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Sarcopenia Diagnostic Technique Based on Artificial Intelligence Using Bio-signal of Neuromuscular System: A Proof-of-Concept Study

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*Kwangsub Song and Hae-Yeon Park contributed equally to this work.

HIGHLIGHTS

- We proposed sarcopenia diagnosis system using bio-signal for neuromuscular system.
- To acquire the bio-signal, we captured stimulated muscle contraction signal.
- The proposed system could facilitate sarcopenia diagnosis in stroke patients.

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Sarcopenia Diagnostic Technique Based on Artificial Intelligence Using Bio-signal of Neuromuscular System: A Proof-of-Concept Study

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ABSTRACT

In this paper, we propose an artificial intelligence (AI)-based sarcopenia diagnostic technique for stroke patients utilizing bio-signals from the neuromuscular system. Handgrip, skeletal muscle mass index, and gait speed are prerequisite components for sarcopenia diagnoses. However, measurement of these parameters is often challenging for most hemiplegic stroke patients. For these reasons, there is an imperative need to develop a sarcopenia diagnostic technique that requires minimal volitional participation but nevertheless still assesses the muscle changes related to sarcopenia. The proposed AI diagnostic technique collects motor unit responses from stroke patients in a resting state via stimulated muscle contraction signals (SMCSs) recorded from surface electromyography while applying electrical stimulation to the muscle. For this study, we extracted features from SMCS collected from stroke patients and trained our AI model for sarcopenia diagnosis. We validated the performance of the trained AI models for each gender against other diagnostic parameters. The accuracy of the AI sarcopenia model was 96%, and 95% for male and females, respectively. Through these results, we were able to provide preliminary proof that SMCS could be a potential surrogate biomarker to reflect sarcopenia in stroke patients.

Keywords: Sarcopenia; Diagnosis; Stroke; Surface Electromyography; Muscle strength

INTRODUCTION

Sarcopenia is a decline in muscle mass and strength due to aging, influenced by neuromuscular degeneration, hormonal changes, physical inactivity or nutritional deficits. While it primarily affects the elderly, it is also common among stroke patients. The reduced physical performance associated with sarcopenia may increase the risk of falls during rehabilitation exercises among stroke patients [1,2]. Moreover, sarcopenia can lead to various complications, making it a significant cause of deteriorating health [3,4]. Consequently, the survival rate of sarcopenia patients is notably lower than those without the condition [5-7]. Therefore, early sarcopenia diagnoses and implementation of preventive are essential.

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Conflict of Interest

The authors have no potential conflicts of interest to disclose.

Author Contributions

Conceptualization: Choi S, Yoon MJ, Im S; Data curation: Song K, Song S, Yoo YJ; Methodology: Song K; Supervision: Choi S, Lee H, Im S; Writing - original draft: Song K; Writing - review & editing: Yoon MJ, Rim H, Park HY, Im S.

To diagnose sarcopenia, patients need to undergo evaluations of handgrip, skeletal muscle mass index (SMI), and gait speed [8,9]. However, conventional diagnostic methods for sarcopenia, particularly handgrip and gait speed assessments, may not be suitable for stroke patients with mobility issues (i.e., hemiplegic stroke patients). Stroke often results in unilateral motor impairment and may affect their ability to perform the handgrip test, which may pose technical difficulties in both performing and interpreting the results [10,11]. Therefore, stroke patients are at risk of sarcopenia, may also face difficulties in its diagnosis. Hence, there is a crucial need for a suitable sarcopenia diagnostic technique that takes into consideration the motor impairment.

Sarcopenia diagnosis requires experts at hospitals due to the need for 3 assessments, resulting in considerable time consumption. Additionally, the evaluation time is prolonged for stroke patients due to mobility limitations. Consequently, the medical costs associated with sarcopenia diagnosis are high. Regular monitoring of sarcopenia is vital for maintaining health, but it is challenging for stroke patients due to mobility issues and the necessity of experts and equipment. Therefore, these issues hinder the smooth diagnosis of sarcopenia in many patients, emphasizing the necessity of an easily accessible and convenient diagnostic technique.

