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RESEARCH ARTICLE

Classification of Stroke Severity Using Clinically Relevant Symmetric Gait Features Based on Recursive Feature Elimination With Cross-Validation

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ABSTRACT Stroke is a leading cause of disability among elderly individuals, and gait impairment is a typical characteristic related to the stroke severity experienced by patients. The aim of this study is to propose a novel stroke severity classification method using symmetric gait features with recursive feature elimination with cross-validation (RFECV). An experiment was conducted on data acquired from thirteen chronic stroke patients and eighteen elderly participants. They walked on a treadmill at four different speeds based on their preferred speed. Symmetric gait features representing the ratio between the left- and right-side values were used as inputs along with the general gait features that did not completely contain the patients' gait characteristics. We used four different machine learning (ML) techniques to determine the optimal subset for differentiating between the elderly and stroke groups according to severity based on RFECV. In addition, to verify the performance of RFECV and the symmetric gait features, four different feature sets were used: 1) all forty-five general features, 2) all twenty-one symmetric features, 3) the optimal general feature subset obtained by using RFECV, and 4) the optimal symmetric feature subset obtained by using RFECV. The best classification result was obtained by RF-RFECV with an RF classifier derived from the symmetric features (accuracy: 96.01%). The result proved that the stroke severity classification performance increased when symmetric gait data and the RFECV technique were applied. The findings of this study can help clinicians diagnose the stroke severity experienced by patients based on information obtained using ML technology.

INDEX TERMS Machine learning, assessment of stroke severity, symmetric gait data, feature selection, rehabilitation.

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I. INTRODUCTION

Stroke is a leading cause of disability among elderly individuals, and the number of stroke patients is increasing rapidly

every year with the aging of the global population [1], [2], [3]. A stroke causes neurological deficits due to an acute focal injury in the central nervous system (CNS) caused by cerebral infarction, a subarachnoid hemorrhage (SAH), or an intracerebral hemorrhage (ICH) [4]. Because of these factors, stroke patients experience posture, balance, and motor function difficulties. According to a previous study, one-third of post-stroke (PS) survivors require care in more than one activity of everyday life [5], and only approximately 25% of patients return to their daily lives with normal physical function [6]. This not only reduces a stroke patient's individual quality of life but also incurs considerable social costs [7]. Appropriate patient-specific motor rehabilitation techniques can reduce the disability resulting from a stroke and quickly return patients to society [8]. To this end, a proper diagnosis that can accurately evaluate the patient's current condition needs to be made. In fact, accurate diagnosis helps to improve the effectiveness of rehabilitation treatments by eliminating unnecessary treatments and maximizing the use of necessary rehabilitation treatments [8].

Traditional assessment methods, such as the National Institute of Health Stroke Scale (NIHSS), Fugl-Meyer Assessment (FMA), and Berge Balance Scale (BBS), are widely used in clinical practice for evaluating the severity levels and recovery degrees of patients. The NIHSS is an assessment method proposed by Thomas Brott et. al. [9], consisting of a total of 15 neurologic examination items, such as consciousness level, language, visual field loss, motor strength, sensory loss, etc. The NIHSS has the advantage of requiring few tools and having high interrater reliability [9]. However, the NIHSS is a score system that includes factors such as mental statuses, eye movements, and functional abilities, so this scale is not sufficient for use as an evaluation indicator in terms of functional rehabilitation. The FMA was proposed by Fugl-Meyer et. al. as a method to evaluate physical performance, such as motor recovery, sensation, and range of joint motion in patients [10], and it is well known as a comprehensive quantitative measure of motor impairment in stroke patients [11]. The BBS is a score that evaluates patients' balance abilities through a task consisting of 14 items, such as sitting, standing, and turning. Even though the BBS was originally designed by Berg et. al. as a measurement method for assessing the balance abilities of older adults [12], it is also used to assess the degrees of rehabilitation exhibited by stroke patients who have balance deficits due to its advantages of reliability and validity in the clinical field [13]. The above mentioned methods are widely used in research and clinical practice to evaluate the severity of stroke patients, but they consume much time for completing each trial and require a highly experienced expert rater to maintain reliability and repeatability [14].

To solve this problem, this paper proposes a simple gait test-based method that can quantitatively evaluate the severity of stroke symptoms. Gait, which requires both balance and motor function, is a simple and important movement used during rehabilitation training to return patients to their daily

lives. In addition, gait reflects the main physiological characteristics of neurological disorders, and gait dysfunctions are common features of neurological disorders in the initial and progressive states of diseases [15]. For these reasons, we hypothesize that gait characteristics can effectively represent stroke severity.

In several recent studies, gait performance was utilized as one of the medical indicators for predicting the severity of neurodegenerative disorders based on the relationship concerning the degradation of gait performance in accordance with the progression of brain-related disorders [16], [17]. Schmid et. al. used gait speed as an important indicator of function and prognosis after a stroke [18]. They classified patients into household ambulation, limited-community ambulation, and full-community ambulation groups according to their gait speeds. S Mulroy et. al. classified hospitalized stroke patients into four different groups using gait speed, peak mid-stance knee extension, and peak dorsiflexion in the swing phase [19]. B Balaban et. al. utilized quantitative three-dimensional gait analysis features, such as temporal-spatial, kinematics, and kinetics, to understand the complex gait dysfunctions in hemiparetic patients [20]. F Wahid et. al. applied multiple regression normalization methods for spatial-temporal gait parameters and then classified Parkinson's disease using the corresponding parameters [21].

However, these previous studies that used gait for the diagnosis of neurodegenerative disorders have several limitations. First, in most studies, experiments were conducted only at the preferred gait speeds of participants. Generally, many gait features can be influenced by different preferred gait speeds, which makes it difficult to determine whether a gait feature difference between groups is due to impairment caused by stroke or the walking speeds of the patients [22]. Therefore, a classification algorithm that is less affected by gait speed is necessary, as such an approach can distinguish between patients and elderly people even under various gait speeds. Second, the complexity of the data makes it difficult to understand the observed gait characteristics based on the severity of stroke patients and reduces the accuracy of diagnosis [23]. As the number of calculated gait parameters increases, it becomes increasingly difficult to determine the type and the optimal number of gait features that are relevant to patient severity among the various available features. Identifying the optimal subset of gait features to better understand stroke patients' gait characteristics is necessary to aid the diagnosis process. Third, when analyzing patient gait characteristics, only the gait analysis value of the paretic side is used as an assessment index. Generally, gait performance is described by lower limb kinematics, kinetics, and spatial-temporal parameters. However, since a patient's physical condition or walking habits can affect their walking characteristics, it is inappropriate to identify the patient's walking characteristics only with paretic leg walking factors. Several previous studies have shown the correlations between various gait features and the degree of symmetry between the

paretic and non-paretic sides [24], [25]. From this viewpoint, we think that the symmetric ratio between the paretic and non-paretic side values is an important factor for evaluating the severity of stroke patients, and we expect stroke patients' symmetric gait performance to degrade as the degree of stroke severity increases.

