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Machine-learning prediction of self-care activity by grip strengths of both hands in poststroke hemiplegia

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Abstract

To investigate the relationships between grip strengths and self-care activities in stroke patients using a non-linear support vector machine (SVM).

Overall, 177 inpatients with poststroke hemiparesis were enrolled. Their grip strengths were measured using the Jamar dynamometer on the first day of rehabilitation training. Self-care activities were assessed by therapists using Functional Independence Measure (FIM), including items for eating, grooming, dressing the upper body, dressing the lower body, and bathing at the time of discharge. When each FIM item score was ≥6 points, the subject was considered independent. One thousand bootstrap grip strength datasets for each independence and dependence in self-care activities were generated from the actual grip strength. Thereafter, we randomly assigned the total bootstrap datasets to 90% training and 10% testing datasets and inputted the bootstrap training data into a non-linear SVM. After training, we used the SVM algorithm to predict a testing dataset for cross-validation. This validation procedure was repeated 10 times.

The SVM with grip strengths more accurately predicted independence or dependence in self-care activities than the chance level (mean ± standard deviation of accuracy rate: eating, 0.71 ± 0.04, $P < .0001$; grooming, 0.77 ± 0.03, $P < .0001$; upper-body dressing, 0.75 ± 0.03, $P < .0001$; lower-body dressing, 0.72 ± 0.05, $P < .0001$; bathing, 0.68 ± 0.03, $P < .0001$).

Non-linear SVM based on grip strengths can prospectively predict self-care activities.

Abbreviations: AR = accuracy rate, FIM = Functional Independence Measure, GSB = grip strengths of both hands, N = sum of true positive, true negative, false positive, and false negative, SA = self-care activities, SD = standard deviations, SVM = support vector machine, TN = true negative, TP = true positive.

Keywords: activities of daily living, grip strength, rehabilitation, self-care, stroke

1. Introduction

Upper limb hemiparesis after a stroke limits self-care activities (SA)[1] involving movement of both arms, such as holding a rice bowl and using chopsticks, washing the face and body, and fastening buttons. Previous studies noted that 50% to 85% of stroke patients experienced upper limb hemiparesis and were unable to perform SA.[2–4] The dominant and nondominant arms must be coordinated to play roles that require mutual complement, including manipulation and stabilization in daily SA. Therefore, the unaffected upper limb of patients with hemiparesis must vary its use for the affected limb in accordance with the degree of hemiparesis to perform SA.

Because coordinated use of both hands is required in SA, training for interlimb coordination is important to prepare poststroke patients to naturally use both hands.[5,6] Previous studies noted that frequent overall use of an upper limb can result in faster recovery for that limb,[7] while disuse often leads to "learned non-use."[8] Therefore, using the upper limbs as much as possible in SA, such as eating, dressing, toileting, and bathing is important.

As a basis of SA, muscle weaknesses are the most common impairments related to upper limb hemiparesis following stroke.[9,10] Studies on patients after stroke use grip strength to measure muscle weakness and characterize hemiparesis as it is correlated with elbow and shoulder strengths.[11] In older community-dwelling populations, grip strength could predict a decline in motor and cognitive functions and mortality.[12,13] Therefore, grip strengths of both hands (GSB) could be an important predictor of SA among patients with hemiparetic stroke.[14] However, most previous studies[15,16] focused on upper limb hemiparesis and functional movement on body side

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contralateral to the brain lesion after stroke. Because the dominant and nondominant arms coordinate to perform complementary movements, including manipulation and stabilization, the upper limb of the body side ipsilateral to the brain lesion must vary its use in accordance with the degree of hemiparesis to carry out SA. Therefore, the focus was not only on the body side contralateral to the brain lesion after stroke but also on the ipsilateral side (i.e., both hands) with poststroke hemiparesis.

Despite the benefit of upper limb use in daily life, little is known about the relationship between GSB and SA or whether grip strengths predict independence and dependence in SA in patients with poststroke hemiparesis. Therefore, prediction of the ability to perform SA based on GSB remains difficult. In recent years, non-linear support vector machine (SVM) with kernel functions to map data to a higher dimension space has been recognized as a powerful learning method to predict patient outcome.[17]

The non-linear prediction of SVM can analyze the complex relationship between patient outcomes; thus, in this study, the SVM was used to predict SA by GSB, which could establish an evidence-based approach in the training and instruction of poststroke patients using bilateral upper limbs in daily life. To the best of the authors' knowledge, no study has demonstrated the non-linear machine learning method based on GSB prediction of independence and dependence in SA. If GSB reflecting bilateral arm functions predicts SA including both arms, this knowledge could help patients, their caregivers, and clinicians understand the prognosis for bilateral arm functions and SA. Therefore, this study aimed to assess the relationships between grip strengths and SA in patients with poststroke hemiparesis and to predict SA by grip strengths. As a hypothesis, SA and GSB, whichever included hemiparesis, were stochastically related, and GSB could predict SA in stroke patients.

2. Methods

2.1. Eligibility criteria

Average values and standard deviations (SD) of grip strength in 21 people with poststroke hemiparesis from a previous study[18] were used to determine the sample size. The average ± SD of paretic and nonparetic grip strengths for 21 subjects were 7.6 ± 9.2 kg and 16.3 ± 8.7 kg, respectively, in the previous study.[18] Sample size calculation was based on a desired 80% statistical power to detect a 3-kg difference (standard effect size, 0.30) in grip strength, with a 2-sided α of 5%. A sample size of 174 was derived by insertion of α (0.05), 1-β (0.80), and standard effect size (0.30) values in the Hulley matrix.[19] Therefore, for this study, we planned to retrospectively recruit a total of 174 stroke patients from a hospital database.

Eligibility criteria included hemiplegia, a period of less than 1 month since the stroke event, and grip strength that can be assessed in accordance with the testing protocol. Experimental procedures were approved by the Research Ethics Committee of the St. Marianna University, Yokohama City Seibu Hospital (approval number, 320), and were performed in accordance with the principles of the Declaration of Helsinki.

