a level of reliability that may support their integration into clinical practice.

TABLE 1. Diagnostic AI studies in tSCI

Study	Study design	Sample size	Input	AI model	Task	Key metric
Tay et al., 2014 ²⁹⁾	Retrospective	14	DTI	SVM/KNN classifiers	SCI vs. normal classification	Accuracy ≈ 0.94
McCoy et al., 2019 ¹⁵⁾	Retrospective	47	T2-weighted MRI	2D CNN segmentation pipeline	Intramedullary lesion segmentation	Dice ≈ 0.93
Jasim and Brindha, 2021 ⁹⁾	Retrospective	30	CT spine images	DCNN/CNN variants	SCI detection	Accuracy: 0.81–0.88
Sadeghi-Adl et al., 2025 ²¹⁾	Pediatric cohort	68	T2-weighted MRI	Custom CNN	SCI vs. control; AIS severity classification	Accuracy 96.6% (SCI); 94.9% (AIS)
Karthik et al., 2024 ¹¹⁾	Retrospective	191	T2-weighted MRI	nnU-Net segmentation	Automated lesion and cord segmentation	Dice ≈ 0.93
Fei et al., 2023 ⁶⁾	Retrospective	89	DTI	U-Net/CNN variants	Cord internal structure & lesion segmentation	Dice: 0.54–0.69 Precision: 0.53–0.65

AI: artificial intelligence, tSCI: traumatic spinal cord injury, DTI: diffusion tensor imaging, SVM: support vector machine, KNN: K-nearest neighbors, SCI: spinal cord injury, MRI: magnetic resonance imaging, CNN: convolutional neural network, CT: computed tomography, DCNN: deep convolutional neural network, AIS: American Spinal Injury Association Impairment Scale.

Similarly, ML-based radiomics have been applied to quantify spinal cord edema, hemorrhage, and cross-sectional morphometry.^{11,24)} These models provide imaging biomarkers, reducing errors that can arise from subjective human interpretation. Okimatsu et al.¹⁶⁾ applied deep learning-based radiomics (DLR) to sagittal T2-weighted MRI to automatically extract features associated with cervical spinal cord injury (SCI) and demonstrated its ability to classify patients based on injury severity. This approach highlights the potential of AI to aid in early triage of patients, particularly in complex cervical spine injuries where medical imaging ambiguity is common.

CT has also been studied as a diagnostic tool for SCI. For example, Jasim and Brindha⁹⁾ proposed a deep CNN trained with the Crow Search-Rider Optimization Algorithm (CS-ROA DCNN) to detect SCI in CT scans. Their model integrated adaptive thresholding for spinal cord segmentation, sparse fuzzy clustering for disc localization, and automatic feature extraction before classification. The model achieved an accuracy of 0.874, a sensitivity of 0.896, and a specificity of 0.883, demonstrating that CT-based approaches can provide clinically meaningful diagnostic performance. These results highlight the potential utility of CT in AI-based diagnostic workflows, especially in acute trauma settings where MRI is less accessible.

In addition to medical images, clinical information such as demographic variables, vital signs, and laboratory data have been used as AI data for the diagnosis of tSCI. For example, Park et al.¹⁹⁾ developed ML models for gait-based classification of incomplete spinal cord injuries and cauda equina syndrome. Using classifiers such as SVMs, random forest, and XGBoost, Their approach achieved the highest classification accuracy of 74.4% through XGBoost, highlighting that non-imaging clinical data, rather than medical images, can be used as training data for AI-based classification models. These findings suggest that non-imaging clinical data can be used as training data for AI-based classification models and broaden the applicability of diagnostic AI in SCI.

Although pediatric spinal cord injuries account for a small proportion of overall cases, their diagnosis is challenging due to the difficulty of standardized neurological examinations. Recent study has used CNN-based models to distinguish pediatric SCI from typically developing (TD) and determine their injury severity.²¹⁾ The model achieved 96.6% accuracy in distinguishing SCI from TD and 94.9% accuracy in classifying AIS category, demonstrating the potential of AI-based models for tSCI, even in pediatric cases where clinical assessment reliability is low.

AI for tSCI diagnosis demonstrate significant potential. By automating labor-intensive tasks like segmentation and identifying subtle features invisible to the human eye, these models can serve as supporting tools in acute care. As multimodal approaches and external validation become more widespread, AI will play an increasingly important role in the diagnosis of tSCI.