Machine learning (ML) strategies have gained popularity because they offer clinically relevant gait features for disease diagnosis [17], [21]. ML provides a feature selection method to identify the optimal subset combinations of gait parameters that are clinically relevant to stroke severity. The selected features help to understand abnormal gait patterns and improve the accuracy of stroke patient severity assessments by minimizing redundancy. In this study, four different ML strategies were employed to select optimal gait features and classify stroke patients and elderly people based on their gait characteristics: a support vector machine (SVM) [26], gradient boosting (GB) [27], a decision tree (DT) [28], and a random forest (RF) [29]. The wrapper method, which has the advantage of powerful classifier interactions for feature selection, was applied in this study [30], [31].

The purpose of this study was to use the symmetry in multiple gait parameters for the classification of stroke patients who had different severity levels at diverse speeds. Furthermore, we proposed a robust algorithm based on an optimally selected feature subset (constructed with the minimum number of features using recursive feature elimination) to achieve improved stroke severity classification performance. The results of this study have future implications for stroke diagnosis strategies and can be clinically utilized for severity diagnosis through the gaits of stroke patients in the future.

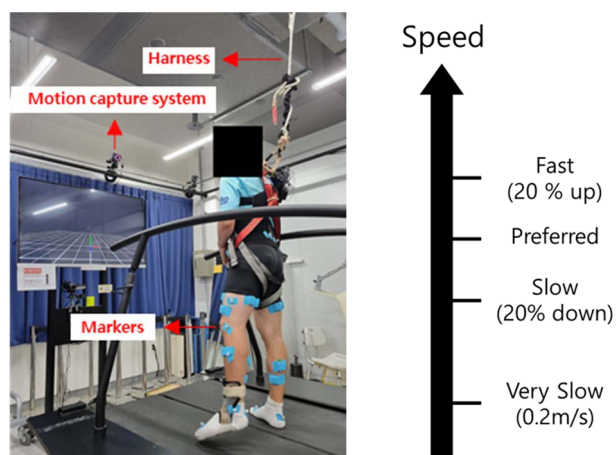


FIGURE 1. Experimental environment settings for gait data collection from elderly people and stroke patients.

II. MATERIALS AND METHODS

A. EXPERIMENTAL PARTICIPANTS

This study was approved by the Korea Institute of Science and Technology (KIST) Institutional Review Board

(IRB No. 2020-010). Written informed consent was obtained from each participant prior to the experiment, and the experiments were conducted in strict accordance with the KIST Ethics guidelines. Participants were recruited with the following exclusion criteria: (1) unable to walk without any support, (2) possessed a history of neurophysiological or musculoskeletal problems in the past six months, and (3) unable to understand the instructions of the researcher, with less than 24 points in the mini-mental status examination (MMSE). During the experiment, participants were allowed to stop at any time if they did not want to continue to participate.

In this study, an experiment was conducted on stroke patients with more than 6 months of onset and the elderly in the control group. Total thirteen post-stroke patients (mean age: 52.6 ± 10.80 years; height: 165.9 ± 9.47 cm; body mass: 67.6 ± 10.37 kg; gender: 9 males, 5 females) and eighteen healthy elderly people (mean age: 74.9 ± 2.71 years; height: 157.7 ± 7.18 cm; body mass: 60.9 ± 8.73 kg; gender: 9 males, 9 females) were recruited for research.

B. GAIT DATA ACQUISITION

Gait data were acquired using a motion analysis system that was embedded with a force platform and included ten 3-dimensional motion capture cameras (Vicon Nexus, Oxford, United Kingdom). Sixteen reflective markers were attached to each participant's lower limb according to a Plug-in-Gait model marker set to calculate kinetic, kinematic, and spatial-temporal data at a sampling frequency of 100 Hz [32], [33]. All marker data were passed through a low-pass filter, which was a fourth-order Butterworth filter with a 4 Hz cutoff frequency [21].

After practicing enough to become used to walking on a treadmill (M-Gait, Motek, Amsterdam, Netherlands), the participants were initially asked to walk at their preferred walking speeds for one minute. Then, the participants walked at a 30% faster speed and a 30% slower speed for 1 minute to determine whether the differences in their gait characteristics were caused by the speed of the gait or the severity of the disease. Last, the participants were requested to walk at 0.2 m/s, which was the slowest speed among participants, to make them all walk at the same speed. All experiments were conducted with sufficient rest in the middle of the trial and were carried out wearing a safety harness, as shown in Fig. 1. The average preferred walking speeds of the PS patients and the elderly were 0.65 ± 0.15 m/s and 0.8 ± 0.27 m/s, respectively. Each participant walked for a total of 4 minutes, with 1 minute at a different speed, and a total of forty-five general gait parameters and twenty-one symmetric gait parameters were extracted for each gait cycle.

The 45 general gait parameters comprised kinetics, kinematics data, and spatial-temporal parameters. The kinetic data were calculated separately by dividing the paretic side and the non-paretic side to extract the maximum forces, moments, and power values of both lower extremities at the hip, knee, and ankle joint. Each of the data points was calculated in the sagittal plane while considering the gait.

