2026 IEEE/SICE International Symposium on System Integration (SII)
January 11-14, 2026. Cancún, México

Prediction of Observational Gait Analysis Score in Stroke Using Sagittal Plane Gait Video and Clinical Assessment Data

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Abstract— **Observational gait analysis is commonly used in clinical settings to assess gait dysfunction and to make treatment plans. Gait Assessment and Intervention Tool (G.A.I.T.) is one of the most useful scales for observational gait analysis. However, observational gait analysis such as G.A.I.T. requires experienced clinical skills and adequate time to score. This study proposes machine learning-based prediction method of the G.A.I.T. score on individuals with stroke by pose estimation from a single RGB camera and clinical assessment data obtained in conventional rehabilitation. Twenty-five individuals with subacute stroke participated in this study. The participants were captured by single RGB camera for self-selected speed gait on the sagittal plane. In total, 40 features from conventional clinical assessment and gait parameters by single RGB camera-based pose estimation were used as input data. Five different machine learning regression models predicted the overall score of G.A.I.T. related to lower limb and trunk motions in the sagittal plane. The predicted score was compared to the actual score evaluated by an experienced physical therapist. Model performance was assessed by root mean squared error (RMSE) and coefficient of determination. The results showed that CatBoost with Boruta achieved the lowest RMSE and the highest R2 among the five models for predicting the overall score of the G.A.I.T. related to movement on the sagittal plane. This study reveals that the proposed prediction method using clinically available RGB camera gait video and clinical assessment data has the potential to predict the G.A.I.T. score on individuals with stroke.**

I. Introduction

In clinical settings, gait analysis is one of the crucial assessments for gait disorders. Gait analysis can provide important medical information to make treatment plans for individuals with gait disorders due to injury or disease. Three-dimensional marker-based motion capture system is a representative tool for gait assessment that can accurately measure various gait parameters such as gait speed, step length, and joint kinematics [1], [2]. In particular, temporospatial gait parameters and lower limb joint angles in the sagittal plane during gait were commonly used as important variables. These gait parameters can provide valuable information to understand the gait mechanism and determine the effectiveness of rehabilitation treatment on individuals with gait disorders [3], [4]. Temporospatial and kinematic variables from medical gait analysis have been used to predict fall risk in elderly individuals [5] and to assess the treatment effect of rehabilitation in neurological disorders [6], [7]. However, three-dimensional marker-based motion capture system could not be used easily in clinical settings because it requires a large space, multiple cameras, trained personnels, considerable cost, and time constraints [8].

Clinicians require a quick and simple method to obtain the gait parameters for the assessment of gait disorder and treatment plan. Observational gait analysis, in which the clinician visually assesses gait, is commonly used in clinical settings. This analysis can assess the subject's gait function and various gait parameters from recorded gait video or direct gait observation [9]. Using recorded gait video is relatively easy and useful for clinicians because it can be checked repeatedly. Therefore, observational gait analysis was widely used to evaluate various diseases and gait dysfunctions [10], [11]. Gait Assessment and Intervention Tool (G.A.I.T.) is one of the most useful scales for observational gait analysis in clinical settings because previous studies has reported that the G.A.I.T. was verified valid, reliable, sensitive to change, homogeneous, and comprehensive [10], [12]. The G.A.I.T. provides 31 items about spatial coordinated movement components in specified temporal gait events of stance and swing phase. This assessment has also been used to assess gait function in patients with stroke who have complex gait impairment due to various symptoms. Although G.A.I.T. can assess various gait parameters in clinical settings without marker-based multi-camera motion capture system, it requires experienced physical therapy skills and time-consuming to score.