2.2. Grip strength

Grip strength was measured with a Jamar dynamometer (Sammons Preston, Mississauga, Ontario, Canada) on the first day of the rehabilitation training (first assessment). The second handle position was used for grip strength measurement because this position was best for exerting maximum voluntary grip strength.[20] Subjects were seated in a hard chair, with the arm hung to the side in an upright posture, the elbow flexed at 90°, the forearm in a neutral position between supination and pronation, and the wrist in a neutral position between flexion and extension in accordance with a standard testing position.[9,13,21] When the subject could not maintain this position, the tester held the subject's elbow and wrist in this position. The same verbal commands were used for all participants to encourage maximal force during the assessments. Measurements were performed on each hand once, randomly starting with the dominant or nondominant hand and alternating hands in between measurement trials. The test–retest reliability of the grip strength test with the same position has previously been found to be excellent.[11,21] We determined handedness through an interview about the side of the hand used in daily life activities, such as using chopsticks, brushing teeth, and writing.

2.3. SA

Functional Independence Measure (FIM)[22] consists of 18 daily living items, graded on a scale of 1 to 7, with 1 indicating total assistance and 7 indicating complete independence. We focused on 5 FIM items that require bimanual coordination of the upper limbs: eating, grooming, dressing the upper body, dressing the lower body, and bathing. The FIM items were assessed by an occupational therapist or physical therapist who maintained contact with the subject at the time of discharge (second assessment). This ensured sensitivity or responsiveness of grip strengths as a prospective prediction scale for SA after stroke. In this study, when a subject had a score of ≥6 points for each of the 5 FIM items, the subject was considered independent. All patients received arm and leg training and training for activities of daily living for 5 days per week by an occupational therapist and physical therapist.

2.4. Data analysis

Grip strengths at the first assessment were used as features in a non-linear SVM. The SVM focuses on grip strength patterns of both hands and finds a hypersurface that maximizes the margin between 2 distributions to classify them into each subject's independence or dependence in SA. One thousand bootstrap datasets for each independence and dependence in SA, including eating, grooming, dressing the upper body, dressing the lower body, and bathing, were generated by randomly drawing a series of actual sample datasets from the grip strength to reduce the classification variability of SVM due to limited actual sample size. This bootstrap resampling method is widely used in demographic studies.[23] Total bootstrap datasets for GSB and SA were then randomly and blindly assigned 90% training and 10% testing datasets, and 90% bootstrap training data were inputted into a non-linear SVM. This inputting of non-linear SVM with bootstrap training data ensured the stability of the SVM classification, eliminating the influence of sample size limitation.[23,24] Using the bootstrap training dataset, the SVM algorithm was proposed to establish a prediction model. After the training, the SVM prediction model using the 90% bootstrap training dataset was used to predictively classify 10% testing dataset into either each subject's independence or dependence in SA at the second assessment for cross-validation. This validation procedure, including random assignment into training and testing datasets and prediction of independence or dependence in SA, was repeated 10 times, and the accuracy rate for each activity (eating, grooming, dressing the upper body, dressing the lower body, and bathing) was calculated as $AR = TP + TN/N$, where AR was the accuracy rate, TP was true positive, TN was true negative, and N was the sum of true positive, true negative, false positive, and false negative. If the prediction of independence and dependence is by chance level, then the accuracy rate should be 0.5. Therefore, to assess the clinical utility of SVM, whether the accuracy rate of SVM was significantly higher than that of chance level, Wilcoxon signed-rank test was performed. We defined statistical significance as $P < .05$. This ensured that a trained SVM could prospectively be generalized.[25] All analyses were performed using the Sklearn package with Python language and R 3.5.2 software (R Foundation for Statistical Computing, Vienna, Austria).

3. Results

The number of stroke events consecutively recorded in the database of the Department of Rehabilitation Medicine, St. Marianna University, Yokohama City Seibu Hospital from 2009 to 2012 was 440. A total of 177 (40.2%) stroke inpatients were retrospectively enrolled in the present study. Table 1 shows the characteristics of patients who met the eligibility criteria. The mean ± SD of grip strength at the first assessment was 21.6 ± 12.9 kg and 20.2 ± 10.8 kg for dominant and nondominant hands, respectively. Figure 1 shows the ratio of independent patients for SA at the second assessment. Of all the patients, 80.2% could eat independently, 68.9% could groom independently, 70.1% could dress the upper body independently, 57.6% could dress the lower body independently, and 50.8% could take a bath independently at the second assessment. The relationship between GSB and independence or dependence in SA (eating, grooming, dressing the upper body, dressing the lower body, and bathing) is shown in Figure 2. As shown, GSB that exist across independence and dependence in SA were randomly scattered. Clearly, the GSB were not linearly divided by independence and dependence in SA. Subsequently, 1000 bootstrap data for each independent and dependent SA were generated from the actual grip strength. The actual and bootstrapping data were almost equivalent for mean, standard deviation, and data distribution (Table 2 and Fig. 3).

Table 1

Characteristics of patients who satisfied the eligibility criteria.

Participants (n)	177
Age (yr)	70.1 ± 11.0
Sex (n)	
Male	114
Female	63
Dominant hand (n)	
Right	164
Left	13
Diagnosis (n)	
Infarction	152
Hemorrhage	25
Paralysis side (n)	
Right	94
Left	83
Since stroke event (d)	
First assessment	3.4 ± 2.8
Second assessment	21.3 ± 16.6
Grip strength (kg) at first assessment	
Dominant hand	21.6 ± 12.9
Nondominant hand	20.2 ± 10.8
FIM score at second assessment	
Eating	7 (6–7)
Grooming	7 (5–7)
Upper-body dressing	7 (5–7)
Lower-body dressing	6 (4–7)
Bathing	6 (4–7)

Values are mean ± standard deviation, and *n*.
FIM = Functional Independence Measure.