Likewise, kinematics data were also extracted from both lower extremity multi-joints in the sagittal plane, and the range of motion (ROM) maximum angle value were calculated at the foot-off and foot strike points. The spatial-temporal data consisted of cadence, stance time, swing time, stride time, step time, strike length, step length, and step width data. To classify severity based on gait parameters representing the differences between the groups, in the case of elderly participants, the foot on the dominant side was assumed to be the non-paretic side. Since the general gait parameters on one side may have been affected by each participant's usual gait habits, gender, height, and muscle mass, the symmetric ratio between the paretic and non-paretic side values was calculated in this study. In a previous study, the symmetry ratio (SR) value between the non-paretic side and paretic side was calculated as shown in Equation (1) [34]. The better the patient's left-right symmetry, the closer the SR value is to 1, and it can be interpreted that when the SR value is higher than 1 and less than 1, the paretic side and non-paretic side are dominant, respectively. However, a larger or smaller value may be obtained on the paretic side depending on the participants or parameter types from the perspective of symmetry, which makes it difficult to use the SR value itself as a value for indicating left-right symmetry. Therefore, in this study, the symmetry of each patient was evaluated by using the symmetry normalization ratio (SNR) value, which becomes close to 1 as the degree of symmetry increases and less than 1 as the degree of asymmetry increases regardless of whether the left or right side is examined, as shown in Equation 2. In addition, the gait parameter temporal symmetry ratio (TSR), which has been widely used in previous studies, was added as a symmetric parameter for classifying patients. All general and symmetric gait feature data were collected with a sampling frequency of 100 Hz. As a result of the gait analysis, a total of more than 4000 gait cycles were obtained from 31 participants.

$$\begin{aligned} \text{Symmetry Ratio (SR)} \\ &= \frac{(\text{Affected side parameters})}{(\text{Non Affected side parameters})} \end{aligned} \quad (1)$$

$$\begin{aligned} \text{Symmetry Normalization Ratio (SNR)} \\ &= 1 - \left| \frac{\text{Affected side parameters}}{\text{Non Affected side parameters}} - 1 \right| \end{aligned} \quad (2)$$

$$\begin{aligned} \text{Temporal Symmetry Ratio (TSR)} \\ &= \frac{\text{Paretic swing time/Paretic stance time}}{\text{Non paretic swing time/Non paretic stance time}} \end{aligned} \quad (3)$$

C. CLINICAL TEST FOR SEVERITY CLASSIFICATION

The BBS consists of 14 different scales that assess balance and fall risk [12]. It contains various tasks that require the participant to maintain positions while keeping their balance and perform specific behaviors such as sitting, standing, turning, and stepping. [35]. The BBS is one of the indicators for evaluating the rehabilitation degrees of stroke patients and is widely used in clinical practice [13]. An experienced

rater directed a PS patient to perform the specific motions in order and evaluated their performance by providing a score between 0 to 4 points according to the guidelines. In this study, the PS patients were divided into two groups, a severe stroke group with less than 40 points and a mild stroke group with more than 40 points, based on the total BBS scores.

D. FEATURE SELECTION AND CLASSIFICATION

1) FEATURE SELECTION

Feature selection is required in classification tasks to lessen the learning time by reducing the number of training data and to increase accuracy by removing information that is unnecessary for classification [30]. In this study, the recursive feature elimination with cross validation (RFECV) method was applied. RFE is a wrapper-style feature selection method that selects the most relevant subset by removing unnecessary features until the desired number of features remains. However, the number of features is an important hyper-parameter that must be tuned during the training process, and it is difficult to know the proper number of features to select with the RFE technique from the beginning. To address this issue, RFECV, a feature set derivation method that automatically corresponds to the best number of features yielding the highest classification performance by averaging the model performance based on cross-validation, can be a solution. In this study, four different kinds of methods, SVM-RFECV, GB-RFECV, DT-RFECV, and RF-RFECV, were used to select the optimal gait parameter subset.

- SVM-RFECV: An SVM with a linear kernel function is an efficient feature selection tool that finds a separating hyperplane with the maximal margin from the optimal decision function. [36], [37].
- GB-RFECV: GB is an ensemble algorithm of boosting methods that sequentially combines weak classifiers to create strong classifiers with high classification performance [27].
- DT-RFECV: A DT is an algorithm that analyzes data and presents patterns that exist between the data as a combination of predictable rules; it is a typical classification model and is among the most intuitive methods that have the advantage of representing results in a visually readable form [28].
- RF-RFECV: An RF is an ensemble algorithm of bagging methods; this approach achieves increased prediction performance by creating multiple DTs for the same data and combining their results [29].

The optimal number and type of gait features relevant to the disease were different for each model, and the details are shown in Table 2 below. Student's *t test* was conducted to investigate the differences between the selected features of two different groups (elderly-mild stroke & mild stroke-severe stroke & elderly-severe stroke). The significance level was set to $\alpha = 0.05$, and the number of features demonstrating statistical significance ($p < 0.05$) and the percentage of features out of the total are represented in

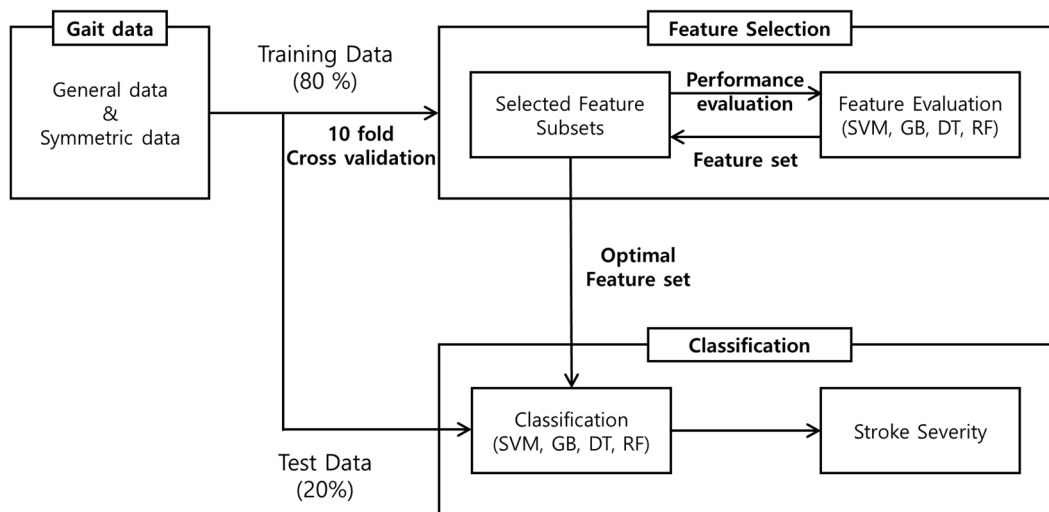


FIGURE 2. ML modeling framework using RFECV for stroke patient severity classification.