Single camera-based human pose estimation has the potential to solve these limitations. This method can easily estimate human body keypoints without markers and allows gait analysis with less time constraints on the therapist and patient. One of the limitations in single camera-based gait analysis using human pose estimation is not accurate sufficiently compared to marker-based multi-camera motion capture system [13], [14]. Gait analysis using human posture estimation has some non-negligible errors in the lower limb joint angles during gait. Therefore, data from gait analysis using human pose estimation should always be interpreted with caution when it is used as a substitute for a marker-based motion capture system. However, gait analysis using human pose estimation has high potential to be used as an assistant

*This work was supported in part by JST, PRESTO Grant Number JPMJPR24ID, Japan.

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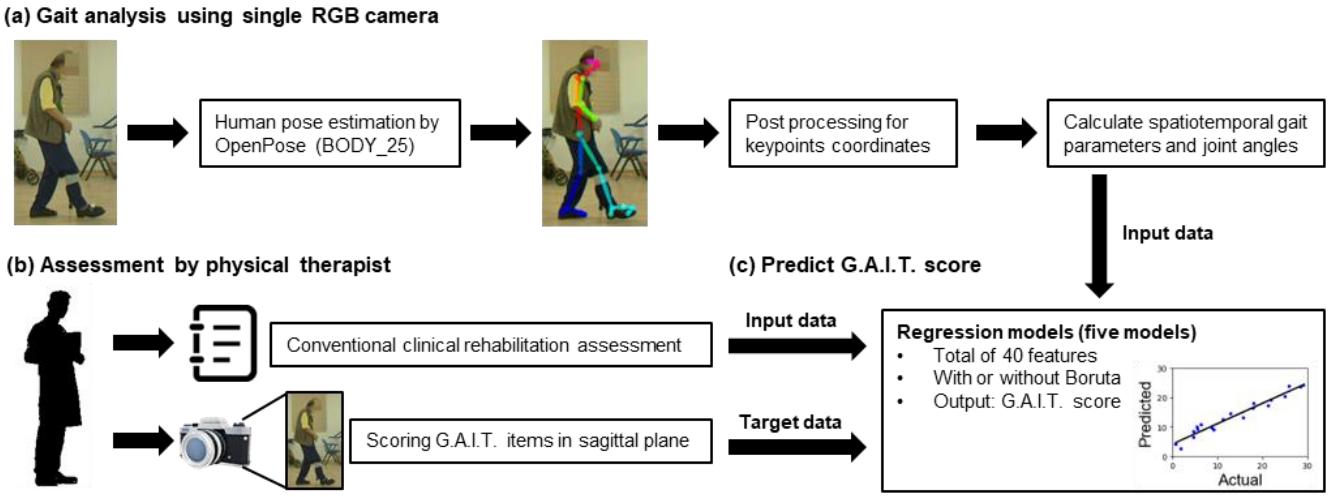

Fig. 1. Overview of the experimental procedure and process of obtaining the dataset. The input data were obtained from both gait video and clinical assessment. **(a)** Body keypoints were estimated by OpenPose from sagittal plane gait video. Spatiotemporal gait parameters and lower limb joint angles were calculated by keypoints data. **(b)** The physical therapist performed clinical assessment on the participants. The physical therapist also scored only items related to the motions in the sagittal plane of the G.A.I.T. from the same sagittal plane gait video. **(c)** Five different machine learning regression models were employed to predict the overall G.A.I.T. score of items related to the motion in the sagittal plane. Use of the Boruta algorithm on these models was also assessed.

tool for clinicians' assessment. Combining this method and machine learning could be used as a screening tool in Parkinson's disease [15] and autism spectrum disorders [16]. Automatic classification of elderly individuals and young individuals have also been attempted using the keypoint data obtained from the camera [17]. A previous study on the gait of healthy subjects has attempted to develop an automatic scoring system for observational gait analysis, and the score of this system is corelated to the score of university students [18]. However, the accuracy of the scoring prediction for the observational gait analysis remains unclear, and the scoring has not been performed on patients.

