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Development of machine learning models for gait-based classification of incomplete spinal cord injuries and cauda equina syndrome

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Incomplete tetraplegia, incomplete paraplegia, and cauda equina syndrome are major neurological disorders that significantly reduce patients' quality of life, primarily due to impaired motor function and gait instability. Although conventional neurological assessments and imaging techniques are widely used for diagnosis, they are limited by temporal constraints and physical accessibility. This study explores the integration of machine learning and 3D motion capture gait data for effective classification of these conditions. Gait data from 214 patients were analyzed, and key features were identified using recursive feature elimination. Machine learning models, including support vector machine, random forest, and XGBoost, were trained and validated. The XGBoost model achieved the highest accuracy (74.42%) and F1-score (74.27%), with age, cadence, and double support emerging as the most influential features. Sex-based differences revealed that males exhibited greater dynamic gait variables, while females showed higher stability-oriented metrics. Age-based analysis indicated significant gait changes after 60 years, highlighting the role of stability-related features. These findings demonstrate the potential of integrating 3D motion capture and machine learning as a scalable, noninvasive diagnostic tool. By detecting subtle gait variations, this approach can aid in early diagnosis and personalized treatment planning for individuals with neurological impairments.

Keywords Cauda equina syndrome, Gait analysis, Incomplete paraplegia, Incomplete tetraplegia, Machine learning, Motion capture

Spinal cord injury (SCI) is a major neurological disorder that significantly impacts more than 20 million individuals worldwide[1]. The annual incidence of SCI has been reported to be 23.77 cases per million population, leading to neurological deficits and paralysis, which severely affect patients' quality of life[2]. The most widespread method of SCI assessment and classification is the International Standard for the Neurological Classification of Spinal Cord Injury, developed by the American Spinal Injury Association (ASIA) in 1982, where ASIA grade A indicates complete paraplegia, and ASIA grades B through D indicate incomplete paraplegia[3]. Of these, ASIA grades C and D are classified as having incomplete impairments with some remaining motor functions. Incomplete tetraplegia is primarily associated with damage to the cervical spine (C1–C5), whereas incomplete paraplegia is primarily associated with damage to the thoracic spine (T2–L2)[4]. Cauda equina syndrome (CES), a peripheral nerve injury that clinically mimics SCI, is a clinical syndrome caused by compression of the lumbosacral nerve roots below the spinal cord cones[5]. Incomplete tetraplegia, incomplete paraplegia, and cauda equina syndrome require rapid and accurate diagnosis and appropriate treatment because of the different locations of neurological damage, which require different therapeutic approaches, and the risk of permanent neurological damage if treatment is delayed.

Existing diagnostic approaches for incomplete spinal cord injuries and cauda Equina Syndrome primarily rely on clinical neurological examinations and radiological imaging. However, these methods have several limitations. Neurological assessments are often subjective and prone to inter-examiner variability, which may result in the oversight of subtle motor or sensory abnormalities[6]. Cauda Equina Syndrome in particular is challenging to identify early, as its symptoms overlap with those of other lumbar spine disorders and lack specific

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early biomarkers[7]. Although imaging and electrophysiological tests can support diagnostic confirmation, they are frequently limited by restricted accessibility, high cost, and long acquisition times, and may not adequately reflect early-stage functional impairment[8]. As a result, there has been increasing interest in developing noninvasive diagnostic techniques, and recently, gait data analysis using three-dimensional (3D) motion capture systems has been recognized as an important tool for characterizing neurological impairments and supporting treatment planning[9].

Recent studies have increasingly applied machine learning and deep learning techniques to the diagnosis of various neurological disorders[10–15]. Among input modalities, three-dimensional motion capture gait data have gained attention for their potential to capture subtle motor impairments. A machine learning model based on long short-term memory was used to analyze gait data of patients with mild cognitive impairment and Alzheimer disease to effectively classify these two conditions[16]. In addition, various studies have successfully distinguished Parkinson disease, Huntington disease, and amyotrophic lateral sclerosis by analyzing gait data of patients with neurodegenerative diseases using various machine learning algorithms[17–21]. Inertial measurement unit-based gait analysis has also been reported to be effective in classifying older adults, patients with stroke, and patients with Huntington disease[22]. A machine learning-based gait pattern recognition framework was developed using metaheuristic feature selection, achieving high classification performance across diverse clinical and athletic populations[23].

Additionally, a systematic review was conducted on the application of machine learning techniques to gait patterns in cerebral palsy and stroke, further supporting the diagnostic value of gait data[24]. Some studies have analyzed the gait patterns of patients with incomplete SCI using 3D motion capture data[25], whereas others have reported an in-depth analysis of gait characteristics using wearable inertial sensors and applying predictive models[26]. Protocols have also been developed for the comprehensive analysis of patients with incomplete SCI and healthy controls using machine learning models[27]. These studies suggested that gait data are important indicators of neurological impairment.

However, existing research using machine learning tends to focus on neurodegenerative diseases, and studies on incomplete SCI have primarily analyzed the differences between patients with incomplete SCI and healthy controls. Very few studies have clearly distinguished between incomplete paraplegia and incomplete tetraplegia or analyzed gait patterns, including cauda equina syndrome. In addition, most existing studies used publicly available datasets, lacked clinically detailed analyses, and were not based on actual patient data. Therefore, this study aimed to develop a machine learning model that can accurately classify incomplete paraplegia, incomplete tetraplegia, and cauda equina syndrome with residual motor function using real clinical data. By doing so, we expect to build a model that reflects the subtle differences between diseases that have not been covered in existing studies and further contribute to early diagnosis and customized treatment plans for patients with neurological damage.

Results

This study analyzed changes in gait performance according to age, particularly focusing on the distinct gait alterations observed in individuals aged 60 years and older. Previous studies have reported that individuals over 60 years old experience physiological changes, including reduced muscle strength, impaired balance, slower reaction times, and decreased joint flexibility, all of which are associated with deterioration in gait performance[28]. Accordingly, patients were categorized into four subgroups based on age (< 60 years vs. ≥60 years) and sex (male vs. female).

Table 1 summarizes the demographic characteristics of the study cohort. Of the 214 patients, 124 (57.9%) were male and 80 (42.1%) were female. Regarding age distribution, 105 (49.1%) were under 60 years, while 109 (50.9%) were 60 years or older. Incomplete tetraplegia and incomplete paraplegia were more prevalent among older patients (≥ 60 years), whereas cauda equina syndrome was more frequently observed in younger patients (< 60 years), with a mean age of 54.67 years, the lowest among the three conditions.