Despite these promising advances, several challenges remain before AI can be fully integrated into routine clinical diagnosis of tSCI. The performance of diagnostic AI models is highly dependent on imaging quality and acquisition protocols. Variations in MRI scanner field strength (e.g., 1.5T vs. 3.0T), sequence parameters, and coil configurations can lead to inconsistencies in image contrast and lesion delineation, affecting model generalizability. Moreover, artifacts caused by patient motion, cerebrospinal fluid pulsation, or metallic implants can obscure cord boundaries and degrade segmentation accuracy. In clinical

settings, the heterogeneity of imaging equipment and data formats across institutions further complicates model training and validation. In addition, most studies to date have used relatively small, single-center datasets, limiting external reproducibility. Addressing these challenges through standardized imaging protocols, artifact correction techniques, and multicenter validation will be critical for ensuring robust and clinically reliable AI-assisted diagnosis of tSCI.

PROGNOSIS: AI IN PREDICTING OUTCOMES OF tSCI

Predicting neurological and functional outcomes following tSCI has been considered an important challenge in clinical practice. The accuracy of prognosis is clinically important because it determines patient counseling, rehabilitation planning, and new therapeutic interventions. Conventional predictive models, such as logistic regression based on initial AIS grade and demographics, provide reasonable overall prognostic predictions for patient cohorts but often achieve insufficient accuracy at the individual patient level.²⁰⁾ Since AI models are trained on large-scale data and make inferences about individual cases, they can provide more personalized and accurate prognostication than conventional methods.

TABLE 2 summarizes the prognostic AI models for tSCI proposed in recent studies.^{2,4,10,13,16,26)}

One of the prognostic AI in tSCI involved ML algorithms trained on clinical registries. DeVries et al.⁴⁾ developed an unsupervised ML model using the Rick Hansen Spinal Cord Injury Registry (RHSCIR) to predict walking ability at discharge or one year follow-up. Compared to conventional logistic regression models, ML approaches have been shown to be more suitable for handling imbalanced datasets and reduce false negative classifications.

Recently, Kishikawa et al.¹³⁾ developed predictive models using artificial neural networks (ANNs) and multiple linear regression (MLR) to predict functional recovery in cervical SCI patients using clinical parameters, such as age at injury, sex, height, body weight, and lesion type, obtained at admission.¹³⁾ They evaluated that ANN had a better performance of 75.0% than the conventional MLR with 31.3% accuracy. These results suggest that ANNs may be better suited for predicting individualized outcomes than conventional statistical methods.

Radiological biomarkers have long been recognized as important indicators of neurological prognosis. Recent studies suggest that DLR approaches can be used to automatically quantify

TABLE 2. Prognostic AI studies in tSCI

Study	Study design	Sample size	Input	AI model	Predicted outcome	Key metric
DeVries et al., 2019 ⁴⁾	Retrospective	862	AIS, motor scores, age	Unsupervised ML	Walking ability after 1 year	AUC: 0.87–0.91 F1 score: 0.87–0.91
Okimatsu et al., 2021 ¹⁶⁾	Retrospective	215	AIS probabilities, age, initial AIS at admission, MRI	Ensemble classifier (CNN, DL, random forest)	AIS grade after 1 month	Accuracy: 0.714 Recall: 0.565 Precision: 0.590
Kishikawa et al., 2024 ¹³⁾	Retrospective	60	Age, sex, height, body weight	ANN, MLR	AIS grade at discharge	Accuracy: 0.750 (ANN), 0.313 (MLR)
Shimizu et al., 2023 ²⁶⁾	Retrospective	101	AIS at admission, intramedullary hemorrhage, T2-weighted MRI	XGBoost, CatBoost	AIS grade after 6 months	AUC: 0.90 Accuracy: 0.837 Precision: 0.852
Belliveau et al., 2016 ²⁾	Retrospective	2,514	Age, AIS, abbreviated injury scale scores	ANN	Mortality, walking ability after 1 year	AUC: 0.87–0.90 Accuracy: 0.877
Kapoor and Xu, 2023 ¹⁰⁾	Retrospective	20,790	AIS grade	Ridge classifier	AIS grade	Accuracy: 0.736

AI: artificial intelligence, tSCI: traumatic spinal cord injury, AIS: American Spinal Injury Association Impairment Scale, ML: machine learning, AUC: area under the curve, MRI: magnetic resonance imaging, CNN: convolutional neural network, DL: deep learning, ANN: artificial neural network, MLR: multiple linear regression.

the characteristics of SCI and predict functional recovery. Okimatsu et al.¹⁶⁾ developed a CNN-based radiomics to predict short-term neurological outcomes in cervical SCI patients. By integrating MRI with clinical data, their ensemble model achieved moderate predictive performance, with accuracy of 71.4%. Although not yet clinically viable, this study suggests that radiological biomarkers could be used in AI models to assess prognosis in tSCI.