The purpose of this study is to propose machine learning-based prediction method for G.A.I.T. scores, which is one of the representative observational gait analysis methods for individuals with stroke, using data that can be easily obtained in clinical settings. In order to enhance the feasibility in clinical settings, spatiotemporal gait parameters and lower limb joint angles by pose estimation from single RGB camera, and clinical assessment data obtained in conventional rehabilitation were used for the proposed method. This prediction method could contribute to reduce time-consuming work of clinicians and provide valuable information for treatment quickly.

II. Methods

This study proposes prediction method of the G.A.I.T. score from gait video and conventional clinical assessment in rehabilitation. Overview of the experimental procedure and process of obtaining dataset is shown in Fig. 1.

A. Participants

Twenty-five individuals with subacute stroke (mean ± standard deviation, age: 66.2 ± 10.2 years, height: 1.56 ± 0.09 m, weight: 56.0 ± 10.1 kg) participated in this study. The inclusion criteria were first-time stroke, unilateral ischemic or hemorrhagic stroke, at least 30 days after the onset of stroke, and the ability to walk 20 meters with or without assistance to prevent falls. The exclusion criteria were age < 20 years, inability to follow verbal requests, history of an orthopedic surgery in the year before participating in this study, trunk or leg pain during walking and standing, and severe comprehensive aphasia or unilateral spatial neglect. All the procedures were approved by the Ethics Committee of the Brain Attack Center, Ota Memorial Hospital (162), and written informed consent for study participation, publication of gait data, and images was obtained from all participants.

B. Experimental Protocol

All participants underwent conventional clinical assessments by physical therapists (Table 1). Subsequently, the participants were asked to walk on a 15 m straight walkway at their self-selected gait speed. Gait was recorded by a single RGB camera (Basler AG, Ahrensburg, Germany) for pose estimation. Pixel resolution and sampling rate were 720x520 and 100 Hz. The RGB camera was placed 4 m away on the hemiparetic side of each participant from the straight walkway for capturing motion in the sagittal plane. Therefore, the preparation of the setup was very simple, and the camera was connected to a laptop using a wire.

A physical therapist who had more than five years experiences scored the G.A.I.T. from the gait video. Evaluation of G.A.I.T. was performed based on a previous study [12]. The physical therapist scored only items related to trunk and hemiparetic side lower limb motions in the sagittal plane in the G.A.I.T. because the camera provides video of gait in the sagittal plane. This score ranges from 0 to 34, with 0 representing the highest gait function and 34 the lowest gait function.

C. Data Analysis

The spatiotemporal gait parameters and hemiparetic side lower limb joint flexion-extension angle were calculated from

TABLE 1
Features as the input data for the five models

Category	Features
Conventional clinical assessment	Functional Ambulation Category (FAC)
	Lower limb Brunnstrom Stage (BRS)
	Lower limb Stroke Impairment Assessment Set motor function (SIAS-M-hip, SIAS-M-knee, SIAS-M-ankle, and SIAS-M-total)
	Lower limb light touch sensation and Lower limb position sensation
	Lower limb modified Ashworth scale (MAS-knee-flex, MAS-knee-ext, MAS-ankle-flex, and MAS-ankle-ext)
Spatiotemporal gait parameters	Hemiparetic side stance time (ST) and swing time (SW)
	Less-affected side stance time (ST_LA) and swing time (SW_LA)
	Stance time ratio (ST_ratio) and swing time ratio (SW_ratio)
	One gait cycle time (T), cadence, and mean gait velocity (V)
	Stride length (Stride)
	Hemiparetic side step length (SL) and less-affected side step length (SL_O)
Maximum Hemiparetic side lower limb joint angles	Hip flexion angle in initial contact (Hip_flex_IC) and swing phase (Hip_flex_SW)
	Hip extension angle in single leg stance phase (Hip_ext_SS)
	Knee flexion angle in initial contact (Knee_flex_IC), loading response (Knee_flex_LR), and swing phase (Knee_flex_SW)
	Knee extension angle in loading response (Knee_ext_LR) and swing phase (Knee_ext_SW)
	Ankle dorsiflexion angle in initial contact (Ankle_flex_IC), and swing phase (Ankle_flex_SW)
	Ankle plantarflexion angle in swing phase (Ankle_ext_SW)
	Trailing limb angle in single leg stance phase (TLA_flex_SS and TLA_ext_SS)