Table 3. These analysis results helped identify gait features that influenced the groupwise classification process.

To validate the effectiveness of using a feature selection method to classify stroke patients, feature selection algorithms were separately applied for general features and symmetric features. The optimal features were determined by applying the SVM, GB, DT, and RF learning algorithms for 45 general features and 21 symmetric features through a feature selection method that was conducted to improve classification accuracy and hasten the learning process by eliminating redundant features.

2) CLASSIFICATION & STATISTICAL ANALYSIS

In this study, three groups, elderly, mild stroke, and severe stroke, were classified using the diverse data obtained from the gait test. The classification process was conducted for the following four different types to verify that symmetric parameters are important for the diagnosis of stroke among the numerous gait parameters and that feature selection technology is important for achieving increased classification accuracy.

Types I-IV represent 1) all 45 general features, 2) all 21 symmetric features, 3) the optimal general feature subset obtained by using RFECV, and 4) the optimal symmetric feature subset obtained by using RFECV. For types I and II, the model was trained using all general gait parameters and all symmetric gait parameters in each cycle, respectively. All 45 and 21 data were used as input values for each type, and four different classifiers, SVM, GB, DT, and RF classifiers, were applied for classification without a feature selection process. For types III and IV, the model was trained using the optimal general gait parameters and symmetric gait parameters obtained through the RFECV feature selection method, respectively. The data obtained via the four different feature selection algorithms were applied to each of the four

classifiers, and 16 classification performance results were obtained for each type, as shown in Table 8 below.

TABLE 1. Four different types of gait parameters were used as input values for classification.

Case	Parameters	Number of features
Type I	General	45
Type II	Symmetry (SNR)	21
Type III	Selected features – General	-
Type IV	Selected features – Symmetry (SNR)	-

The gait data were split into an 80% training set and a 20% testing set for classification. We used tenfold cross-validation to prevent data overfitting, calculate statistically unbiased classification results, and find each classifier’s optimal hyper-parameters, as shown in Fig. 2.

To validate the notion that symmetric parameters are more important than general gait parameters when classifying stroke patients, the classification results obtained with only general parameters consisting of spatial-temporal, kinematics, and kinetics parameters were compared with those obtained using the symmetric parameters representing the left-to-right ratio. We also compared the classification performances achieved using all gait parameters and utilizing only the optimal gait data obtained through ML to verify the importance of feature selection when classifying stroke patients through a gait test. To evaluate the performance of the feature selection-based stroke patient severity classification algorithm presented in this study, five different measures were used: sensitivity, specificity, precision, F1 score, and average accuracy. Each measure was calculated as written in equations (4) – (8). Every true positive (TP), true negative (TN), false positive (FP), and false negative (FN) was calculated for the test set. The data acquisition and

classification analysis processes were conducted using the Python 3.10 programming environment.

$$Sensitivity = \frac{TP}{(TP + FN)} \times 100 \tag{4}$$

$$Specificity = \frac{TN}{(TN + FP)} \times 100 \tag{5}$$

$$Precision = \frac{TP}{(TP + FP)} \times 100 \tag{6}$$

$$F1score = 2 \times \frac{(Precision \times Sensitivity)}{(Precision + Sensitivity)} \times 100 \tag{7}$$

$$Ave.Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100 \tag{8}$$

III. RESULTS

A. OPTIMAL GAIT FEATURES FOR CLASSIFICATION

As a result of selecting the features related to the classification performance among the 45 total general features based on the RFECV method, 25, 24, 16, and 19 features were selected by the SVM, GB, DT, and RF algorithms, respectively. As a result of selecting the features among the total 21 symmetric data features, 16, 5, 12, and 9 features were selected for each algorithm, as shown in Table 2 below. Regarding the general gait features, the RF-RFECV algorithm achieved decreased classification performance when the selected number of subsets was greater than the number of optimal features. In contrast, the SVM-, GB-, and DT-RFECV produced similar classification accuracies even if the selected number of subsets exceeded the number of optimal features, as shown in Fig. 3. For symmetric features, the GB and RF algorithms yielded decreased classification performance when the number of subsets was greater than the number of optimal features, and the SVM and DT algorithms achieved similar classification performance in this situation, as shown in Fig. 4. The numbers and types of optimal features selected by each algorithm were different. In terms of general and symmetric features, several gait characteristics were commonly selected by each algorithm.

TABLE 2. Feature selection results obtained using four different ML algorithms (SVM, GB, DT, RF) for general and symmetric gait features.

ML Method	General Features	Symmetric Features
SVM	25	16
GB	24	5
DT	16	12
RF	19	9

Table 3 represents the numbers of features that were significantly different based on the *t test* results between the binary groups. The numbers of gait features that were different from the binary groups were obtained separately from general and symmetric gait characteristics.

In the symmetric gait feature set, more than 30% of the selected features (out of the 21 total gait features) exhibited

TABLE 3. The number of features that showed significant differences among each group out of all selected parameters based on the results of a *t test*.

Groups compared	General features (%)	Symmetric features (%)
Elderly – Mild stroke	5 (11%)	7 (33%)
Elderly – Severe stroke	14 (31%)	16 (76%)
Mild stroke – Severe stroke	9 (20%)	13 (61%)

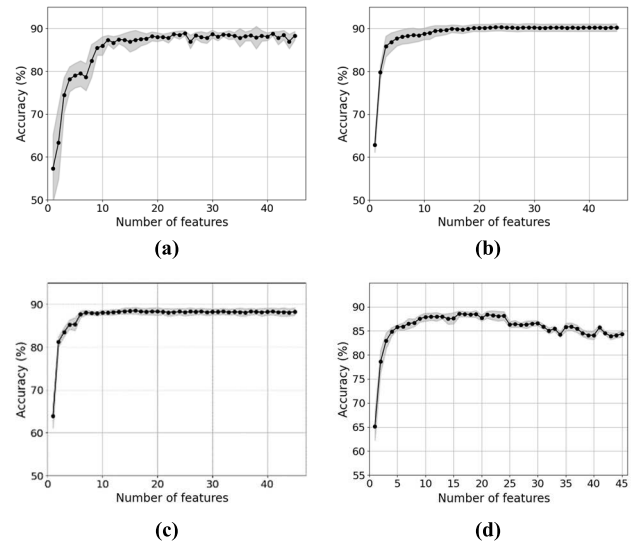


FIGURE 3. Average classification accuracies achieved according to the number of general gait features selected by (a) the SVM, (b) GB, (c) the DT, and (d) the RF. The dots and shaded areas represent the average accuracy and the variability of 10 cross-validations, respectively.