To address these issues, we propose an artificial intelligence (AI)-based sarcopenia diagnostic technique utilizing bio-signals from the neuromuscular system. Sarcopenia causes neuromuscular system degeneration, affecting the state of motor units composed of motor neurons and muscle fibers [12,13]. Sarcopenia reduces the cross-sectional area (CSA) of myelin in motor neurons, affecting nerve conduction velocity, and decreases the CSA of muscle fibers. Thus, the degeneration of motor neurons and muscle fibers directly impacts physical performance. Obtaining information about motor neurons and muscle fibers is crucial for diagnosing sarcopenia, we attempted to collected bio-signals from the neuromuscular system using as set of various electrical stimulation frequencies defined as stimulated muscle contraction signals (SMCSs). Finally, our proposed system consists of a wearable device for measuring SMCS and algorithm for analysis. The algorithm includes an algorithm for extracting cepstrum coefficients from SMCS data collected by the wearable device and an AI-based sarcopenia classifier. Hence, we trained AI models to classify sarcopenia by collecting SMCS data from stroke patients, aiming to develop an effective sarcopenia diagnostic technique for stroke patients.

MATERIALS AND METHODS

Patient recruitment

To validate the performance of the proposed system, we analyzed preliminary results from a cohort study on stroke-induced sarcopenia, collected from 2 university-affiliated hospitals. This research received ethical approval from Clinical Research Ethics Committee from Bucheon St. Mary's Hospital (Institutional Review Board [IRB] number: HC22ONDI0052) and St. Vincent's Hospital (IRB number: VC22ONDI0185), and every participant or legal guardian signed informed consent before measurement.

Bio-signal collection

The overall block diagram of the proposed system is shown in **Fig. 1**. It consists of a wearable device for collecting bio-signals and algorithm for analyzing the bio-signals and diagnosing sarcopenia. The algorithm is divided into preprocessing, feature extraction, and

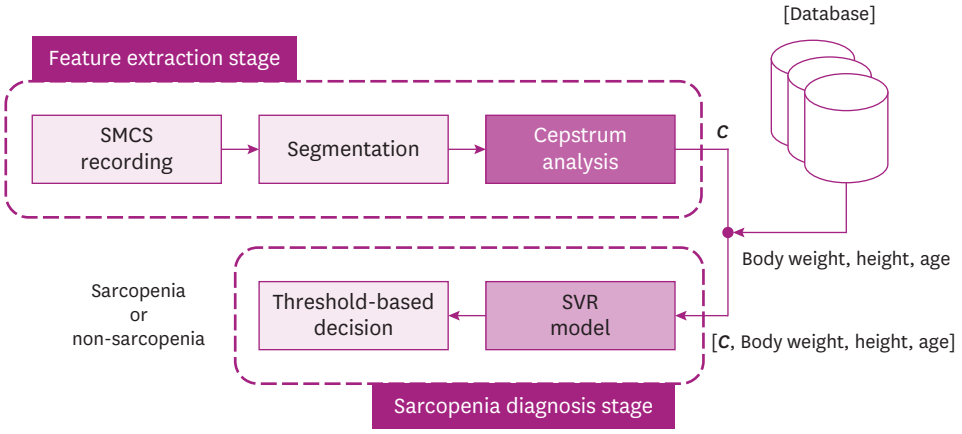

Fig. 1. Block diagram of the proposed sarcopenia classification technique.
SMCS, stimulated muscle contraction signal; SVR, support vector machine regression.