the body keypoints using OpenPose. OpenPose is an open-source human pose estimation system that estimates the human joint location and feature points from each RGB image using a two-branched multistage convolution neural network [19]. The Body_25 OpenPose model was used in the study. This model consists of 25 body keypoints: the nose, neck, mid-hip, and bilateral key-points of the eyes, ears, shoulders, elbows, wrists, hips, knees, ankles, heels, big toes, and small toes. Missing keypoint data from OpenPose were interpolated using the third-order spline method, and the keypoint data were filtered with a 6 Hz cut-off frequency fourth-order low-pass Butterworth filter.

Gait velocity was calculated from the average speed of the mid-hip keypoint in the direction of the straight walk [20]. Timing of initial contact and timing of toe-off were calculated based on the mid-hip, knees, ankles, and big toe keypoints, referring to previous studies [20], [21], [22]. Stance time is defined as the period from the observed side initial contact to the observed side toe-off, whereas the swing time is defined as the period from the observed side toe-off to the observed side initial contact. The stance time and swing time on both sides were used to calculate stance time ratio and swing time ratio. These ratios were defined as the stance time on the hemiparetic side divided by the stance time on the less-affected side, and the swing time on the hemiparetic side divided by the swing time on the less-affected side, respectively. Step length on both sides were defined as the anterior-posterior distance between the heel keypoint at initial contact of one side and the heel keypoint at initial contact of other side. Conversion from pixels to meters was based on a 0.1 m tape placed on the straight walk way. Hip, knee, and ankle joint flexion-extension (dorsiflexion-plantarflexion) angles were calculated from vectors of proximal and distal segments composed of the keypoints near the joint [20]. In one example, the hemiparetic side ankle dorsiflexion–plantarflexion angle was calculated from the hemiparetic side shank segment vector and hemiparetic side foot segment vectors.

D. Models and Evaluation

In this study, five different machine learning regression models were employed to predict the overall G.A.I.T. score of items related to the motion on the sagittal plane: Random Forest, CatBoost, Gradient Boosting, XGBoost, and AdaBoost. These regression models were developed in Python using scikit-learn. In total of 40 features from conventional clinical assessment, spatiotemporal gait parameters, and lower limb joint angles were utilized as the input data for these models (Table 1). The Leave-One-Out Cross-Validation was utilized for training the models. For each fold, all but one subject were utilized to train the models while the excluded subject was utilized to test the models.

To understand how well these trained models predict the G.A.I.T. score, the root mean squared error (RMSE) and coefficient of determination (R^2) were calculated as the model performance. To investigate the impact of feature selection on these models' performance, use of the Boruta algorithm [23] on these models was also assessed. To set percentile in Boruta, 1,000 explanatory variables consisting of random numbers following a standard normal distribution were generated. Correlation coefficients between these variables and the overall G.A.I.T. score were calculated, and hundredfold of their maximum absolute values were set as the percentile of Boruta [24]. In this study, the percentile of Boruta was set to 69. In other parameters of Boruta, n_estimators and max_iter were set to 1000 and 100, respectively.