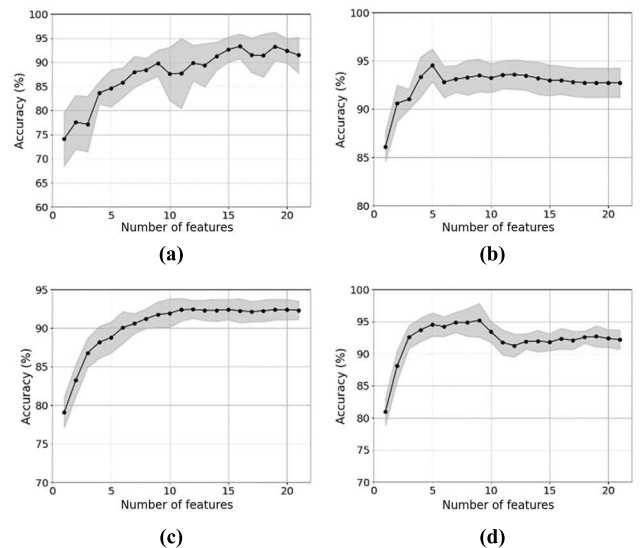


FIGURE 4. Average classification accuracies achieved according to the number of symmetric gait features selected by (a) the SVM, (b) GB, (c) the DT, and (d) the RF. The dots and shaded area represent the average accuracy and the variability of 10 cross-validations, respectively.

significant differences in all three binary comparisons. On the other hand, in the general gait feature set, among the 45 total

gait features, a significant difference of more than 30% was observed between the elderly and severe stroke patient groups alone. The highest rates of significant difference were observed between the elderly and the severe stroke patients in both the general feature and symmetric feature tests, at 71% and 31%, respectively, and the lowest rates of significant difference were observed between the elderly and mild stroke patient groups at 11% and 33% in the general and symmetric feature tests.

B. SEVERITY CLASSIFICATION BASED ON GAIT TEST

The stroke patient classification accuracy achieved using each ML strategy with gait data is represented in the tables below. Tables 4-7 are the results of calculating confusion matrices based on the algorithm that achieved the highest classification performance using gait feature types I-IV, respectively. For type I (using all 45 general gait parameters), the DT classifier yielded the best performance (sensitivity: 84.98%, specificity: 92.94%, precision: 88.19%, F1 score: 86.36, and average accuracy: 89.47%). For type II (using all 21 symmetric gait features), the best performance was achieved when using the GB classifier (sensitivity: 91.09%, specificity: 94.59%, precision: 96.26%, F1 score: 93.11, and average accuracy: 93.36%), and better performance was obtained in this scenario than for type I in all areas regardless of the employed classification algorithm method. For type III and type IV, where the optimal features were determined among the general and symmetric features using RFECV, the highest classification performance was achieved by the GB classifier using SVM-RFECV and the SVM classifier using GB-RFECV, respectively. In the case of type III, the specificity of the GB classifier with SVM-RFECV was higher than those of RF-RFECV with the RF classifier and SVM-RFECV with the DT classifier, but the sensitivity and the average result were not superior. Among all four types, type IV using RF-RFECV with the RF classifier yielded the best classification performance (sensitivity: 95.32%, specificity: 97.03%, precision: 96.51%, F1 score: 95.88, and average accuracy: 96.01%). At this time, the nine selected features used as inputs among the 21 symmetrical characteristics were the TSR, foot progression angle ROM ratio, ankle joint angle ROM ratio, knee joint angle ROM ratio, hip joint angle ROM ratio, foot progression maximum angle ratio, ankle joint maximum angle ratio, knee joint maximum angle ratio, and hip joint maximum angle ratio.

In addition, the overall performance was higher for type II and type IV when using symmetric features than that achieved for type I and type III using general features. After selecting the optimal features, a comparison between type I and type III showed no significant change in the general features, but the comparison between type II and type IV showed that improved classification performance was achieved with the symmetric features. The overall results are detailed in Table 8, as shown below.

TABLE 4. The confusion matrix result obtained for type I (all general gait features) using the DT classifier, which achieved the best classification performance.

		Predicted Class		
		Elderly	Mild Stroke	Sev. Stroke
True Class	Elderly	0.95	0.05	0
	Mild Stroke	0.19	0.79	0.02
	Severe Stroke	0.02	0.17	0.81

Overall Accuracy = 89.47%

TABLE 5. The confusion matrix result obtained for type II (all symmetric gait features) using the GB classifier, which achieved the best classification performance.

		Predicted Class		
		Elderly	Mild Stroke	Sev. Stroke
True Class	Elderly	0.99	0.01	0
	Mild Stroke	0.24	0.76	0
	Severe Stroke	0.02	0.	0.98

Overall Accuracy = 93.36%

TABLE 6. The confusion matrix result obtained for type III (optimal general gait features) using SVM-RFECV with the GB classifier, which achieved the best classification performance.

		Predicted Class		
		Elderly	Mild Stroke	Sev. Stroke
True Class	Elderly	0.99	0.01	0
	Mild Stroke	0.38	0.62	0
	Severe Stroke	0.03	0	0.97

Overall Accuracy = 89.98%

TABLE 7. The confusion matrix result obtained for type IV (optimal symmetric gait features) using RF-RFECV with the RF classifier, which achieved the best classification performance.

		Predicted Class		
		Elderly	Mild Stroke	Sev. Stroke
True Class	Elderly	0.98	0.02	0
	Mild Stroke	0.12	0.88	0
	Severe Stroke	0	0	1

Overall Accuracy = 96.01%

IV. DISCUSSION

The aim of this study was to classify elderly, mild-stroke, and severe-stroke patients by a simple gait test using an ML

strategy. General gait features representing spatial and temporal information and symmetric gait features quantitatively representing the left- and right-side differences were used as gait characteristics. In addition, a feature selection technique consisting of a total of four ML algorithms was applied for each type of feature to compare and analyze the classification accuracy differences observed before and after application.