Gait parameters for each condition are summarized in Table 2, revealing subtle differences across the groups. Patients with cauda equina syndrome exhibited relatively higher cadence and walking speed compared to those with incomplete tetraplegia and incomplete paraplegia. Meanwhile, double support and single support percentages were comparable across all groups, while minor differences were noted in stride length and step time.

We compared the effectiveness of four feature selection methods: RFE, SFM, LASSO, and Ridge. Each method was tested in combination with three classifiers: SVM, RF, and XGB. The corresponding AUC values for

Category	Incomplete tetraplegia (*n* = 95)	Incomplete paraplegia (*n* = 68)	Cauda equina syndrome (*n* = 51)	Total (*n* = 214)
Sex				
Male	65	28	31	124
Female	30	30	20	80
Age				
< 60 years	44	32	29	105
≥ 60 years	51	36	22	109
Average age (years)	62.56	59.26	54.67	59.63

Table 1. Demographic characteristics of study participants according to neurological condition and age group.

Variable	Incomplete tetraplegia	Incomplete paraplegia	CES	Reference (normal)
Cadence (steps/min)	69.15 ± 23.63	69.34 ± 27.03	72.94 ± 24.99	116
Double support (%)	44.74 ± 12.10	44.60 ± 10.21	42.62 ± 14.49	19.8
Foot off (%)	71.86 ± 6.35	71.86 ± 5.41	71.09 ± 7.55	60.1
Limp index	0.99 ± 0.04	0.99 ± 0.03	1.00 ± 0.05	1.02
Opposite foot contact (%)	49.25 ± 3.20	49.45 ± 1.67	50.33 ± 2.21	50.2
Opposite foot off (%)	22.07 ± 6.41	22.16 ± 4.91	21.82 ± 7.67	10.1
Single support (%)	27.12 ± 6.11	27.28 ± 5.01	28.49 ± 7.18	40.6
Step length (m)	0.34 ± 0.12	0.31 ± 0.09	0.35 ± 0.11	0.63
Step time (s)	1.04 ± 0.52	1.09 ± 0.65	0.98 ± 0.56	0.52
Step width (m)	0.21 ± 0.04	0.21 ± 0.04	0.21 ± 0.04	0.15
Stride length (m)	0.67 ± 0.23	0.61 ± 0.18	0.69 ± 0.22	1.27
Stride time (s)	2.07 ± 1.09	2.14 ± 1.26	1.97 ± 1.09	1.04
Walking speed (m/s)	0.41 ± 0.25	0.35 ± 0.17	0.45 ± 0.26	1.23

Table 2. Gait parameters for incomplete tetraplegia, incomplete paraplegia, cauda equina syndrome, and clinical reference values.

each combination are shown in Fig. 1. SFM achieved the highest AUC when paired with SVM and RF. RFE and LASSO also showed competitive performance. Based on these results, we selected SFM for the final model due to its consistent performance across classifiers.

Model performance was evaluated using accuracy, precision, recall, F1-score, and AUC. As shown in Table 3; Fig. 2, the XGB model demonstrated the highest overall performance in terms of accuracy, recall, and F1-Score, while the SVM model achieved superior results in precision and AUC. The RF model showed consistent but relatively lower precision compared to the other models. To further assess predictive capability, Fig. 3 presents the confusion matrices comparing predicted and actual labels across all cross-validation folds.

All independent variables were quantitatively evaluated using SFM to determine their contribution to classification outcomes. Figure 4 presents the average feature importance scores computed for the SVM, RF, and XGB models, highlighting the most influential variables across classifiers. Figure 5 illustrates the average feature importance stratified by sex and age groups across all three models.

Statistical comparisons of gait metrics by sex and age are summarized in Table 4. Males exhibited higher values for single support, step length, step width, stride length and walking speed, whereas females showed higher values for double support, foot off, opposite foot off and step time. Participants aged ≥ 60 years demonstrated increased double support, foot off, opposite foot contact, opposite foot off, step time and stride time, while those < 60 years showed higher cadence, single support, step length, step width, stride length and walking speed.

As presented in Table 5, classification accuracy varied by sex and age. Although the male group achieved slightly higher accuracy than the female group, this difference was not statistically significant. In contrast, the < 60 years group showed significantly higher accuracy than the ≥ 60 years group ($p < 0.05$), indicating that age had a substantial impact on model performance.

Discussion

This study aimed to develop a machine learning model to accurately classify incomplete paraplegia, incomplete tetraplegia, and cauda equina syndrome with residual motor function using real-world clinical data. The goal was to support early diagnosis and personalized treatment planning by capturing the subtle inter-condition differences that are often overlooked in existing studies.

Classification was performed using SVM, RF, and XGB models, and predictive performance was evaluated using sensitivity, specificity, accuracy, and AUC. The XGB model demonstrated superior performance compared to the other models.

Feature importance analysis identified age, cadence, and double support as key variables in all models. Age is an important contributor to the overall change in gait patterns in patients with neurological impairments, reflecting how age-related physiological decline affects gait stability and efficiency[29]. Cadence indicates the frequency of steps within a certain period of time during walking, which is useful for assessing a patient's neurological status and degree of recovery of muscle function[30]. Double support is a metric strongly related to gait stability and is an important assessment factor, especially for elderly patients or those with severe neurological impairment and reduced gait balance[31]. This study reaffirmed the clinical relevance of these variables using real-world clinical data and supported findings from previous research. Furthermore, these variables play a key role in assessing the extent of neurological impairment and recovery of gait function and provide a useful basis for personalized rehabilitation planning.