Shimizu et al.²⁶⁾ also demonstrated that medical image features can be used as data to predict neurological recovery in SCI patients. AIS grade at admission, intramedullary hemorrhage and longitudinal extent on T2-weighted MRI were found to be the important features for their ML model to predict AIS outcome at 6 months. These results highlight the potential of imaging biomarkers to improve the prognostic accuracy of ML models in tSCI.

Large-scale registry datasets have also been used to develop prognostic models for SCI. A recent study using the National Spinal Cord Injury Statistics Center (NSCISC) database applied several ML algorithms to predict AIS grade at discharge based on hospitalization data covering over 20,000 patients (1972–2016).¹⁰⁾ The Ridge Classifier achieved the highest performance, with 73.6% accuracy, and Shapley analysis identified admission AIS grade and neurological category as the most influential variables in predicting prognosis. Demographic factors such as age, sex, marital status, and race had a minimal impact on prediction. These results highlight the powerful prognostic value of early neurological assessment and demonstrate that ML techniques can improve predictive accuracy and provide interpretability through feature importance analysis in a large SCI cohort.

AI-based prognostic models for tSCI has proven to be more efficient at utilizing nonlinear data and easily integrating multi-modality data, resulting in better performance than conventional methods. As data sets grow in size and diversity and multi-center data-driven model training becomes possible, AI-based prognostic prediction of tSCI will become increasingly important in clinical practice.

Although AI-based models have shown promising performance in predicting functional outcomes after tSCI, several challenges remain regarding their clinical applicability. Most existing models are trained on relatively small or homogeneous datasets, which may not capture the full variability of lesion patterns, injury mechanisms, and rehabilitation responses seen in real-world patients. Consequently, the generalizability of these models to diverse clinical populations is still limited. Furthermore, while AI predictions can provide early prognostic insights, their direct translation into clinical benefit—such as guiding individualized rehabilitation programs or improving long-term functional outcomes—has not been fully validated. Ethical and practical concerns, including overreliance on algorithmic outputs, data privacy, and the need for clinician interpretability, also remain. To realize the true potential of AI in prognostication, future studies should focus on multicenter datasets, prospective validation, and integration of AI predictions into multidisciplinary rehabilitation planning.

CHALLENGES AND FUTURE DIRECTIONS

Although AI has shown significant promise in tSCI diagnosis and prognosis, several challenges remain before it can be fully employed in clinical practice.

Most AI-based tSCI models are limited by small dataset sizes and reliance on single-center, retrospective data. These datasets run the risk of overfitting, where the model learns patterns specific to a single institution and fails to generalize across diverse populations. Additionally, the rarity and heterogeneity of tSCI (injuries from the cervical to thoracic spine, complete versus incomplete lesions, and age-related variations) make it inherently difficult to collect large, representative datasets. In particular, pediatric cases are significantly less accessible and there are relatively few groups studying these data. Approaches such as multi-center collaboration and standardized data collection protocols may be essential in overcoming these limitations.

Most AI models for tSCI have not undergone external validation. Without prospective or inter-institutional testing, the clinical utility of these models remains uncertain. Furthermore, inconsistent reporting of performance metrics, such as accuracy, area under the curve, sensitivity, and F1-score, makes it difficult to compare results across studies. Providing standardized reporting guidelines could improve the transparency and comparability of research results.

DL models, especially CNNs and ANNs, often function as “black boxes,” generating predictions without clear rationale. Especially in high-stakes decision-making scenarios like tSCI, this opacity prevents clinicians from trusting AI-generated results. Explainable AI techniques, such as saliency maps, feature attribution methods, or simplified surrogate models, can help reduce opacity from results by clarifying which features have the greatest impact on predictions.

Even if AI models achieve high accuracy, the clinical application relies on smooth integration into existing clinical workflows. To be seamlessly implemented in emergency and acute care settings, it requires a user-friendly interface and compatibility with hospital picture archiving and communication systems. Furthermore, AI-generated results should complement, rather than replace, clinicians' decision, and serve as a supporting tool that can improve clinicians' efficiency and consistency.