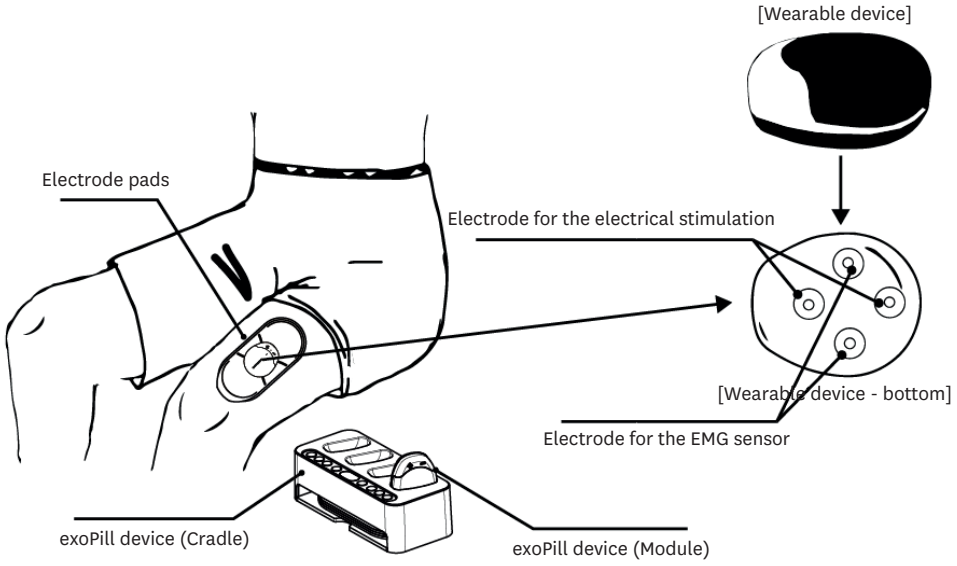

Fig. 2. Outline of stimulated muscle contraction signal recording system using the wearable device.
EMG, electromyography.

artificial intelligence classification model stages for analyzing SMCS. The wearable device is connected to the cradle shown in **Fig. 2**, and then transfers the collected signals to a mobile device via Bluetooth. All collected data through the device is stored on a cloud server.

SMCS recording system

The wearable device consists of 4 electrodes, as shown in **Fig. 2**. Two electrodes are for surface electromyography (sEMG) sensors, and the other 2 electrodes are for electrical stimulation. The wearable device is attached to the femoris quadriceps using a hydrogel pad connected through magnets as shown in **Fig. 2**. Using the wearable device, we stimulated the femoris quadriceps and recorded SMCS from both limbs. The electrical stimulation frequencies were collected for 8 seconds from 5 Hz to 30 Hz in increments of 5 Hz. As the electrical stimulation frequency increased, the interval between electrical stimulations decreased. Therefore, SMCS recorded during electrical stimulation frequencies higher than 35 Hz had intervals that were excessively short, making it impossible to analyze the

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response signals of the neuromuscular system. For this reason, we used electrical stimulation frequencies up to 30 Hz.

Segmentation and feature extraction

To independently analyze the response signals of the neuromuscular system based on the electrical stimulation frequency, segmentation based on the electrical stimulation frequency was performed. During data collection, besides sEMG we recorded the timing of electrical stimulation. Segmentation on the data recorded aligns with the timing of stimulation.

Since we recorded long-term signals using the electrical stimulation frequency, SMCS exhibits strong periodicity. Therefore, when performing Fourier transform analysis on SMCS, fundamental frequency and harmonic frequency components are prominently visible in the frequency domain. These components arising from periodicity need to be separated and processed separately when extracting feature vectors as they have low relationship with sarcopenia. Hence, because cepstrum analysis method can separate fundamental frequency and harmonic frequency from other frequency components, we analyzed SMCS using cepstrum analysis [14,15]. We extracted a 200-dimensional complex cepstrum coefficients c from SMCS of both femoris quadriceps, and reconstructed a feature vector by averaging the coefficients of the left and right sides. However, as not all extracted features play a significant role in classifying sarcopenia, we employ a feature selection procedure to further improve the results.