Sex-based analysis revealed that step length and stride length were dominant features in males, while double support and foot off were more influential in females. Males generally exhibited higher values in dynamic gait parameters such as step length, stride length, and walking speed, whereas females had higher values in stability-related metrics. Prior research has shown that older women tend to compensate for gait instability by increasing double support[32], suggesting a sex-specific adaptation strategy. Our results indicate that gait characteristics after neurological injury may differ by sex. When analyzed by age group, walking speed and cadence were the most

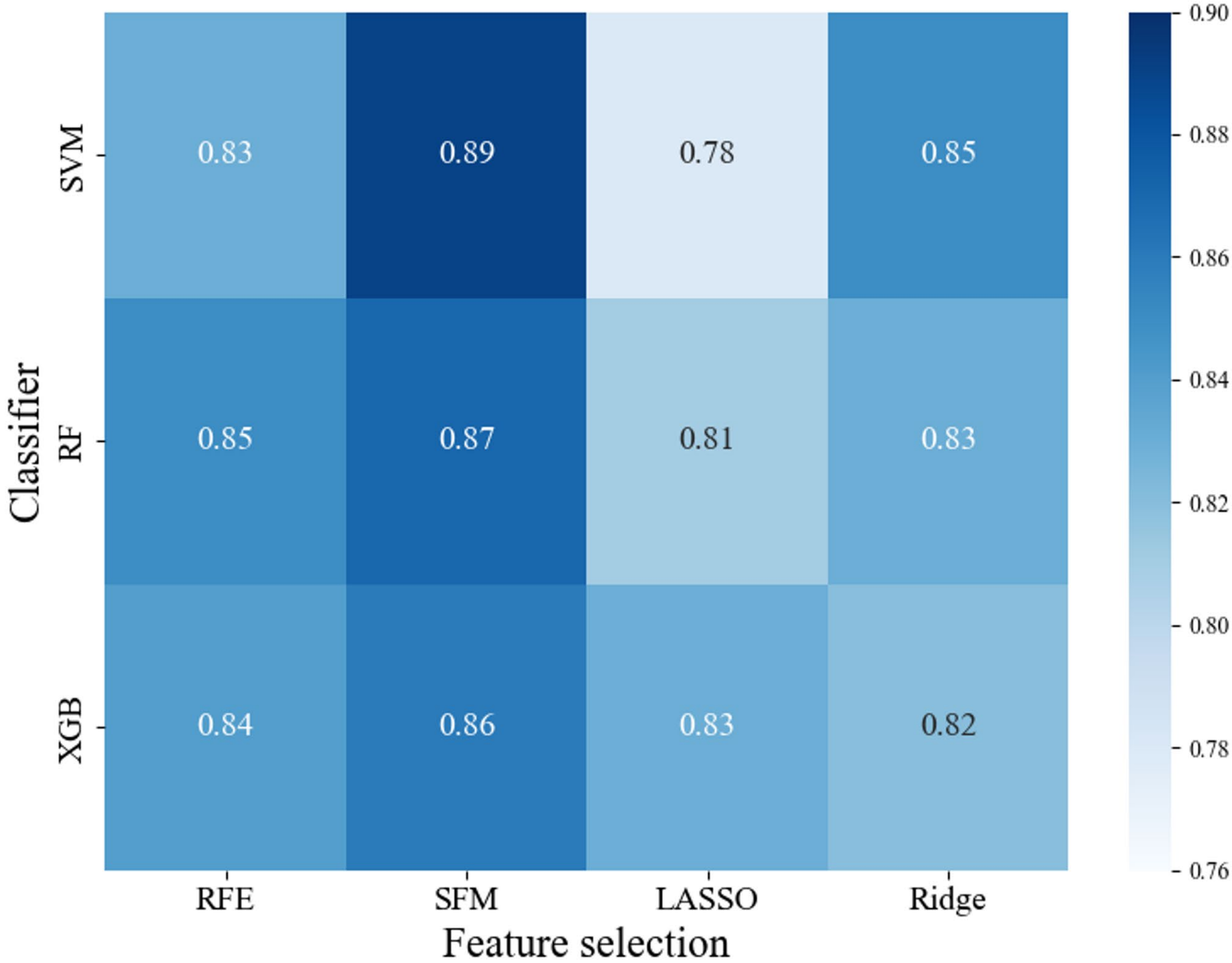

Fig. 1. AUC for each combination of SVM, RF, and XGB machine learning models and RFE, SFM, LASSO, and Ridge methods through heatmap. The higher the heatmap value, the closer it is to black, and the higher the performance for the classification of neurological conditions. SVM, support vector machine; RF, random forest; XGB, extreme gradient boosting; RFE, recursive feature elimination; SFM, select from model.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC (%)
SVM	73.95 ± 4.59	75.72 ± 4.04	73.95 ± 4.59	73.26 ± 4.73	89.55 ± 4.09
RF	72.51 ± 3.58	74.49 ± 5.22	72.51 ± 3.58	72.12 ± 3.86	87.87 ± 2.61
XGB	74.42 ± 2.96	74.80 ± 3.03	74.42 ± 2.96	74.27 ± 3.12	86.34 ± 1.87

Table 3. Performance metrics of SVM, RF, and XGB for classification models.

important variables in the < 60-year-old group, whereas stability-related variables such as double support were the most important variables in the ≥ 60-year-old group. After the age of 60 years, cadence and walking speed significantly decreased, and stability-related variables such as double support increased. This may be because older adults use strategies that prioritize gait stability, and age-related declines in muscle strength and balance may be major contributing factors. Furthermore, there was a clear trend of decreased stride length and cadence in the ≥ 60-year-old group, which may be due to age-related muscle weakness and decreased joint mobility. These findings support the development of age- and sex-specific diagnostic models.

This study differs from previous studies in that it analyzed the subtle gait differences among diseases based on real clinical data from patients with neurological impairments. Although most previous studies focused on evaluating the overall characteristics of gait changes in degenerative neurological diseases, this study explored the subtle differences among incomplete tetraplegia, incomplete paraplegia, and cauda equina syndrome and applied them to a machine learning model for precise classification. In addition, we employed SFM to evaluate feature importance across subgroups and analyzed stratified differences by age (< 60 vs. ≥60 years). This approach