TABLE 2
Coefficient of determination in the five models

Model	R^2	
	With Boruta	Without Boruta
Random Forest	0.56	0.52
CatBoost	0.65	0.55
Gradient Boosting	0.47	0.42
XGBoost	0.36	0.26
AdaBoost	0.59	0.46

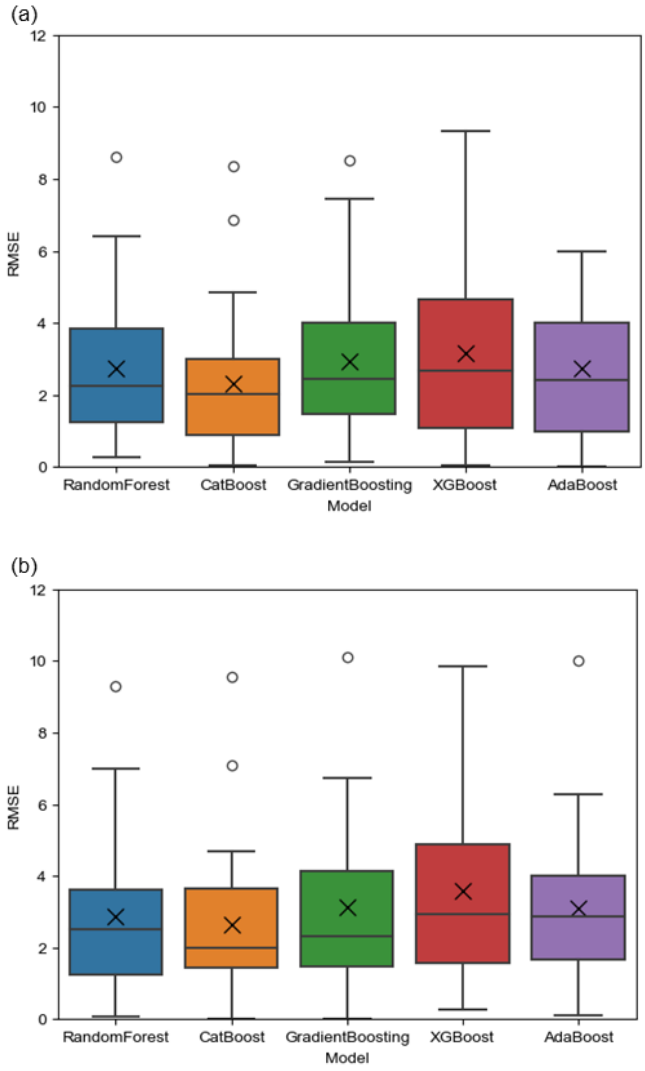

Fig. 2. RMSE of the G.A.I.T. score between actual value and predicted value in the five models. Upper and lower graphs showed RMSE of the G.A.I.T. score in the five models with Boruta (a) and the five models without Boruta (b), respectively. Boxes and horizontal lines represent ranges of Q1, Q3, and median values. The circles and × indicate outlier and mean, respectively.