To select meaningful features for sarcopenia, we composed input vectors with the best-performing feature vectors in terms of classification performance. Additionally, since the structure of the neuromuscular system varies according to gender, we trained separate models for each gender. Consequently, the input vectors for each model were constructed differently. Ultimately, for the sarcopenia classification model for males, the feature vector consisted of c at 15 Hz, 20 Hz, and 25 Hz, while for females, the model used c at 20 Hz and 25 Hz as the feature vector. Finally, the constructed feature vectors were utilized as input vectors for the models, selecting only meaningful features based on the area under the receiver operating characteristic (ROC) curve (AUC) in the training dataset. And, the input vector is concatenated with the height, body weight, and age.

Support vector machine regression (SVR)-based classification model

To classify sarcopenia, we trained a classification model based on SVR. The SVR minimizes overfitting issues even with small datasets, making it suitable for our study's small dataset size. Additionally, SVR can utilize various nonlinear functions as kernels, enabling it to perform well on nonlinear datasets. For these reasons, we chose SVR to train our sarcopenia classification model. The features extracted in section 'Segmentation and feature extraction' were used as input vectors for the SVR model. To ensure a stable model, we performed normalization using the mean and standard deviation of the input vectors from the training dataset. The kernel function was set to a second-order polynomial function, and the kernel scale was automatically searched within the range of (0.001, 1,000), with values scaled logarithmically. And, we trained sarcopenia classification models for each gender based on SVR. When training the SVR model, we defined the target values of the model as 0 (without sarcopenia) or 1 (sarcopenia). Thus, the SVR model outputs values between 0 and 1. Finally, SVR predicted value between 0 and 1 is evaluated using different threshold for each gender to classify between sarcopenia and without sarcopenia.

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RESULTS

Subjects

In total, clinical assessments from 46 stroke patients were used for analysis, with 24 male and 22 female participants. To obtain sarcopenia labels for each patient, we collected handgrip (Baseline Smedley Digital hand dynamometer model 12-0286; Fabrication Enterprises Inc., Elmsford, NY, USA) and SMI data that that were collected at 6 months post-stroke onset. To measure handgrip necessary for the diagnosis of sarcopenia, we used a hand dynamometer. Additionally, for measuring SMI, dual energy X-ray absorptiometry (DEXA) was employed, following the guidelines of the European Working Group on Sarcopenia in Older People 2 (EWGSOP2) [16], where gait speed is used for diagnosing severe sarcopenia, we classified probable sarcopenia based on the EWGSOP2 guidelines. Finally, 26 patients (male: 14, female: 12) were classified as having sarcopenia. Of note, a few patients, despite showing SMI values indicative of nonsarcopenia, showed lower grip strength than the diagnostic criterion. However, they still showed significant differences in their grip strength value compared to the sarcopenic group. The clinical information of the enrolled patients is presented in **Table 1**.

Experimental configuration

We utilized a wearable device (exoPill, EXOSYSTEMS, Seongnam, Korea; **Fig. 3A**) and hydrogel pads (StiMus Electrode, HUREV Corp., Wonju, Korea; **Fig. 3B**), as shown in **Fig. 3**, to record SMCS. As described in section 'SMCS recording system,' SMCS was collected from both femoris quadriceps using the embedded sEMG in the wearable device.

We trained a model for classifying sarcopenia based on SVR. To validate the performance of the SVR model, we utilized leave-one-out cross-validation, where one data point was used as the test data while the rest were used as training data. Thus, each data point was used as a test data point once. As mentioned in section 'Segmentation and feature extraction,' we performed feature selection based on AUC on the training dataset. Depending on the type of feature, different criteria were used for feature selection. For male models, we selected features where c at 5 Hz was less than 0.35 or greater than 0.65, at 25 Hz was less than 0.30 or greater than 0.75, and at 30 Hz was less than 0.20 and greater than 0.80. For female models,