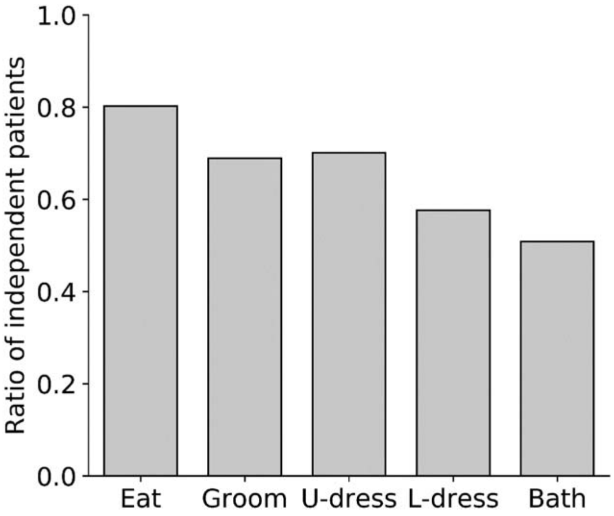


Figure 1. Gray columns denote ratios of independent patients for self-care activities, including eating, grooming, dressing the upper body, dressing the lower body, and bathing at the second assessment.

One thousand datasets in total were then randomly and blindly divided into 90% training and 10% testing datasets. After establishing the SVM prediction model by training the bootstrap GSB, the testing dataset was predictively classified as independence or dependence in SA individually related to eating, grooming, dressing the upper body, dressing the lower body, and bathing. For SVM prediction, the average ± SD accuracy rates were 0.711 ± 0.038 for eating, 0.769 ± 0.026 for grooming, 0.751 ± 0.026 for dressing the upper body, 0.724 ± 0.045 for dressing the lower body, and 0.677 ± 0.034 for bathing (Fig. 4). These indicate that 71%, 77%, 75%, 72%, and 68% data were correctively predicted for independence or dependence in eating, grooming, dressing the upper body, dressing the lower body, and bathing, respectively. The accuracy rate of SVM was significantly higher than that of chance level (Wilcoxon signed-rank test: eating, $P < .0001$; grooming, $P < .0001$; upper-body dressing, $P < .0001$; lower-body dressing, $P < .0001$; bathing, $P < .0001$).

4. Discussion

Our results showed that the non-linear SVM for bootstrap grip strength patterns of both hands could predict each patient's independence and dependence in SA. Particularly, in approximately 70% of data, either independence or dependence in eating, grooming, and dressing the upper body was accurately predicted by non-linear SVM. To the best of the authors' knowledge, this is the first systematic study to show that grip strength patterns of both hands non-linearly predicted independence in SA.

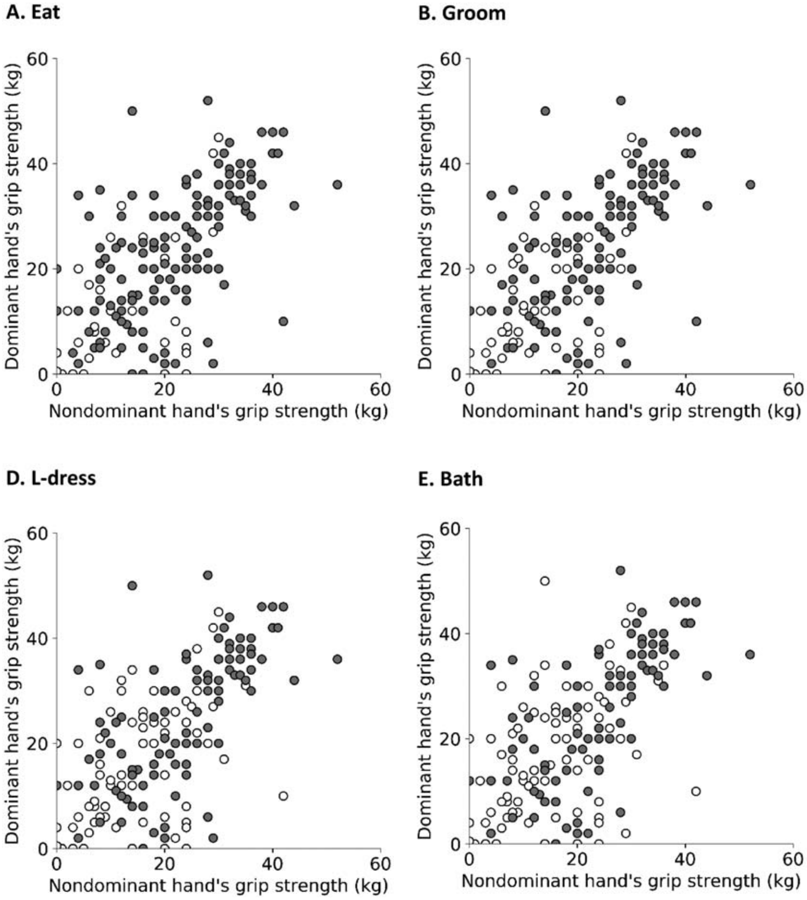


Figure 2. Scatterplots showing the relationship between the actual data for GSB and SA, including eating (A), grooming (B), dressing the upper body (C), dressing the lower body (D), and bathing (E). Black circles denote independent patients, whereas white circles denote dependent patients. They were not linearly divided into independence and dependence in SA by GSB. Eat=eating, Groom=grooming, GSB=grip strengths of both hands, L-Dress=dressing the lower body; Bath, bathing, SA=self-care activities, U-Dress=dressing the upper body.

The relationships between upper limb hemiparesis and associated daily activities have been extensively investigated in stroke patients.[15] Previous studies[9,10,26–28] suggested a correlation between grip strength and upper limb functions in stroke patients. Moreover, weakness of grip strength has been recognized as a contributor of upper limb dysfunction. Therefore,

Table 2

Actual and bootstrapping grip strengths.