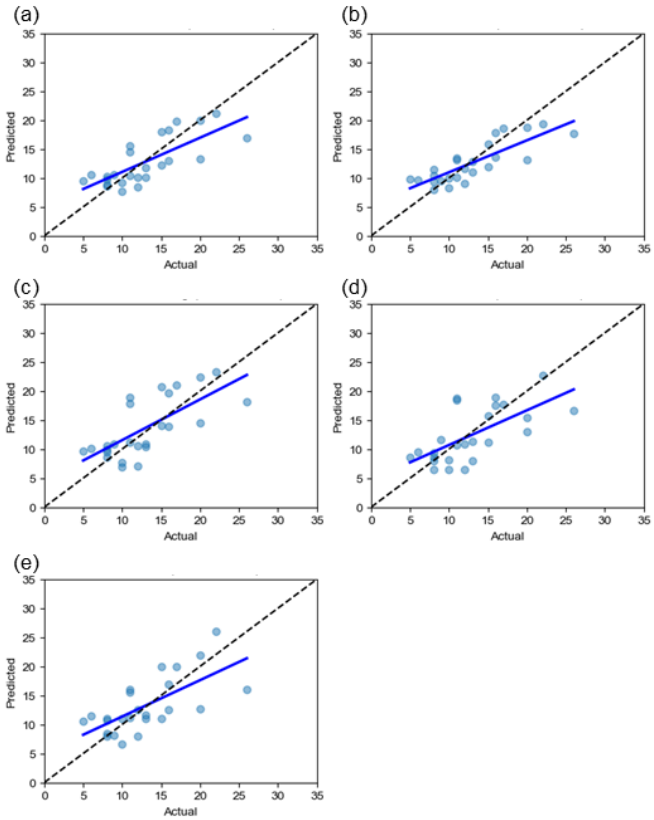

Fig. 3. Scatter plot of the G.A.I.T. score comparing actual value and predicted value in five models with Boruta. (a) Random Forest; (b) CatBoost; (c) Gradient Boosting; (d) XGBoost; (e) AdaBoost. Actual value was scored by the experienced physical therapist. Predicted value was scored by the five models in this study. Blue line and black dashed line showed liner fit and ideal prediction line, respectively. The G.A.I.T. score related to sagittal plane motion ranges from 0 to 34, with 0 representing the highest gait function and 34 the lowest gait function.

SHapley Additive exPlanations (SHAP) was performed on the five models in this study to assess the importance of features on the model output [25]. SHAP attempts to explain sample predictions based on the game theory optimal Shapley values. SHAP values were obtained to assess which of each feature contributed to the prediction of the G.A.I.T. scores.

III. Results and Discussion

A. Model performance

Table 2 and Fig. 2 show R^2 and RMSE of the G.A.I.T. score between actual value and predicted value in the five models. After performing Boruta, the number of features was reduced to 29. Using Boruta improved model performance in all the models. In these models, CatBoost with Boruta achieved the highest R^2 and the lowest RMSE in all the models. Mean ± standard deviation of the RMSE for these five models (with Boruta, without Boruta) were as follows; Random Forest (2.73 ± 1.98, 2.87 ± 2.07), CatBoost (2.31 ± 1.97, 2.64 ± 2.15), Gradient Boosting (2.94 ± 2.25, 3.12 ± 2.32), XGBoost (3.16 ± 2.57, 3.58 ± 2.57), and AdaBoost (2.74 ± 1.81, 3.08 ± 2.14). Fig. 3 shows scatter plots of the G.A.I.T. score comparing actual value by the physical therapist and predicted value in five models with Boruta. The proposed method could predict