The main findings from this research can be summarized as follows. (1) When using gait to classify the severity of stroke patients, the symmetrical characteristics representing the left-right ratio are crucially important factors. (2) Through the feature selection method, it was confirmed that the gaits of stroke patients could be classified with higher accuracy when utilizing features that were relevant to the severity of the disease.

Higher classification performance was achieved when performing classification with symmetric features than with only general features. Gait involves movement that requires both motor function and sensory feedback and uses both legs simultaneously [38], and it is performed by the coordination of the nervous and muscular systems. Therefore, it can be said that the difference between the left and right sides is an important factor for an appropriate gait evaluation analysis. Additionally, several limitations are encountered when using only general features, such as the joint angle or the time and length of a particular side, as criteria for classifying the elderly and stroke patients according to severity. First, the general gait features may be affected by physical conditions. Participants with long lower limbs are expected to have greater values for their spatial gait features, such as length-related parameters [39]. From the viewpoint of biomechanics, they can be expected to have smaller ranges of joint motion if they have similar walking speeds and stride lengths to those of other patients. As another example, for obese participants, the range of motion of the knee joint in the stance phase, the ratio of the stance time during the whole gait cycle, and the stride width are less than those of typical people [40]. Second, people's usual gait habits or fall histories may also affect their general gait features [41]. The habits of dragging legs and toeing out affect not only the spatial gait characteristics but also the angle-related parameters. In addition, a stroke patient has compensation movements that occur on the contralateral side to replace the insufficient movement of the paretic leg [42]. Due to the above reasons, it is difficult to classify elderly people and stroke patients with only general gait parameters. Therefore, it is necessary to observe the difference between both legs to understand a patient's gait characteristics. For example, the TSR, which was selected as an important factor by all four ML algorithms as a result of RFECV, compares the ratios of the stance phase to the swing phase between the left and right legs. In the case of general gait characteristics, which calculate absolute values of the stance and swing phases, identifying patient gait characteristics is difficult because of the effects of gait speed and habit. On the other hand, since stroke patients have lower stance-phase ratios and higher

swing-phase ratios on the paretic side than on the non-paretic side, they generally exhibit high TSR values according to equation 3, helping to determine the patients' gaits [25]. For these reasons, we hypothesized that symmetric gait features would better represent patient gait characteristics, and the actual classification results showed that higher performance was achieved with symmetric gait features than with general gait features.

The RFECV technique selected in this study helped improve accuracy by determining the optimal type and number of features required for classification. RFECV achieved improved classification performance by selecting only informative features while excluding redundant features. In some feature selection algorithms, a higher number of features led to higher classification performance, as shown in Figs. 3 and 4, but in other algorithms, similar classification performance was maintained even when the number of features than was larger than the selected optimal number of features. This can be interpreted as the ML algorithm not finding informative features that presented significant differences between groups or judging that none of the features were redundant. Nevertheless, RFECV reduced the number of features to be calculated, shortening the training time and preventing overfitting. Above all, RFECV could help clinicians understand a patient's gait characteristics by calculating the specific gait input values that are the representational features for each group.

This research has several potential limitations. First, the number of participants in this study was insufficient, and an imbalance between the elderly and mild & severe stroke patients was observed, which may have caused a statistical problem. This study was conducted on 13 chronic stroke patients and 18 normal elderly patients; the former were divided into 5 severe stroke and 8 mild stroke patients based on their BBS scores. To overcome the limitations and imbalances regarding the number of data, repeated experiments conducted at various speeds yielded more than approximately 130 walking cycles per participant, and classification was conducted with a total of more than 4000 cycles. Second, all experiments in this study were performed on a treadmill. The same participant's over-ground walking and treadmill walking characteristics may have been different because of this condition [43]. For example, constant-speed gait is unlike over-ground walking, and fear of falling may have caused the participants to exhibit abnormal gait patterns. For this reason, it is thought that the classification accuracy was not improved further because there was a limit to fully understanding walking characteristics according to a patient's severity. Third, the patient severity was divided into only two simple levels based on the BBS score. The BBS is an assessment tool for evaluating balance ability through an exercise evaluation and has high simultaneous correlations with gait-requiring balance and exercise ability. However, in clinical fields, the severity of patients is determined not only by the BBS but also by the NIHSS or FMA. Therefore, when using a different classification assessment tool, a different classification

TABLE 8. Stroke severity classification results obtained using the gait characteristics in types I-IV.

	Feature Selector	Number of Features	Classifier	Sensitivity	Specificity	Precision	F1 Score	Accuracy
Type I	-	45	SVM	75.9	87.93	89.28	80.85	86.61
	-	45	GB	83.07	89.37	94.65	86.03	88.04
	-	45	DT	84.98	92.94	88.19	86.36	89.47
	-	45	RF	75.76	90.32	85.31	78.47	86.41
Type II	-	21	SVM	85.04	92.24	92.54	88.19	90.5
	-	21	GB	91.09	94.59	96.26	93.11	93.36
	-	21	DT	91.73	95.01	90	90.8	91.72
	-	21	RF	87.97	94.09	92.29	89.94	91.93
Type III	SVM-RFECV	25	SVM	81.28	90.79	91.52	85.43	89.17
	SVM-RFECV	25	GB	86.08	91.19	95.19	88.99	89.98
	SVM-RFECV	25	DT	80.98	91.38	87.73	83.73	88.04
	SVM-RFECV	25	RF	73.66	88.44	84.94	77.65	85.8
	GB-RFECV	24	SVM	77.11	88.48	90.67	82.2	87.12
	GB-RFECV	24	GB	81.84	89.15	95.11	85.81	88.76
	GB-RFECV	24	DT	79.25	90.37	88.36	82.86	87.74
	GB-RFECV	24	RF	77.94	89.64	86.48	81.39	86.82
	DT-RFECV	16	SVM	79.49	89.66	89.18	83.33	86.92
	DT-RFECV	16	GB	82.45	89.39	94.04	85.47	87.43
	DT-RFECV	16	DT	79.25	90.42	88.36	82.94	88.35
	DT-RFECV	16	RF	79.18	90.61	87.64	82.68	88.45
	RF-RFECV	19	SVM	73.92	86.31	88.89	79.1	84.57
	RF-RFECV	19	GB	82.73	91.59	90.39	85.94	89.27
	RF-RFECV	19	DT	79.67	89.85	87.33	82.88	87.53
	Type IV	RF-RFECV	19	RF	83.69	92.17	89.23	86.07
SVM-RFECV		16	SVM	90.73	94.08	94.63	92.36	92.64
SVM-RFECV		16	GB	87.71	92.94	94.81	90.26	91.11
SVM-RFECV		16	DT	91.76	95.37	92.89	92.31	93.25
SVM-RFECV		16	RF	88.18	93.22	93.31	90.32	91.52
GB-RFECV		5	SVM	77.19	88.03	90.17	82.01	86.1
GB-RFECV		5	GB	93.65	95.9	96.64	94.96	95.09
GB-RFECV		5	DT	79.05	89.95	88.33	82.79	87.43
GB-RFECV		5	RF	92.26	95.21	93.99	93.03	93.56
DT-RFECV		12	SVM	80.15	90.52	84.85	82.11	87.33
DT-RFECV		12	GB	88.63	93.83	93.12	90.63	92.33
DT-RFECV		12	DT	94.1	96.4	92.75	93.39	93.87
DT-RFECV		12	RF	82.6	91.83	89.69	85.59	89.37
RF-RFECV		9	SVM	81.31	91.65	87.55	83.99	88.86
RF-RFECV		9	GB	91.22	94.66	96.98	93.48	93.87
RF-RFECV		9	DT	92.88	96.49	91.45	92.08	93.66
	RF-RFECV	9	RF	95.32	97.03	96.51	95.88	96.01