	Grip strengths in the dominant hand (kg)		Grip strengths in the nondominant hand (kg)	
	Actual	Bootstrap	Actual	Bootstrap
Eating				
Independ	23.5±12.3	24.0±12.3	21.8±10.6	21.6±10.8
Depend	13.8±12.3	14.0±12.8	13.8±9.2	14.2±9.2
Grooming				
Independ	24.9±12.2	25.5±12.4	23.1±10.5	22.8±10.4
Depend	14.2±11.1	14.2±11.1	13.9±8.5	14.0±8.4
Upper-body dressing				
Independ	24.7±12.2	24.5±12.2	23.1±10.5	23.0±10.6
Depend	14.3±11.4	14.4±11.5	13.6±8.3	13.5±8.1
Lower-body dressing				
Independ	25.4±12.6	25.6±12.5	23.7±10.6	24.1±10.7
Depend	16.3±11.3	16.2±11.3	15.5±9.1	15.3±9.2
Bathing				
Independ	25.2±12.8	24.3±12.9	24.0±10.6	24.0±10.5
Depend	17.8±11.9	17.8±11.7	16.4±9.6	16.5±9.7

Values are mean±standard deviation.
Actual=actual data, Bootstrap=bootstrap data.

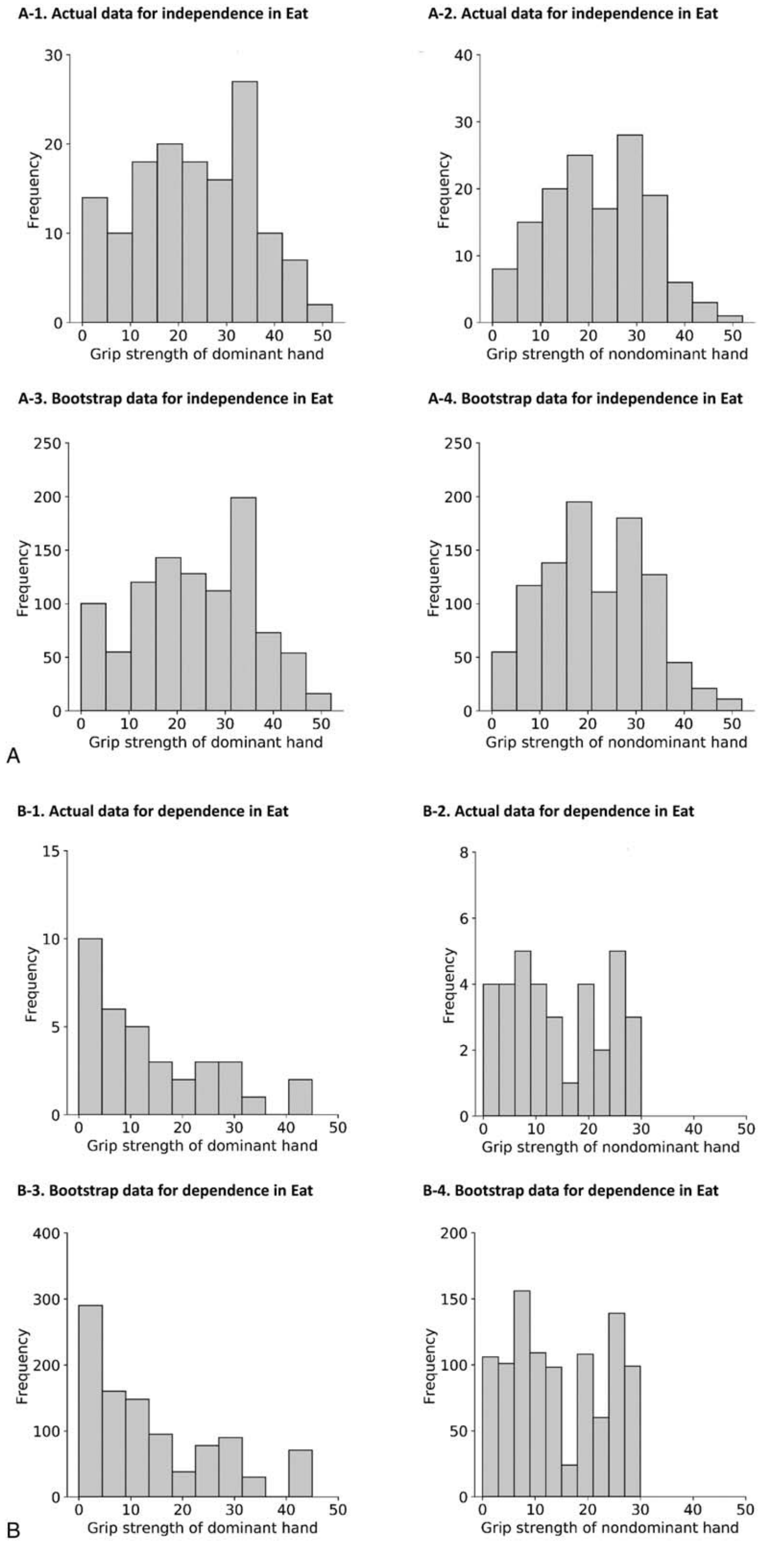


Figure 3. Histograms of actual and bootstrap data for independence in eating (A), dependence in eating (B), independence in grooming (C), dependence in grooming (D), independence in dressing the upper body (E), dependence in dressing the upper body (F), independence in dressing the lower body (G), dependence in dressing the lower body (H), independence in bathing (I), and dependence in bathing (J). The actual and bootstrapping data were almost equivalent in data distribution. Eat = eating, Groom = grooming, L-Dress = dressing the lower body; Bath, bathing, U-Dress = dressing the upper body.

evaluation of grip strength is commonly performed in the rehabilitation setting.[27,29] Nascimento et al[9] investigated the relationship between paretic grip and shoulder strengths in patients after stroke and noted significant correlation between the 2 strengths. Mercier and Bourbonnais[28] also investigated the relationship between paretic grip strength and upper limb motor