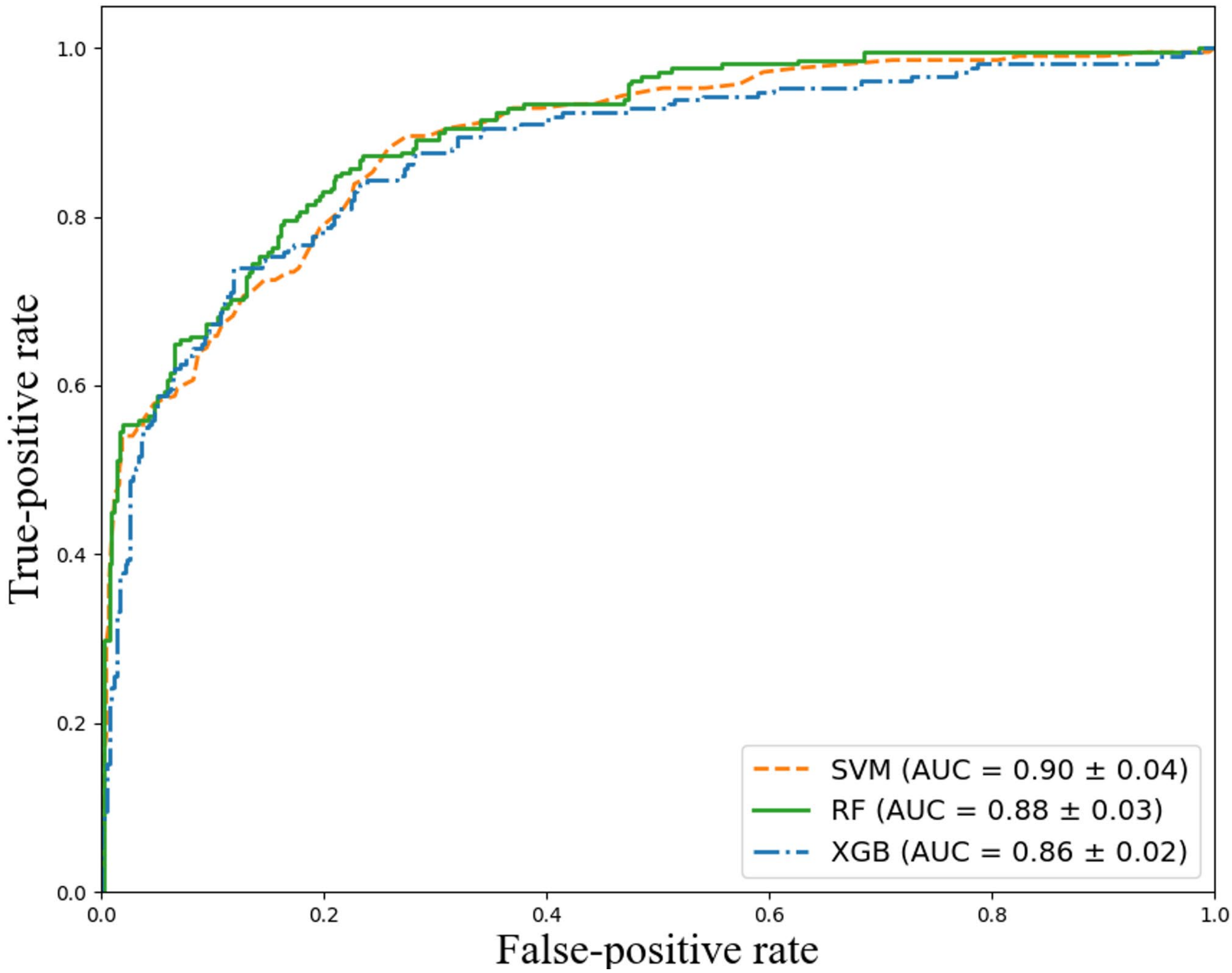

Fig. 2. Receiver operating characteristic analysis results of machine learning models SVM, RF, and XGB for classification using the SFM feature selection method. SVM, support vector machine; RF, random forest; XGB, XGBoost; AUC, area under the curve; SFM, select from model.

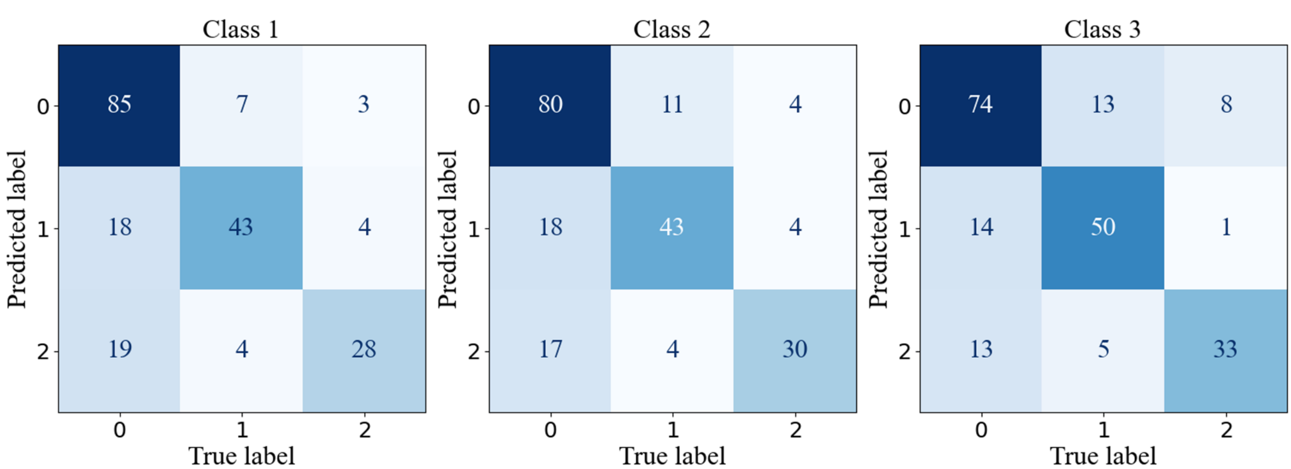

Fig. 3. Confusion matrices for SVM, RF, and XGB. Class 1, incomplete tetraplegia; class 2, incomplete paraplegia; class 3, cauda equina syndrome. SVM, support vector machine; RF, random forest; XGB, XGBoost.