performance is expected. In the future studies, experiments will be conducted to obtain additional data by recruiting multiple subjects who have varying degrees of severity.

V. CONCLUSION

When evaluating the severity of stroke patients, auxiliary measurement methods are necessary to overcome the limitations of existing clinical evaluations that take a long time and involve subjective evaluator judgments. In this study, we proposed symmetric-based gait tests that can evaluate a patient’s severity by measuring their balance and motor abilities simultaneously. The results showed that elderly people, mild stroke patients, and severe stroke patients could be classified with 96.01% accuracy with only 9 symmetric data regardless of their speeds. The nine selected characteristics that were considered important for distinguishing stroke patients from elderly people can be used as rehabilitation

indicators that can be evaluated to determine the effectiveness of recovery if the patient’s corresponding values become similar to those of the elderly group. This reliable ML-based assessment approach is expected to play a complementary role not only in evaluating the degree of severity but also in planning rehabilitation treatments based on evaluations of stroke patient information.

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REFERENCES

[1] A. Petrasovits and C. Nair, “Epidemiology of stroke in Canada,” *Health Rep.*, vol. 6, no. 1, pp. 39–44, 1994.
 [2] V. L. Feigin, M. H. Forouzanfar, R. Krishnamurthi, G. A. Mensah, M. Connor, D. A. Bennett, A. E. Moran, R. L. Sacco, L. Anderson, T. Truelsen, and M. O’Donnell, “Global and regional burden of stroke during 1990–2010: Findings from the Global Burden of Disease Study 2010,” *Lancet*, vol. 383, no. 9913, pp. 245–255, 2014.