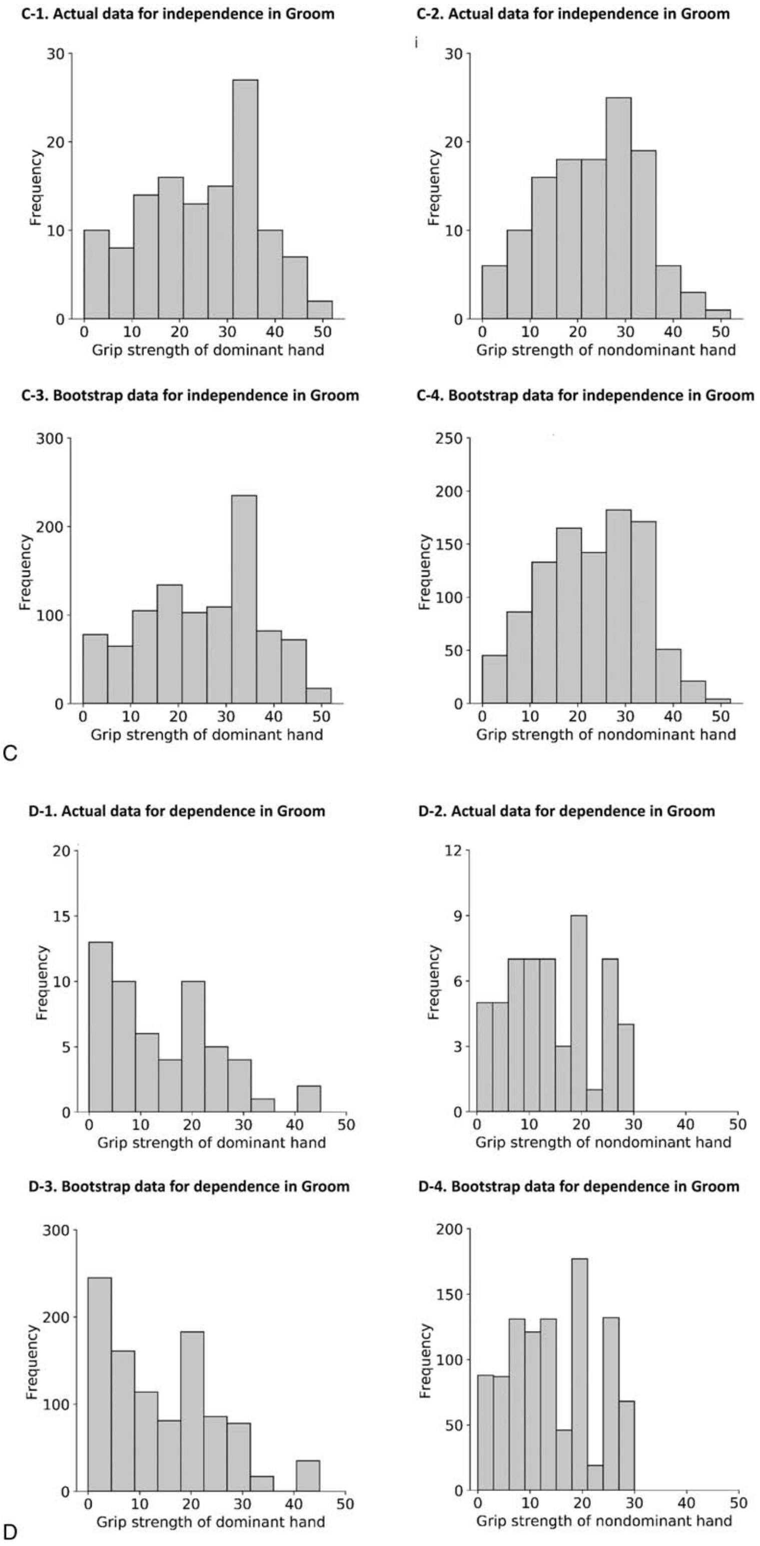
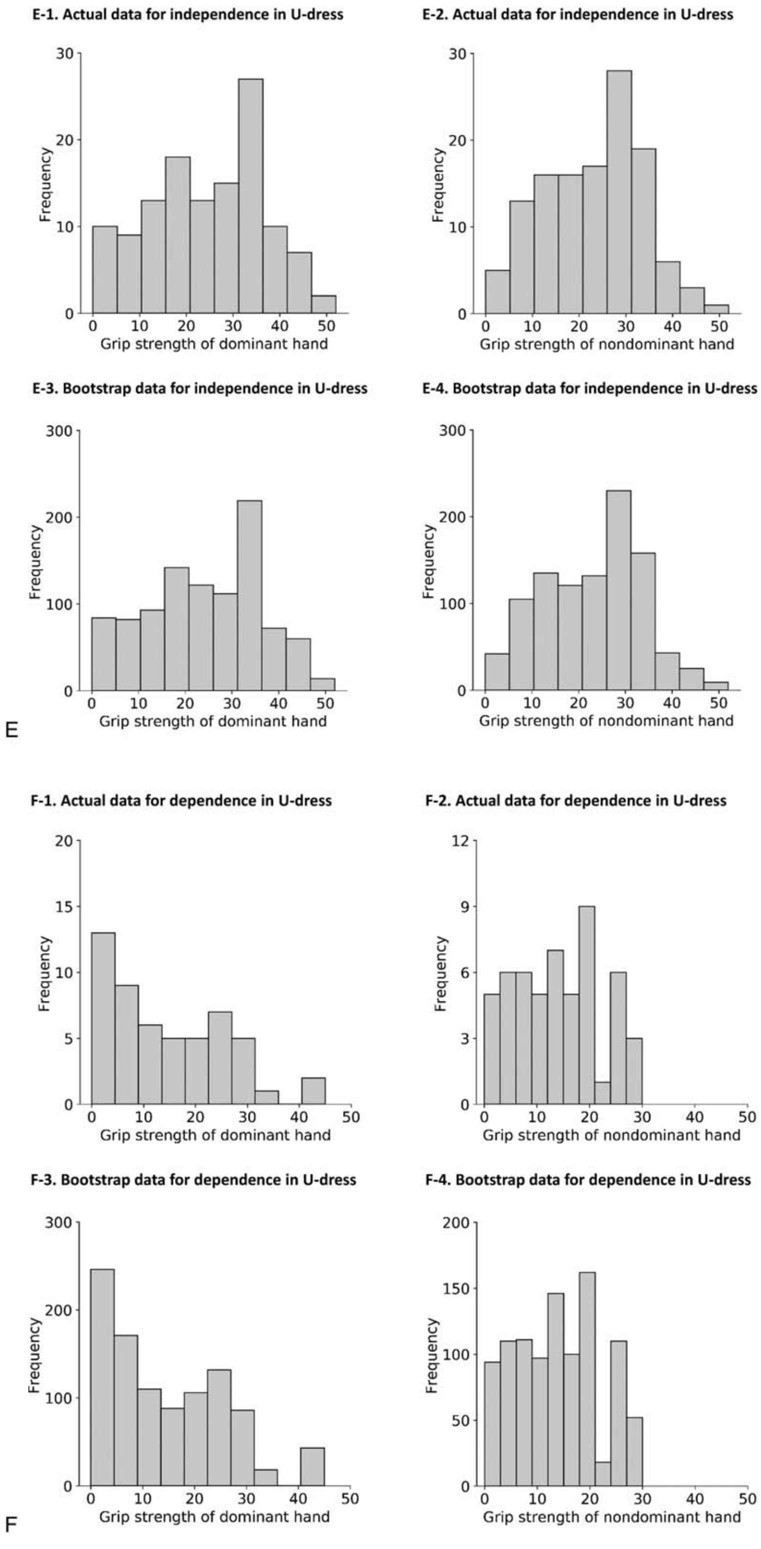