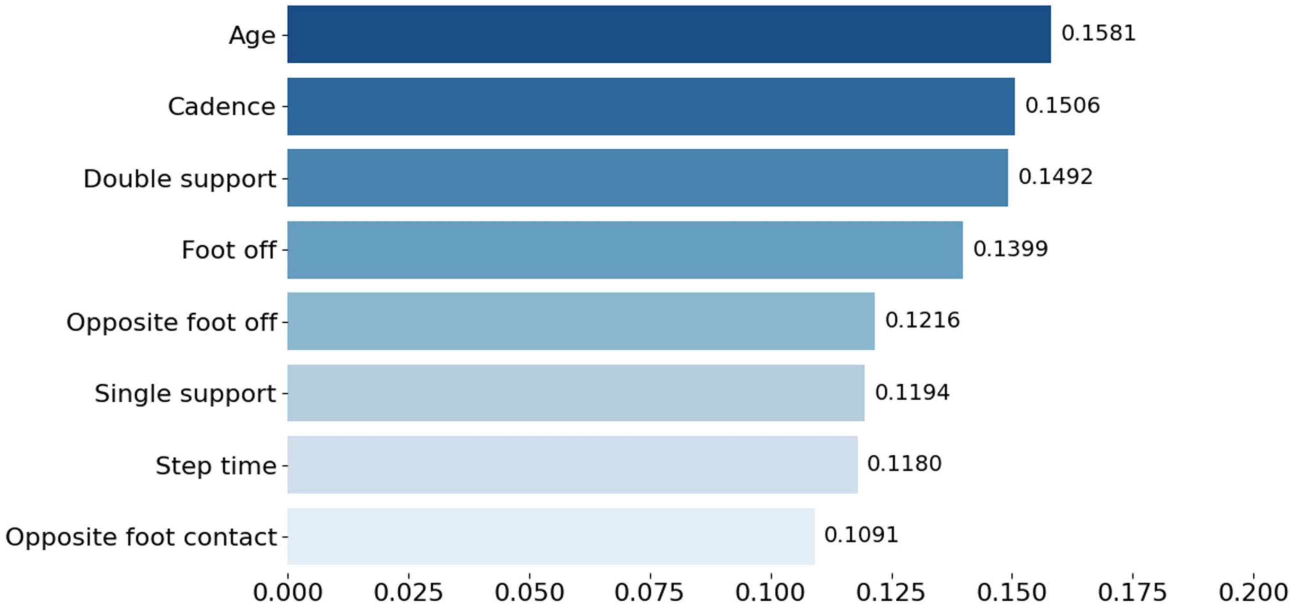

Fig. 4. Average feature importance derived from SVM, RF, and XGB models.

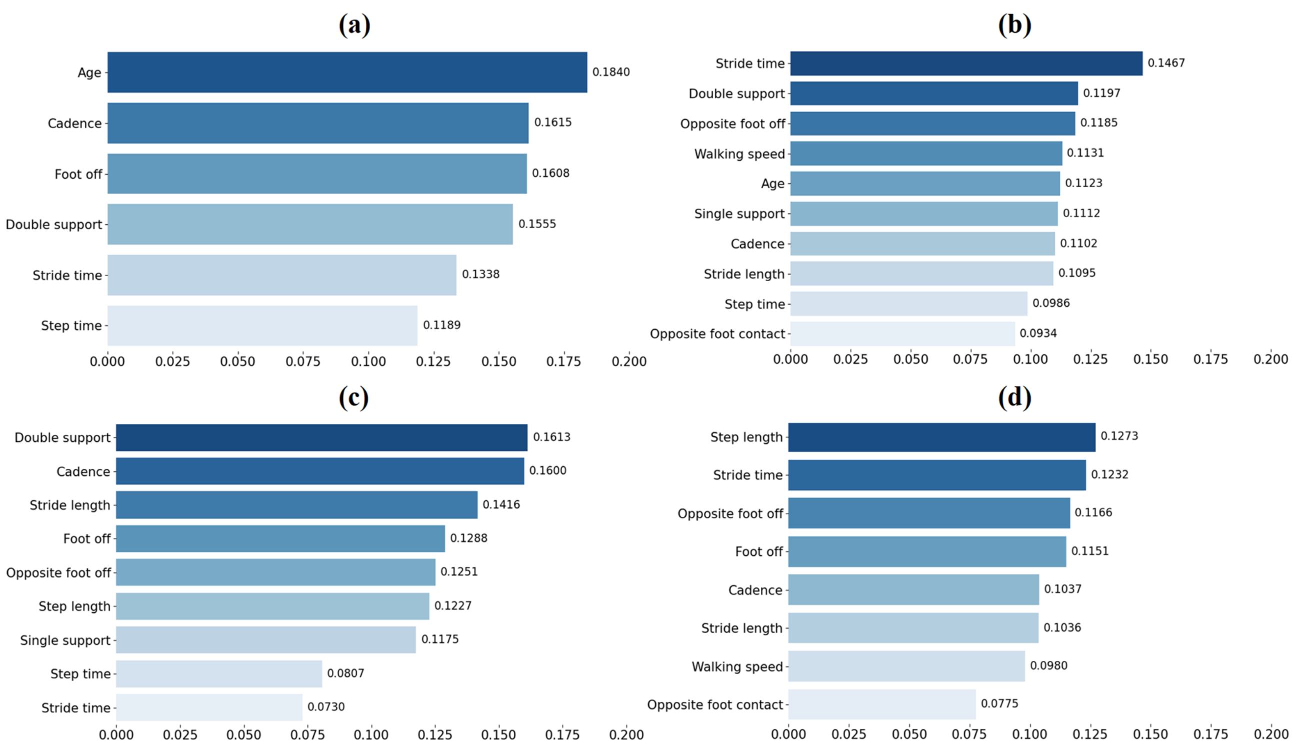

Fig. 5. Average feature importance across models by sex and age group: (**a**) male, (**b**) female, (**c**) < 60 years, and (**d**) ≥ 60 years.

supports the development of personalized treatment strategies that account for disease- and age-specific gait characteristics. Furthermore, this study demonstrated that 3D motion capture systems combined with machine learning can be used to assess gait patterns in a noninvasive and quantified manner. This could be a valuable alternative to the costly and time-consuming traditional imaging diagnostic tools, such as magnetic resonance imaging. Notably, it offers the potential to improve diagnostic accuracy by leveraging gait-based data, even for rare conditions like cauda equina syndrome, thereby contributing to more accessible and efficient clinical decision-making.