Several improvements are needed to further develop AI models for tSCI. First, rather than training with a single data type, the performance of AI models will be significantly improved if training data such as MRI, CT, diffusion tensor imaging, and clinical data are trained together. Second, using data collected over time to monitor a patient's recovery could help make more personalized predictions. Finally, AI models need to be prospectively validated in clinical trials and real-world settings to ensure they are effective and safe.

CONCLUSION

Diagnostic models utilizing MRI and CNN-based segmentation demonstrate excellent performance in detecting spinal cord injuries and determining their severity. Prognostic models, including unsupervised and ANN-based models, show moderate but meaningful improvements over conventional linear regression techniques in predicting functional recovery and long-term outcomes (**FIGURE 1**). However, despite these promising accuracies, the clinical translation of AI remains challenging. Real-world application requires not only technical performance but also explainability to patients and caregivers, model stability, and safety validation within clinical environments. Overinterpretation of AI results without these safeguards may lead

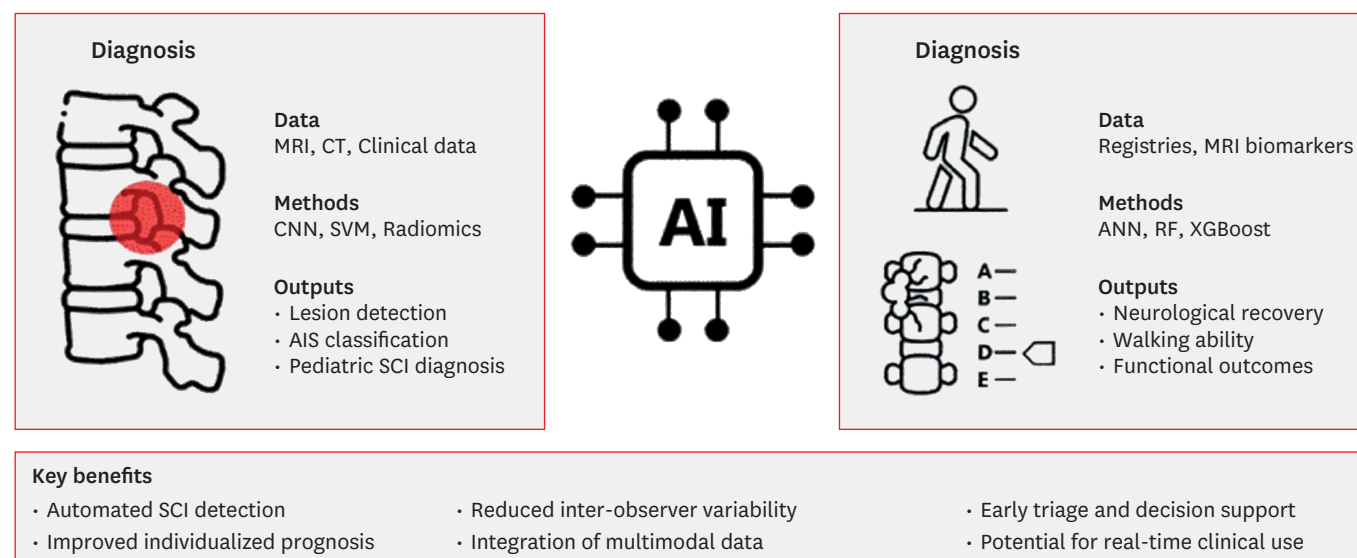


FIGURE 1. Overview of AI applications in tSCI. This schematic diagram illustrates the clinical features of an AI-based approach to tSCI. Input data includes clinical data, CT, and MRI images, which are processed by AI models such as CNN and XGBoost. The output includes injury diagnosis, AIS classification, and prognostic predictions. The integration of this AI system provides benefits including automated SCI detection, reduced inter-observer variability, early triage and decision support, and improved individualized prognosis.

AI: artificial intelligence, tSCI: traumatic spinal cord injury, CT: computed tomography, MRI: magnetic resonance imaging, CNN: convolutional neural network, AIS: American Spinal Injury Association Impairment Scale, SCI: spinal cord injury, SVM: support vector machine, ANN: artificial neural network.

to misinformed decisions. Therefore, future efforts should prioritize external validation, explainable and transparent model design, and multi-institutional collaboration to ensure that AI systems can be reliably and ethically integrated into clinical practice.