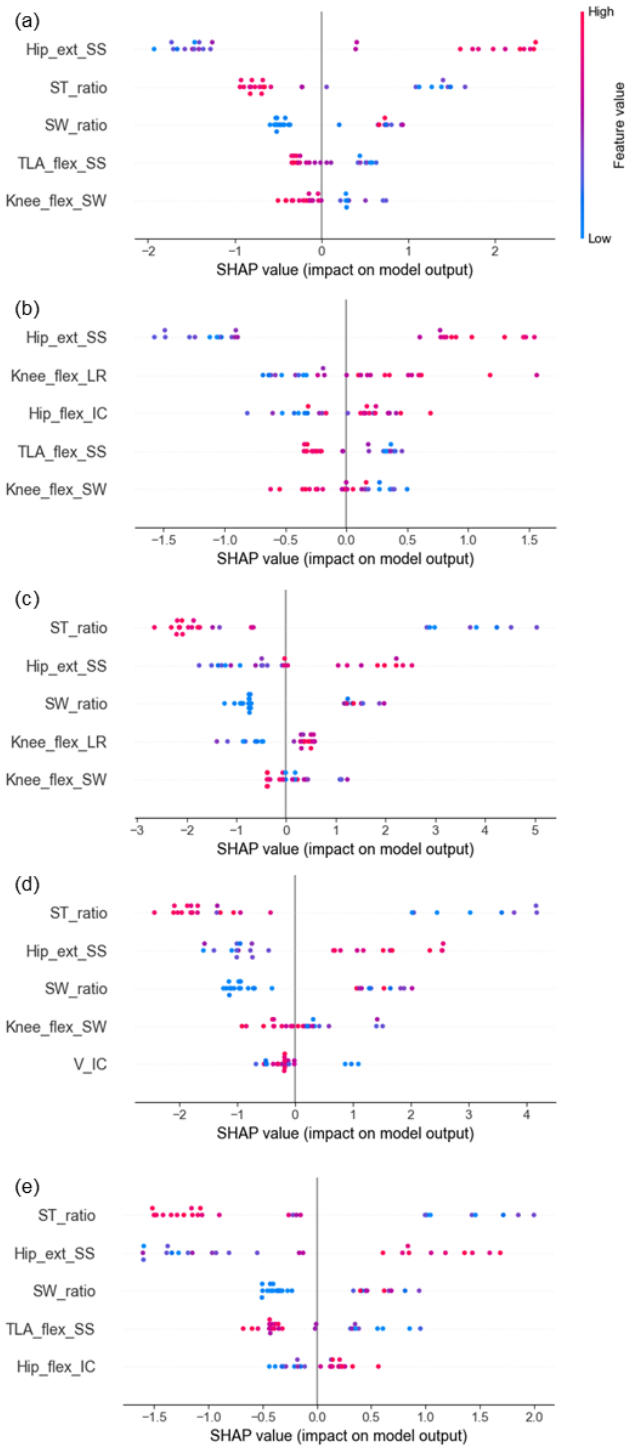

Fig. 4. SHAP summary plot of all the model with Boruta for the G.A.I.T. score in this study. (a) Random Forest; (b) CatBoost; (c) Gradient Boosting; (d) XGBoost; (e) AdaBoost. Top five of features are ordered from top to bottom based on SHAP value. Each dot of these features represents a single sample in the data. The x-coordinate showed SHAP value on each feature. The color of dots and the vertical color line to the right side indicate the value of each feature. Red and blue mean high and low feature value, respectively.

this observational gait analysis score on individuals with stroke with a small error using data that can be easily obtained in clinical settings. In this study, the participants had relatively few severe gait disorders with high G.A.I.T scores related to sagittal plane motion because the inclusion criteria required participants to be able to walk at least 20 meters with assistance and have a low risk of falling. Consequently, individuals who require such extensive substantial assistance or harness support that it is not practical to assess the G.A.I.T. were excluded. The main target population for G.A.I.T. assessment in clinical settings is well represented in our study. Therefore, the proposed method could predict this observational gait analysis score on individuals with stroke with a small error using data that can be easily obtained in clinical settings.

B. *Features' Contribution*

SHAP was utilized to assess the importance of features in the five models. Fig. 4 shows top five features of SHAP value in all the models with Boruta. The features of these models are sorted according to their importance. Hemiparetic side maximum hip extension angle in single leg stance phase (Hip_ext_SS) was identified as the influential parameter for the prediction in the five models. Also, stance time ratio of hemiparetic side and less-affected side (ST_ratio) and the swing time ratio of hemiparetic side and less-affected side (SW_ratio) were identified as the influential parameters in some models. These results indicate that some models in this study set importance to the hip extension angle during late stance and gait symmetry from pose estimation and single RGB camera. Unlike other models, the CatBoost with Boruta identified Knee flexion angle in loading response (Knee_flex_LR) and Hip flexion angle in initial contact (Hip_flex_IC) as influential parameters. Observational gait analysis includes many items related to abnormalities in lower limb joint angles at each gait event. Therefore, these features may have contributed to the improved prediction accuracy of the CatBoost with Boruta.

IV. Conclusion

This study aimed to predict observational gait assessment score by using conventional clinical assessment data and pose estimation from single RGB camera. This study reveals that the proposed machine learning-based prediction method using clinically available RGB camera gait video and clinical assessment data has the potential to predict the G.A.I.T. score on individuals with stroke. This finding could contribute to decrease time required for therapist work and provide valuable information for treatment quickly. Further research should investigate more comprehensive gait assessment predictions with large sample size.

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