Variable	Sex						Age					
	Male		Female		P-value	Cohen's d	< 60 years		≥ 60 years		P-value	Cohen's d
	Mean ± SD	95% CI	Mean ± SD	95% CI			Mean ± SD	95% CI	Mean ± SD	95% CI		
Cadence	72.37 ± 22.91	68.45, 76.28	66.33 ± 27.92	60.12, 72.55	0.112	0.237	76.08 ± 25.65	71.12, 81.04	64.36 ± 23.06	59.99, 68.74	< 0.05	0.481
Double support	41.65 ± 10.19	39.91, 43.39	48.46 ± 13.91	45.36, 51.55	< 0.05	− 0.559	42.38 ± 12.60	39.94, 44.82	45.94 ± 11.47	43.76, 48.12	< 0.05	− 0.295
Foot off	70.46 ± 5.48	69.53, 71.40	73.70 ± 7.21	72.10, 75.31	< 0.05	− 0.506	70.69 ± 6.48	69.44, 71.94	72.62 ± 6.13	71.46, 73.79	< 0.05	− 0.306
Limp index	0.99 ± 0.04	0.99, 1.00	0.99 ± 0.038	0.98, 1.00	0.856	0.000	0.99 ± 0.04	0.98, 1.00	1.00 ± 0.04	0.99, 1.00	0.122	− 0.250
Opposite foot contact	49.42 ± 2.19	49.08, 49.80	49.82 ± 3.16	49.12, 50.52	0.856	− 0.147	49.03 ± 2.23	48.60, 49.47	50.09 ± 2.82	49.55, 50.62	< 0.05	− 0.417
Opposite foot off	20.57 ± 4.81	19.75, 21.39	24.50 ± 7.61	22.81, 26.19	< 0.05	− 0.617	20.71 ± 5.95	19.56, 21.86	23.32 ± 6.36	22.11, 24.53	< 0.05	− 0.424
Single support	28.83 ± 5.07	27.96, 29.70	25.27 ± 6.91	23.73, 26.80	< 0.05	0.587	28.32 ± 6.43	27.07, 29.56	26.71 ± 5.61	25.65, 27.77	< 0.05	0.267
Step length	0.35 ± 0.12	0.33, 0.37	0.31 ± 0.09	0.29, 0.33	< 0.05	0.377	0.35 ± 0.12	0.33, 0.37	0.32 ± 0.10	0.30, 0.34	< 0.05	0.272
Step time	0.98 ± 0.53	0.89, 1.07	1.14 ± 0.62	1.01, 1.28	< 0.05	− 0.277	0.99 ± 0.65	0.86, 1.12	1.09 ± 0.49	1.01, 1.18	< 0.05	− 0.174
Step width	0.22 ± 0.04	0.21, 0.22	0.19 ± 0.04	0.18, 0.20	< 0.05	0.750	0.21 ± 0.04	0.20, 0.22	0.20 ± 0.05	0.19, 0.21	< 0.05	0.221
Stride length	0.68 ± 0.23	0.64, 0.72	0.61 ± 0.17	0.57, 0.64	< 0.05	0.346	0.69 ± 0.23	0.64, 0.73	0.62 ± 0.19	0.59, 0.66	< 0.05	0.332
Stride time	1.93 ± 1.02	1.76, 2.10	2.30 ± 1.31	2.01, 2.59	0.112	− 0.315	1.94 ± 1.25	1.69, 2.18	2.20 ± 1.03	2.03, 2.37	< 0.05	− 0.227
Walking speed	0.43 ± 0.24	0.39, 0.47	0.36 ± 0.21	0.31, 0.40	< 0.05	0.310	0.46 ± 0.26	0.41, 0.51	0.35 ± 0.19	0.31, 0.38	< 0.05	0.483

Table 4. Differences in gait metrics by sex and age. P-values are adjusted using the Benjamini–Hochberg false discovery rate (FDR) method. Values in bold indicate statistical significance at FDR-adjusted $p < 0.05$.

	Female (%)	Male (%)	≥ 60 years (%)	< 60 years (%)
RF	68.33 ± 9.93	75.84 ± 9.15	63.10 ± 7.59	76.76 ± 10.38
SVM	63.25 ± 5.02	70.51 ± 8.42	64.00 ± 7.24	76.72 ± 8.38
XGB	67.00 ± 8.14	76.56 ± 7.68	63.92 ± 8.66	76.76 ± 6.61
P-value (XGB performance differences)	> 0.05		< 0.05	

Table 5. Classification accuracy by sex and age according to model.

Although the XGB model performed well in terms of accuracy, recall, and F1-score, the overall classification performance was limited due to a relatively low AUC. This is likely attributable to data scarcity in certain classes, particularly cauda equina syndrome, which prevented the model from learning in a balanced manner. To address class imbalance, data augmentation techniques suited for numerical gait variables should be considered. SMOTE generates synthetic samples for underrepresented categories such as cauda equina syndrome. Generative models, including GAN and conditional tabular GAN (ctGAN), learn the distribution of the original dataset and can produce more diverse synthetic data, providing a flexible strategy for minority class augmentation. These methods have improved model robustness and classification accuracy in gait-related machine learning applications[33,34].

Some gait variables showed similar values across diagnostic groups, which may have reduced the model's ability to accurately distinguish between them. To mitigate this issue, future research may explore dimensionality reduction techniques or regularization methods. For example, Layer-wise Relevance Propagation (LRP) has been applied to gait classification models to identify class-specific feature contributions and improve interpretability[35]. In addition, model-agnostic interpretability tools such as SHAP and LIME were not implemented in this study. These techniques can provide instance-level explanations of model outputs, which may improve transparency and clinical trust. Future work should consider incorporating such methods to enhance the interpretability of decision processes, particularly when deploying models in clinical settings[36,37].

Another limitation is the absence of expert-labeled gait classifications for direct clinical comparison. While model performance was assessed using quantitative metrics, comparison with expert clinical judgment could provide a more meaningful evaluation of its diagnostic utility. Incorporating such expert-labeled data in future research would allow for more clinically interpretable validation of model outputs.

Finally, this study focused primarily on lower-limb gait variables and excluded upper-limb movement and other clinical data, which represents an additional limitation. Notably, some cauda equina syndrome and incomplete paraplegia samples were frequently misclassified as incomplete tetraplegia. One possible explanation is that lower-limb gait variables alone may not adequately reflect upper-body motor function. Upper-limb movement, such as arm swing, plays a critical role in gait coordination and stability, and may offer complementary information that helps differentiate between neurologically adjacent conditions. Previous studies have shown that three-dimensional gait analysis (3DGA), incorporating full-body motion patterns, can support more individualized interpretation and improve clinical decision-making in patients with incomplete spinal cord injury[15]. Future work should consider incorporating upper-limb kinematics, physiological signals, and multimodal clinical data to enhance model performance. Exploring the relationship between arm motion and gait characteristics may also improve the discriminative power of machine learning models in classifying complex neurological gait patterns.