Figure 3. (Continued).

function and noted significant correlation between grip strength and upper limb motor function. These studies[9,28] suggested that paretic grip strength linearly correlates with paretic limb motor functions and can become the predictor of paretic upper limb functions. Additionally, Faria-Fortini et al[27] evaluated the relationship between the ratio of paretic grip strength to nonparetic grip strength and SA in patients after stroke and noted correlation between the ratio of paretic grip strength and SA. On the contrary, Dromerick et al[15] noted that hemiparesis and SA do not equally recover and indicated that severity of



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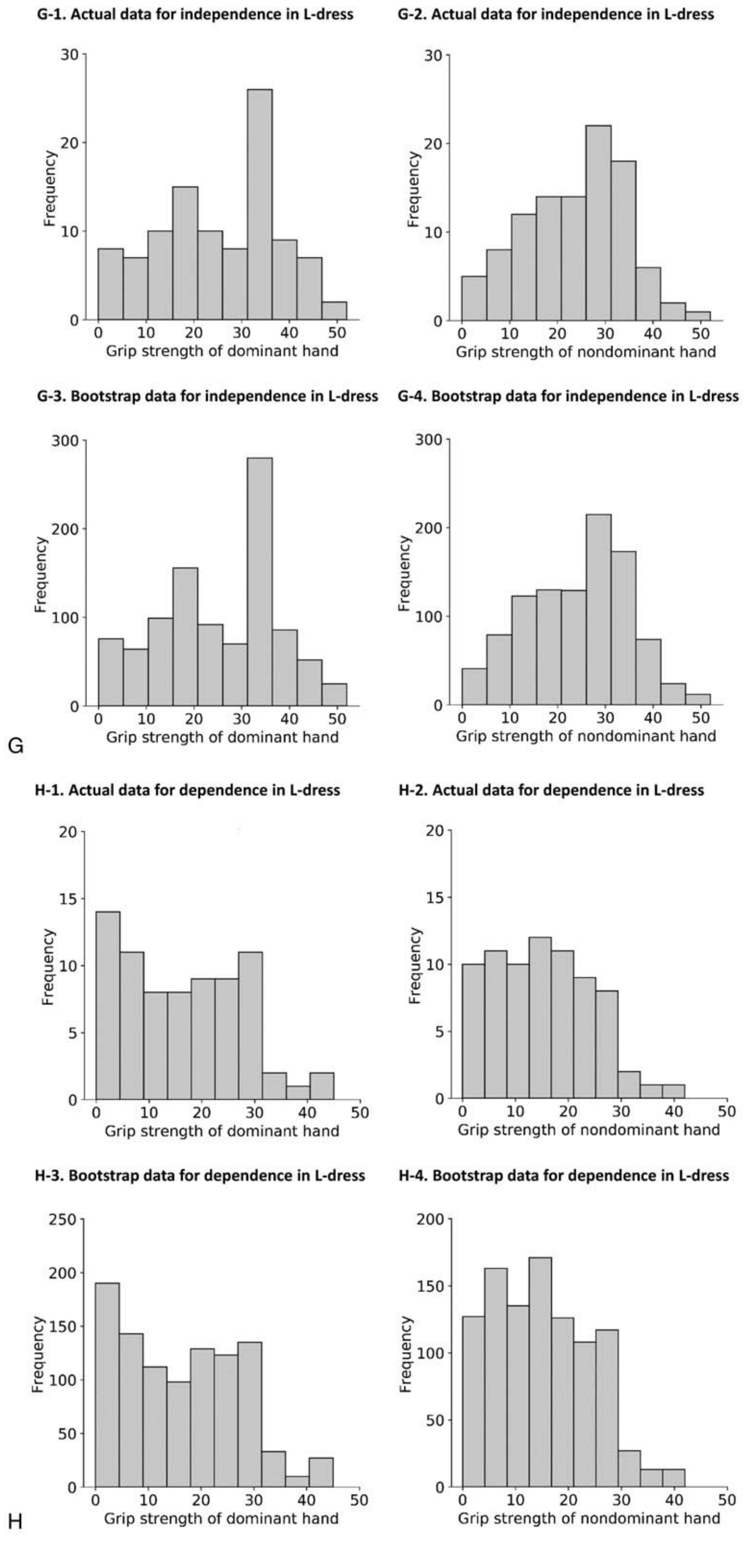
hemiparesis cannot translate to SA. They[15] also suggested that motor impairment does not necessarily predict upper limb use in daily living. However, these studies[9,15,27,28] focused only on paretic limb impairment. Therefore, prediction of independence and dependence in SA using impairment level is difficult. These are serious gaps in the current evidence, and an important issue in stroke rehabilitation is how to predict SA by impairment level. An additional novel observation in the present study was that the non-linear SVM based on GSB predicted each patient's independence in SA in daily life. In this study, independence