- [3] G. Howard and D. C. Goff, "Population shifts and the future of stroke: Forecasts of the future burden of stroke," *Ann. New York Acad. Sci.*, vol. 1268, no. 1, pp. 14–20, Sep. 2012.
- [4] R. L. Sacco, Scott E. Kasner, Joseph P. Broderick, L. R. Caplan, J. J. Connors, A. Culebras, M. S. V. Elkind, M. G. George, A. D. Hamdan, R. T. Higashida, and B. L. Hoh, "An updated definition of stroke for the 21st century: A statement for healthcare professionals from the American Heart Association/American Stroke Association," *Stroke*, vol. 44, no. 7, pp. 2064–2089, 2013.
- [5] R. Bonita, N. Solomon, and J. B. Broad, "Prevalence of stroke and stroke-related disability: Estimates from the Auckland stroke studies," *Stroke*, vol. 28, no. 10, pp. 1898–1902, Oct. 1997.
- [6] S. M. Lai, S. Studenski, P. W. Duncan, and S. Perera, "Persisting consequences of stroke measured by the Stroke Impact Scale," *Stroke*, vol. 33, no. 7, pp. 1840–1844, Jul. 2002.
- [7] Ö. Saka, A. McGuire, and C. Wolfe, "Cost of stroke in the United Kingdom," *Age Ageing*, vol. 38, no. 1, pp. 27–32, 2009.
- [8] P. Langhorne, J. Bernhardt, and G. Kwakkel, "Stroke rehabilitation," *Lancet*, vol. 377, no. 9778, pp. 1693–1702, 2011.
- [9] L. B. Goldstein, C. Bertels, and J. N. Davis, "Interrater reliability of the NIH stroke scale," *Arch. Neurol.*, vol. 46, no. 6, pp. 660–662, Jun. 1989.
- [10] A. R. Fugl-Meyer, L. Jääskö, I. Leyman, S. Olsson, and S. Steglind, "A method for evaluation of physical performance," *Scand. J. Rehabil. Med.*, vol. 7, no. 1, pp. 13–31, 1975.
- [11] D. J. Gladstone, C. J. Danells, and S. E. Black, "The Fugl-Meyer assessment of motor recovery after stroke: A critical review of its measurement properties," *Neurorehabil. Neural Repair*, vol. 16, no. 3, pp. 232–240, Sep. 2002.
- [12] K. Berg, "Measuring Balance in the Elderly: Development and Validation of an Instrument." Montreal, QC, Canada: McGill Univ., 1992.
- [13] L. Blum and N. Korner-Bitensky, "Usefulness of the Berg Balance Scale in stroke rehabilitation: A systematic review," *Phys. Therapy*, vol. 88, no. 5, pp. 559–566, 2008.
- [14] C.-Y. Chou, C.-W. Chien, I.-P. Hsueh, C.-F. Sheu, C.-H. Wang, and C.-L. Hsieh, "Developing a short form of the Berg Balance Scale for people with stroke," *Phys. Therapy*, vol. 86, no. 2, pp. 195–204, Feb. 2006.
- [15] Y. Moon, J. Sung, R. An, M. E. Hernandez, and J. J. Sosnoff, "Gait variability in people with neurological disorders: A systematic review and meta-analysis," *Hum. Movement Sci.*, vol. 47, pp. 197–208, Jun. 2016.
- [16] S. Lord, B. Galna, and L. Rochester, "Moving forward on gait measurement: Toward a more refined approach," *Movement Disorders*, vol. 28, no. 11, pp. 1534–1543, Sep. 2013.
- [17] R. Z. U. Rehman, S. Del Din, Y. Guan, A. J. Yarnall, J. Q. Shi, and L. Rochester, "Selecting clinically relevant gait characteristics for classification of early Parkinson's disease: A comprehensive machine learning approach," *Sci. Rep.*, vol. 9, no. 1, pp. 1–12, Dec. 2019.
- [18] A. Schmid, P. W. Duncan, S. Studenski, S. M. Lai, L. Richards, S. Perera, and S. S. Wu, "Improvements in speed-based gait classifications are meaningful," *Stroke*, vol. 38, no. 7, pp. 2096–2100, Jul. 2007.
- [19] S. Mulroy, J. Gronley, W. Weiss, C. Newsam, and J. Perry, "Use of cluster analysis for gait pattern classification of patients in the early and late recovery phases following stroke," *Gait Posture*, vol. 18, no. 1, pp. 114–125, 2003.
- [20] B. Balaban and F. Tok, "Gait disturbances in patients with stroke," *PM R*, vol. 6, no. 7, pp. 635–642, Jul. 2014.
- [21] F. Wahid, R. K. Begg, C. J. Hass, S. Halgamuge, and D. C. Ackland, "Classification of Parkinson's disease gait using spatial-temporal gait features," *IEEE J. Biomed. Health Inform.*, vol. 19, no. 6, pp. 1794–1802, Nov. 2015.
- [22] G. Yogev-Seligmann, J. M. Hausdorff, and N. Giladi, "The role of executive function and attention in gait," *Movement Disorders*, vol. 23, no. 3, pp. 329–342, Feb. 2008.
- [23] R. E. Bellman, *Adaptive Control Processes*. Princeton, NJ, USA: Princeton Univ. Press, 2015.
- [24] S. J. Olney and C. Richardsb, "Hemiparetic gait following stroke. Part I: Characteristics," *Gait Posture*, vol. 4, no. 2, pp. 136–148, 1996.
- [25] K. K. Patterson, I. Parafianowicz, C. J. Danells, V. Closson, M. C. Verrier, W. R. Staines, S. E. Black, and W. E. McIlroy, "Gait asymmetry in community-ambulating stroke survivors," *Arch. Phys. Med. Rehabil.*, vol. 89, no. 2, pp. 304–310, 2008.
- [26] C. Cortes and V. Vapnik, "Support vector machine," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995.
- [27] J. H. Friedman, "Greedy function approximation: A gradient boosting machine," *Ann. Statist.*, vol. 29, no. 5, pp. 1189–1232, Oct. 2001.
- [28] J. R. Quinlan, "Induction of decision trees," *Mach. Learn.*, vol. 1, no. 1, pp. 81–106, 1986.
- [29] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.
- [30] M. Lee, J.-H. Lee, and D.-H. Kim, "Gender recognition using optimal gait feature based on recursive feature elimination in normal walking," *Expert Syst. Appl.*, vol. 189, Mar. 2022, Art. no. 116040.
- [31] R. Kohavi and G. H. John, "Wrappers for feature subset selection," *Artif. Intell.*, vol. 97, nos. 1–2, pp. 273–324, 1997.
- [32] R. B. Davis, S. Öunpuu, D. Tyburski, and J. R. Gage, "A gait analysis data collection and reduction technique," *Hum. Movement Sci.*, vol. 10, no. 5, pp. 575–587, 1991.
- [33] M. P. Kadaba, H. K. Ramakrishnan, and M. E. Wootten, "Measurement of lower extremity kinematics during level walking," *J. Orthopaedic Res.*, vol. 8, no. 3, pp. 383–392, 1990.
- [34] R. Seliktar and J. Mizrahi, "Some gait characteristics of below-knee amputees and their reflection on the ground reaction forces," *Eng. Med.*, vol. 15, no. 1, pp. 27–34, Jan. 1986.
- [35] S. Madhavan and A. Bishnoi, "Comparison of the mini-balance evaluations systems test with the Berg balance scale in relationship to walking speed and motor recovery post stroke," *Topics Stroke Rehabil.*, vol. 24, no. 8, pp. 579–584, Nov. 2017.
- [36] C. Wang, Z. Xiao, and J. Wu, "Functional connectivity-based classification of autism and control using SVM-RFECV on rs-fMRI data," *Phys. Medica*, vol. 65, pp. 99–105, Sep. 2019.
- [37] E.-M. Cui, F. Lin, Q. Li, R.-G. Li, X.-M. Chen, Z.-S. Liu, and W.-S. Long, "Differentiation of renal angiomyolipoma without visible fat from renal cell carcinoma by machine learning based on whole-tumor computed tomography texture features," *Acta Radiol.*, vol. 60, no. 11, pp. 1543–1552, Nov. 2019.
- [38] M. W. Whittle, *Gait Analysis: An Introduction*. London, U.K.: Butterworth, 2014.
- [39] A. R. Wu, C. S. Simpson, E. H. F. van Asseldonk, H. van der Kooij, and A. J. Ijspeert, "Mechanics of very slow human walking," *Sci. Rep.*, vol. 9, no. 1, pp. 1–10, Dec. 2019.
- [40] S.-U. Ko, S. Stenholm, and L. Ferrucci, "Characteristic gait patterns in older adults with obesity—Results from the Baltimore longitudinal study of aging," *J. Biomechanics*, vol. 43, no. 6, pp. 1104–1110, Apr. 2010.
- [41] Y. Barak, R. C. Wagenaar, and K. G. Holt, "Gait characteristics of elderly people with a history of falls: A dynamic approach," *Phys. Therapy*, vol. 86, no. 11, pp. 1501–1510, 2006.
- [42] C. Beyaert, R. Vasa, and G. E. Frykberg, "Gait post-stroke: Pathophysiology and rehabilitation strategies," *Neurophysiologie Clinique, Clin. Neurophysiol.*, vol. 45, nos. 4–5, pp. 335–355, Nov. 2015.
- [43] S. J. Lee and J. Hidler, "Biomechanics of overground vs. treadmill walking in healthy individuals," *J. Appl. Physiol.*, vol. 104, no. 3, pp. 747–755, Mar. 2008.



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