If the aforementioned limitations of this study are addressed in future research, it is expected to further improve the accuracy of gait analysis and disease classification for patients with neurological impairments and contribute to improving the quality of life and access to healthcare by establishing customized treatment strategies.

Methods

Data collection

In this study, we used gait data collected from 2013 to 2021 at Chungnam National University Hospital from patients diagnosed with various neurological conditions. A 3D motion capture system (Vicon Motion Systems, Ltd., Oxford, UK) was used to acquire all data. All data were recorded using the Vicon MX system (T20 model) in a clinical motion analysis laboratory. After anthropometric measurements were taken, the spatial coordinate system of the laboratory was calibrated. Reflective markers and surface electromyography (EMG) pads were attached to anatomical landmarks according to the Plug-in Gait Lower Body protocol. Patients walked along a predefined path while motion data were recorded. Data acquisition and initial processing were performed using Vicon Nexus software (Vicon, Oxford, UK). Although software versions may have changed during the extended data collection period, the acquisition protocol, marker placement, and calibration procedures remained consistent. All gait assessments were performed following standardized clinical procedures.

This study was a retrospective analysis of previously collected clinical gait data. It was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board (IRB) of Gachon University Gil Hospital (IRB no. GCIRB2023-439). Data access for research purposes began on December 12, 2023, and continued until the end of the study. All data were anonymized prior to analysis.

The initial dataset included 844 reports containing patient information. Data were excluded if they lacked temporal gait parameters, age or sex information, or a confirmed diagnosis of incomplete tetraplegia, incomplete paraplegia, or cauda equina syndrome. For incomplete tetraplegia and paraplegia, only cases corresponding to ASIA grades C and D, indicating partial motor function preservation, were included. After applying these criteria, the final dataset consisted of 214 cases: 95 with incomplete tetraplegia, 68 with incomplete paraplegia, and 51 with cauda equina syndrome. The study flowchart is provided in Fig. 6.

Although approximately 75% of the initial records were excluded (47 missing temporal gait parameters, 573 missing neurological diagnosis, 6 missing age, and 4 missing sex), the final dataset maintained a balanced distribution by sex and age and included all three diagnostic categories. Therefore, the potential for selection bias introduced by these exclusions is considered minimal.

Temporal parameters

In gait analysis, various temporal parameters were used to evaluate patients' gait characteristics.

These parameters quantitatively measure different aspects of gait, serving as key indicators for defining normal gait patterns and detecting abnormalities or deviations in patients' walking behavior.

Temporal gait parameters were automatically extracted using the gait event detection (GED) algorithm built into the Plug-in Gait model. This algorithm detects key events such as heel strike and toe off based on the vertical position and velocity of the heel and toe markers, without the use of force plates. A gait cycle was defined from the heel strike to the subsequent ipsilateral heel strike. The gait cycle duration was computed as the sum of step times from both feet, and parameters such as single support, double support, and foot off were converted into percentages of the total gait cycle time. Only unilateral gait cycles were analyzed to ensure consistency and comparability across all participants. Although gait events were detected separately for the left and right sides, the mean values of bilateral parameters were used for machine learning classification and statistical comparisons, considering the symmetric nature of trauma-related gait impairment in SCI and cauda equina syndrome patients.

The temporal gait parameters evaluated in this study were:

Cadence: number of steps per minute.

Double support: percentage of time when both feet are on the ground during a gait cycle.

Foot off: percentage of time when the foot leaves the ground.

Limp index: a measure of gait asymmetry reflecting mobility impairment.

Opposite foot contact: timing of opposite foot contact when one foot strikes the ground.

Opposite foot off: percentage of time from the moment one foot leaves the ground to the moment the opposite foot leaves the ground.

Single-support time: percentage of time during a gait cycle in which one foot is in contact with the ground.

Step length: distance between the initial contact points of opposite feet.

Step time: time taken to complete one step.

Step width: horizontal distance between the feet.

Stride length: distance for one foot to return to the same position.

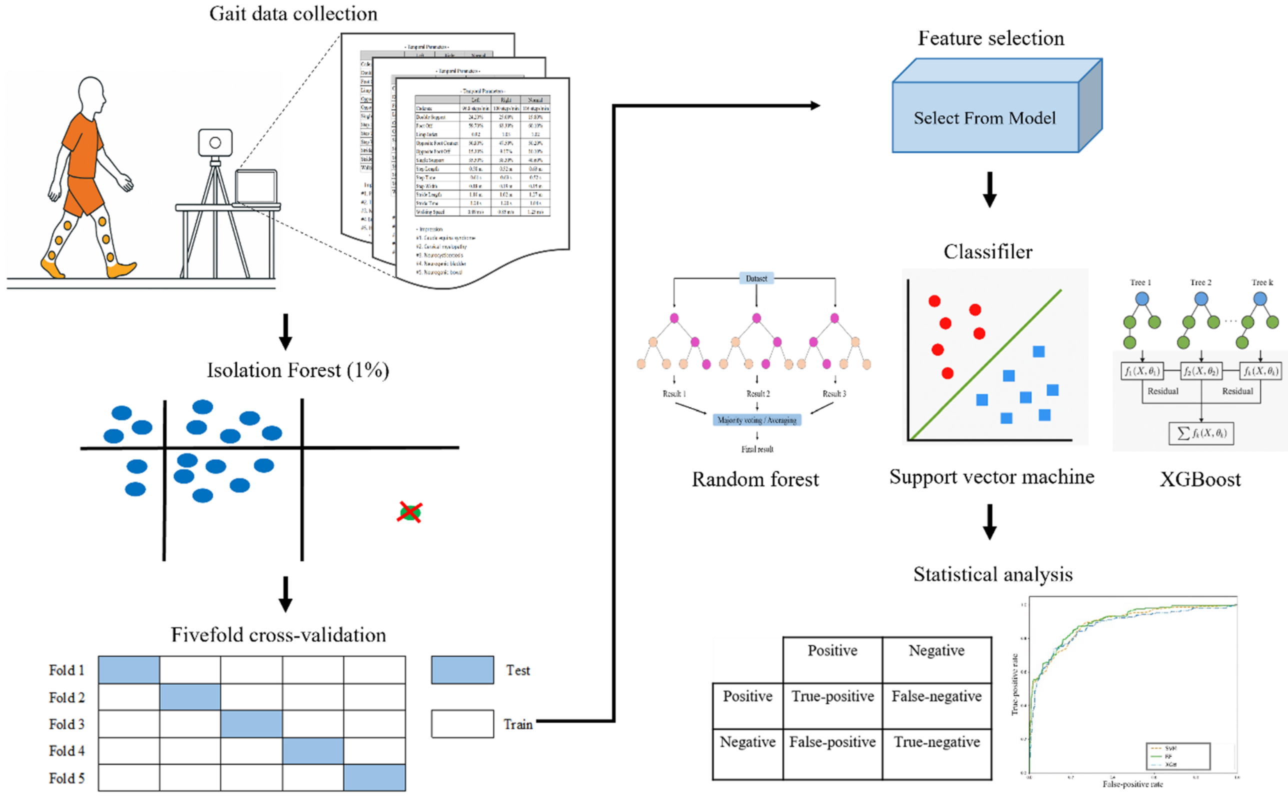

Fig. 6. Overview of the study process, including data preprocessing, feature selection, and statistical analysis, from gait data collection to classification model evaluation.