G-1. Actual data for independence in L-dress

G-2. Actual data for independence in L-dress

G-3. Bootstrap data for independence in L-dress

G-4. Bootstrap data for independence in L-dress

H-1. Actual data for dependence in L-dress

H-2. Actual data for dependence in L-dress

H-3. Bootstrap data for dependence in L-dress

H-4. Bootstrap data for dependence in L-dress

Figure 3. (Continued).

and dependence in SA in each subject with poststroke hemiparesis were clearly predicted by non-linear SVM with GSB. Therefore, this machine-learning method contributes toward prediction of the extent or duration of the loss of SA by GSB and to an increasingly evidence-based approach for advocating rehabilitation training for patients with poststroke hemiparesis.

Previous studies suggested that grip strength is affected by muscle tone and spasticity.[10,21,30] Another study[18] investigating the recovery patterns of grip strengths on both contra- and

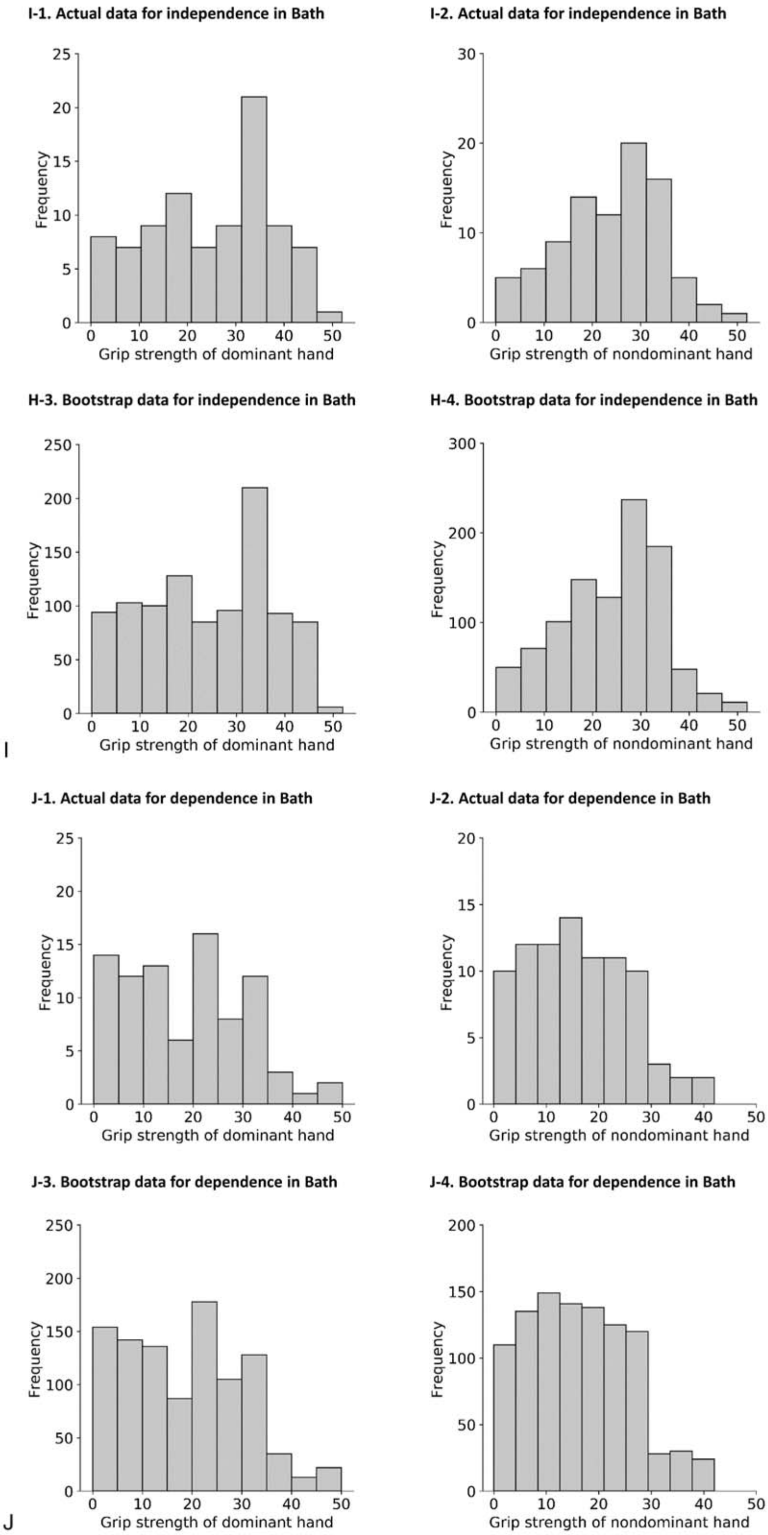


Figure 3. (Continued).