REFERENCES

1. Adegeest CY, Moayeri N, Muijs SPJ, Ter Wengel PV. Spinal cord injury: current trends in acute management. *Brain Spine* 4:102803, 2024 [PUBMED](#) | [CROSSREF](#)
2. Belliveau T, Jette AM, Seetharama S, Axt J, Rosenblum D, Larose D, et al. Developing artificial neural network models to predict functioning one year after traumatic spinal cord injury. *Arch Phys Med Rehabil* 97:1663-1668.e3, 2016 [PUBMED](#) | [CROSSREF](#)
3. Chen Y, Tang Y, Vogel LC, Devivo MJ. Causes of spinal cord injury. *Top Spinal Cord Inj Rehabil* 19:1-8, 2013 [PUBMED](#) | [CROSSREF](#)
4. DeVries Z, Hoda M, Rivers CS, Maher A, Wai E, Moravek D, et al. Development of an unsupervised machine learning algorithm for the prognostication of walking ability in spinal cord injury patients. *Spine J* 20:213-224, 2020 [PUBMED](#) | [CROSSREF](#)
5. Fallah N, Noonan VK, Waheed Z, Rivers CS, Plashkes T, Bedi M, et al. Development of a machine learning algorithm for predicting in-hospital and 1-year mortality after traumatic spinal cord injury. *Spine J* 22:329-336, 2022 [PUBMED](#) | [CROSSREF](#)
6. Fei N, Li G, Wang X, Li J, Hu X, Hu Y. Deep learning-based auto-segmentation of spinal cord internal structure of diffusion tensor imaging in cervical spondylotic myelopathy. *Diagnostics (Basel)* 13:817, 2023 [PUBMED](#) | [CROSSREF](#)
7. Gill SS, Ponniah HS, Giersztejn S, Anantharaj RM, Namireddy SR, Killilea J, et al. The diagnostic and prognostic capability of artificial intelligence in spinal cord injury: a systematic review. *Brain Spine* 5:104208, 2025 [PUBMED](#) | [CROSSREF](#)
8. Hussain O, Kaushal M, Agarwal N, Kurpad S, Shabani S. The role of magnetic resonance imaging and computed tomography in spinal cord injury. *Life (Basel)* 13:1680, 2023 [PUBMED](#) | [CROSSREF](#)
9. Jasim M, Brindha T. Spinal cord segmentation and injury detection using a Crow Search-Rider optimization algorithm. *Biomed Tech (Berl)* 66:293-304, 2020 [PUBMED](#) | [CROSSREF](#)