Stride time: time required to complete one stride.

Walking speed: distance walked in 1 s.

Institutional normative reference values for each gait parameter were obtained from clinical gait analysis reports at Chungnam National University Hospital. These values were obtained under the same measurement conditions (i.e., Vicon MX system and Plug-in Gait protocol) as used in the present study and represent standard gait performance in healthy individuals. They were used as a consistent reference baseline to support interpretation of deviations in gait characteristics among patients with neurological impairments.

Data preprocessing

In this study, 214 cases were classified into three disease groups (incomplete tetraplegia, incomplete paraplegia, and cauda equina syndrome), and the gait patterns were analyzed. The Isolation Forest algorithm was used to remove top 1% of outliers, and to solve the problem of class imbalance, class weights were adjusted inversely to sample size for each group. The weights were automatically calculated based on the reciprocal of the sample proportion per class using the class weight = 'balanced' option of scikit-learn. To address the unit inconsistency of some variables, we converted double support and single support durations, originally measured in seconds, into percentages of the gait cycle time. To do this, we calculated the gait cycle time by summing the step times of the left and right feet and then converting the time values to percentages.

The calculation processes are as follows:

1. Gait cycle time calculation:

$$\text{Gait cycle time (cycle time)} = \text{Lt}_{\text{step time}} + \text{Rt}_{\text{step time}},$$

where Lt and Rt indicates left and right, respectively.

2. Conversion of time values to percentage units:

$$\text{Percentage (\%)} = \frac{\text{Time (s)}}{\text{Gait cycle time (s)}} \times 100.$$

Feature selection and model training
In this study, we used the SelectFromModel (SFM) to select the main features of the gait data. The SFM uses a RandomForestClassifier to calculate the importance of each feature and automatically removes features with importance scores below a predefined threshold. The RandomForestClassifier can be used as a suitable tool for feature selection because it can reliably evaluate the importance of each variable while reflecting nonlinear relationships and interactions between variables. Although SFM was initially selected based on its interpretability and performance in preliminary testing, we additionally evaluated three alternative feature selection methods—RFE, LASSO, and Ridge regression—to validate the robustness of our approach. Each method was applied independently using the same preprocessing pipeline.

The threshold was determined automatically as the mean feature importance to exclude features with low relevance. Based on the selected features, we trained three classifiers: support vector machine (SVM), random forest (RF), and extreme gradient boosting (XGB). To solve the multiclass problem, we applied the One-vs-Rest (OvR) strategy to convert it into multiple binary classification problems. The OvR strategy trains a binary classifier for each class by grouping the remaining classes into a single group, which effectively leverages the performance of binary classification-based algorithms, such as SVMs, for multiclass problems. GridSearchCV was used for hyperparameter optimization, and cross-validation was used to determine the optimal hyperparameter combinations to maximize the generalization performance of the model.

Model evaluation metrics and statistical analysis methods
Model performance was evaluated using fivefold StratifiedKFold cross- validation, in which 80% of the data were used for training and 20% for validation in each fold. StratifiedKFold divides data such that each fold maintains the proportion of classes in the original data, which is useful for minimizing the class imbalance problem. The multiclass classification performance of the model was evaluated based on true positives, true negatives, false positives, and false negatives obtained by comparing the actual and predicted values. We used accuracy, precision, recall, and F1-scores as evaluation metrics. We also analyzed the receiver operating characteristic (ROC) curve to evaluate the classification performance of the model and calculated the area under the ROC curve (AUC). The AUC value ranges from 0 to 1, and a value approaching 1 reflects superior model performance. Finally, we analyzed the classification performance for each class (incomplete tetraplegia, incomplete paraplegia, cauda equina syndrome) using the confusion matrix. The confusion matrix provides a visual representation of the relationship between the model predictions and the actual class, illustrating the number and type of misclassified samples. This was used to assess the tendency of the model to overpredict or misclassify certain conditions. Differences in gait variables between groups divided by sex and age (<60 vs. ≥60 years), as well as differences in model performance across classifiers, were statistically analyzed. To assess the normality of each variable, the Shapiro–Wilk test was performed. Variables that violated the normality assumption were analyzed using the Mann–Whitney U test, while normally distributed variables were compared using independent samples t-tests. To control for Type I error inflation due to multiple comparisons, the false discovery rate (FDR) correction was applied to the analysis of gait parameters. Statistical significance was determined using FDR-adjusted p-values, with $p<0.05$ considered significant. All statistical analyses were performed using IBM SPSS Statistics version 20 (IBM Corp., Armonk, NY, USA).

Data availability
The datasets generated during and/or analysed during the current study are not publicly available due to institutional policies and patient privacy regulations, but are available from the corresponding author on reasonable request.

Code availability
The code is available at https://github.com/park-seulgi/GaitML_SCI_CES_Classification. In our experiments, we used Python 3.12.4, and the following open-source libraries: pandas = 2.1.4, numpy = 1.26.4, scikit-learn = 1.4.2, xgboost = 2.1.0, matplotlib = 3.7.5, seaborn = 0.13.2.

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Author contributions

S.G.P. conducted the machine learning analysis, drafted the manuscript, and performed statistical analyses. S.B.M., S.G.P. performed data analysis and interpretation. Y.J.K., K.G.K. collected the dataset. S.G.P., S.B.M., K.G.K., Y.J.K. participated in the study design and revised the manuscript. All the authors read and approved the final manuscript.

Declarations

Competing interests
The authors declare no competing interests.

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