ipsilateral sides to the brain lesion after stroke noted that bilateral grip strengths improve in a similar pattern of change. This finding implies that the dysfunction of the ipsilesional limb reflects the bilateral descending control of the primary motor cortex over distal movements.[18] Additionally, Hier et al[31] noted that SA was associated with cognitive disorders, such as constructional apraxia, spatial neglect, and motor impersistence. Jongbloed[32] performed a critical review and suggested that the admission SA status is a strong predictor of discharge SA status. In a broader perspective on stroke recovery, the problem of defining SA status

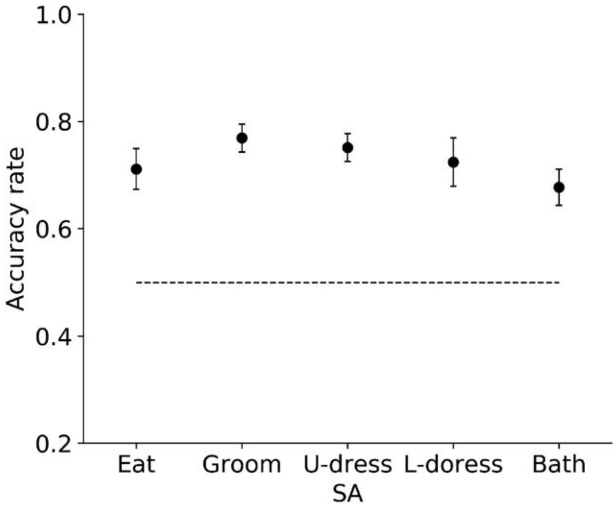


Figure 4. Accuracy rates of SVM classifications with bootstrap GSB for SA. The black circles and error bars denote mean and standard deviation. Approximately 68% to 77% of bootstrap datasets for eating, grooming, and dressing the upper body, either independence or dependence, were accurately predicted by non-linear SVM. Eat=eating, Groom=grooming, GSB=grip strengths of both hands, L-Dress=dressing the lower body; Bath, bathing, SA=self-care activities, SVM=support vector machine, U-Dress=dressing the upper body.

in patients after stroke is complex due to the multidimensionality of the predictors, including stroke severity,[33] metabolic homeostasis,[34] immune activity,[35,36] inflammatory response,[37] perfusion and hemodynamic disturbances,[38,39] and drug actions.[40] In the present study, eligibility criteria included hemiplegia, a period of less than 1 month since the stroke event, and grip strength that can be assessed in accordance with the testing protocol. These permissive criteria included many patients with wide-ranging characteristics. The permissive criteria may prompt the generalization of prediction based on non-linear SVM. By contrast, these permissive criteria minimized detailed classification in accordance with disease-specific characteristics. Therefore, the SVM prediction in the present study does not reflect the complexity of the covariates in GSB after a stroke, which is multifactorial in nature, including muscle spasticity, site of lesion associated with bilateral descending control, cognitive disorders, admission SA status, and multiple factors of stroke recovery, such as metabolic homeostasis, immune activity, and inflammatory response. These permissive sampling criteria are a potential limitation of the present study. In addition, in the present study, the accuracy rates of SVM predictions with bootstrap data for eating, grooming, and upper-body dressing were slightly higher than those for lower-body dressing and bathing. Although this study cannot explain the reason for this difference, one possible reason is that lower-body dressing and bathing did not only include GSB but also included lower extremity functions, such as hip and knee flexion and extension strengths and balance function. Another possible reason is that some patients might have had hemiparesis dominantly in the lower extremity and could not perform lower-body dressing and bathing. Therefore, to investigate the relationship between GSB and SA in consideration of multiple important covariates, a larger number of participants are required. We used bootstrap datasets to ensure the stability of the SVM prediction. Although bootstrap data closely reflected actual data due to equivalence of actual and bootstrap datasets, SVM did not predict actual participant's independence or dependence in SA. Therefore, despite the usefulness of the bootstrap method, a larger number of participants will be needed to predict actual patient's SA related to both upper and lower extremity functions in future studies. Owing to the great heterogeneity, complexity, and interdependence of the outcome modifiers, reliable prediction of prognosis is difficult to achieve through the traditional, currently available tools and models. The non-linear SVM could analyze the relation between outcome and complicating multiple factors, and individually predict each patient's prognosis. Therefore, these machine learning-based algorithms may offer additional resources and can contribute in predicting SA and stroke recovery by a personalized approach and develop integrated models of care in the setting of individualized medicine. With further detailed and strict eligibility criteria in a large number of participants, by classifying participants by their covariates, accurate prediction of actual independence and dependence in SA could be improved, and the results of the present study could be more generally applicable.

In conclusion, GSB could non-linearly predict each patient's independence or dependence during SA by using a machine learning method in patients with poststroke hemiparesis. These findings have implications for rehabilitation regimen and training. Machine-learning prediction of independence in SA by GSB helps design individual regimen and training involving targets with more closely matched achievable levels for specific SA. A rehabilitative regimen can be designed with allowance for variability in each patient's independence level of grip strength and SA. Therefore, the SVM with GSB contributes toward an increasingly evidence-based approach for advocating rehabilitative training for patients after stroke.

Author contributions

Study concept and design: Makoto Suzuki, Seiichiro Sugimura, Takako Suzuki, Shotaro Sasaki, Naoto Abe, Takahide Tokito, Toyohiro Hamaguchi. Acquisition of subjects and data: Seiichiro Sugimura, Shotaro Sasaki. Analysis and interpretation of data: Makoto Suzuki. Preparation of manuscript: Makoto Suzuki, Seiichiro Sugimura, Takako Suzuki, Shotaro Sasaki, Naoto Abe, Takahide Tokito, Toyohiro Hamaguchi.

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Methodology: Makoto Suzuki.
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Writing – original draft: Makoto Suzuki.
Writing – review & editing: Makoto Suzuki, Seiichiro Sugimura, Takako Suzuki, Shotaro Sasaki, Naoto Abe, Takahide Tokito, Toyohiro Hamaguchi.

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