10. Kapoor D, Xu C. Spinal cord injury ais predictions using machine learning. *eNeuro* 10:ENEURO.0149-22.2022, 2023 [PUBMED](#) | [CROSSREF](#)
11. Karthik EN, Valosek J, Smith AC, Pfyffer D, Schading-Sassenhausen S, Farner L, et al. SCISeg: Automatic segmentation of T2-weighted intramedullary lesions in spinal cord injury. *medRxiv*, Forthcoming 2024 [PUBMED](#) | [CROSSREF](#)
12. Kirshblum SC, Burns SP, Biering-Sorensen F, Donovan W, Graves DE, Jha A, et al. International standards for neurological classification of spinal cord injury (revised 2011). *J Spinal Cord Med* 34:535-546, 2011 [PUBMED](#) | [CROSSREF](#)
13. Kishikawa J, Kobayakawa K, Saiwai H, Yokota K, Kubota K, Hayashi T, et al. Verification of the accuracy of cervical spinal cord injury prognosis prediction using clinical data-based artificial neural networks. *J Clin Med* 13:253, 2024 [PUBMED](#) | [CROSSREF](#)
14. Lee BB, Cripps RA, Fitzharris M, Wing PC. The global map for traumatic spinal cord injury epidemiology: update 2011, global incidence rate. *Spinal Cord* 52:110-116, 2014 [PUBMED](#) | [CROSSREF](#)
15. McCoy DB, Dupont SM, Gros C, Cohen-Adad J, Huie RJ, Ferguson A, et al. Convolutional neural network-based automated segmentation of the spinal cord and contusion injury: deep learning biomarker correlates of motor impairment in acute spinal cord injury. *AJNR Am J Neuroradiol* 40:737-744, 2019 [PUBMED](#) | [CROSSREF](#)
16. Okimatsu S, Maki S, Furuya T, Fujiyoshi T, Kitamura M, Inada T, et al. Determining the short-term neurological prognosis for acute cervical spinal cord injury using machine learning. *J Clin Neurosci* 96:74-79, 2022 [PUBMED](#) | [CROSSREF](#)
17. Parashari UC, Khanduri S, Bhadury S, Kohli N, Parihar A, Singh R, et al. Diagnostic and prognostic role of MRI in spinal trauma, its comparison and correlation with clinical profile and neurological outcome, according to ASIA impairment scale. *J Craniovertebr Junction Spine* 2:17-26, 2011 [PUBMED](#) | [CROSSREF](#)
18. Parizel PM, van der Zijden T, Gaudino S, Spaepen M, Voormolen MH, Venstermans C, et al. Trauma of the spine and spinal cord: imaging strategies. *Eur Spine J* 19 Suppl 1:S8-S17, 2010 [PUBMED](#) | [CROSSREF](#)
19. Park SG, Mun SB, Kim YJ, Kim KG. Development of machine learning models for gait-based classification of incomplete spinal cord injuries and cauda equina syndrome. *Sci Rep* 15:20012, 2025 [PUBMED](#) | [CROSSREF](#)
20. Phan P, Budhram B, Zhang Q, Rivers CS, Noonan VK, Plashkes T, et al. Highlighting discrepancies in walking prediction accuracy for patients with traumatic spinal cord injury: an evaluation of validated prediction models using a Canadian Multicenter Spinal Cord Injury Registry. *Spine J* 19:703-710, 2019 [PUBMED](#) | [CROSSREF](#)
21. Sadeghi-Adl Z, Naghizadehkashani S, Middleton D, Krisa L, Alizadeh M, Flanders AE, et al. Severity classification of pediatric spinal cord injuries using structural mri measures and deep learning: a comprehensive analysis across all vertebral levels. *AJNR Am J Neuroradiol* 46:2186-2194, 2025 [PUBMED](#) | [CROSSREF](#)
22. Savic G, Bergström EM, Frankel HL, Jamous MA, Jones PW. Inter-rater reliability of motor and sensory examinations performed according to American Spinal Injury Association standards. *Spinal Cord* 45:444-451, 2007 [PUBMED](#) | [CROSSREF](#)
23. Seboco O, Gebremariam F, Joubert G. Correlation of blunt cervical spinal cord injury magnetic resonance imaging tractography with the American Spinal Injury Association impairment scale motor scores. *SA J Radiol* 25:2038, 2021 [PUBMED](#) | [CROSSREF](#)
24. Sharafi A, Klein AP, Koch KM. Quantitative MRI assessment of post-surgical spinal cord injury through radiomic analysis. *J Imaging* 10:312, 2024 [PUBMED](#) | [CROSSREF](#)
25. Shimizu T, Inomata K, Suda K, Matsumoto Harmon S, Komatsu M, Ota M, et al. A multimodal machine learning model integrating clinical and MRI data for predicting neurological outcomes following surgical treatment for cervical spinal cord injury. *Eur Spine J* 34:3747-3755, 2025 [PUBMED](#) | [CROSSREF](#)
26. Shimizu T, Suda K, Maki S, Koda M, Matsumoto Harmon S, Komatsu M, et al. Efficacy of a machine learning-based approach in predicting neurological prognosis of cervical spinal cord injury patients following urgent surgery within 24 h after injury. *J Clin Neurosci* 107:150-156, 2023 [PUBMED](#) | [CROSSREF](#)
27. Silva NA, Sousa N, Reis RL, Salgado AJ. From basics to clinical: a comprehensive review on spinal cord injury. *Prog Neurobiol* 114:25-57, 2014 [PUBMED](#) | [CROSSREF](#)
28. Sizheng Z, Boxuan H, Feng X, Dianying Z. A functional outcome prediction model of acute traumatic spinal cord injury based on extreme gradient boost. *J Orthop Surg* 17:451, 2022 [PUBMED](#) | [CROSSREF](#)
29. Tay B, Hyun JK, Oh S. A machine learning approach for specification of spinal cord injuries using fractional anisotropy values obtained from diffusion tensor images. *Comput Math Methods Med* 2014:276589, 2014 [PUBMED](#) | [CROSSREF](#)
30. Wilson KV, McDonnell JM, O'Malley S, Lynch D, Larouche J, Cunniffe GM, et al. Morbidity and mortality of traumatic cervical spinal cord injuries in a geriatric cohort. *Ir J Med Sci* 192:1719-1725, 2023 [PUBMED](#) | [CROSSREF](#)