Table 1. Clinical information of the subjects enrolled

Variables	Male (n = 24)			Female (n = 22)		
	Non-sarcopenia (n = 10)	Sarcopenia (n = 14)	p value	Non-sarcopenia (n = 10)	Sarcopenia (n = 12)	p value
Age (yr)	69.1 ± 3.1	79.1 ± 8.7	< 0.005	75.8 ± 7.1	80.5 ± 6.5	> 0.05
Height (cm)	168.2 ± 3.8	169.2 ± 5.2	> 0.05	151.2 ± 6.9	153.0 ± 5.6	> 0.05
Weight (kg)	70.3 ± 8.2	63.7 ± 11.2	> 0.05	58.7 ± 9.3	55.6 ± 8.1	> 0.05
SMI (kg/m^2)	7.0 ± 0.5	5.7 ± 0.6	< 0.001	5.5 ± 0.6	4.5 ± 0.5	< 0.005
Non affected handgrip (kg)	27.7 ± 6.1	19.4 ± 6.1	< 0.05	15.1 ± 2.6	9.3 ± 4.1	< 0.05
Stroke type						
Infraction	7 (70.0)	10 (71.4)	-	7 (70.0)	10 (83.3)	-
Hemorrhage	3 (30.0)	4 (28.6)	-	3 (30.0)	2 (16.7)	-
Affected side						
Right	5 (50.0)	8 (57.1)	-	5 (50.0)	7 (58.3)	-
Left	5 (50.0)	6 (42.9)	-	5 (50.0)	5 (41.7)	-
Medical comorbidity						
Diabetes mellitus	3 (30.0)	7 (50.0)	-	3 (30.0)	6 (50.0)	-
Hypertension	8 (80.0)	9 (64.3)	-	9 (90.0)	10 (83.3)	-
Tbc	0 (0.0)	0 (0.0)	-	0 (0.0)	1 (8.3)	-
Hepatitis	0 (0.0)	0 (0.0)	-	0 (0.0)	0 (0.0)	-

Values are presented as mean ± standard deviation or number (%). SMI is measured using dual energy X-ray absorptiometry.
SMI, skeletal muscle mass index.

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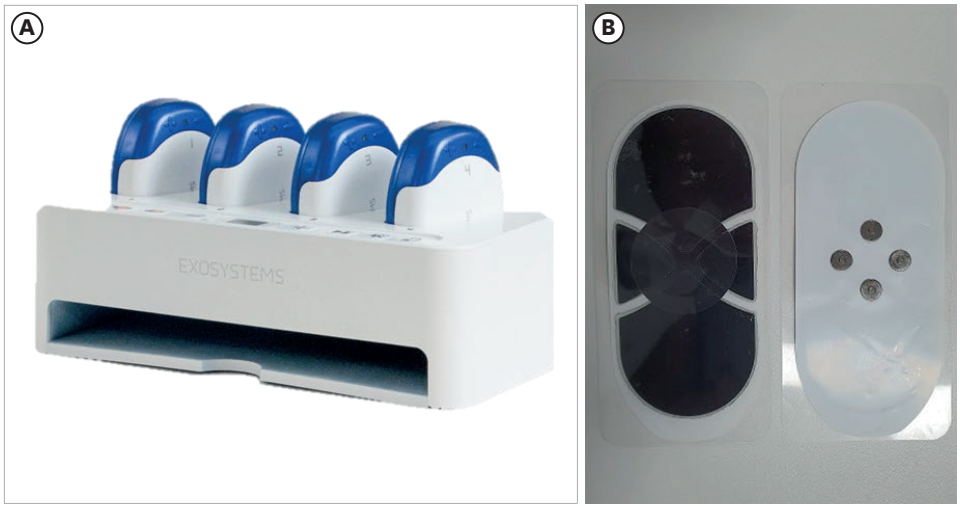

Fig. 3. Equipment for recording the stimulated muscle contraction signal. (A) Wearable device (exoPill), (B) hydrogel pads.

we selected features where *c* at 5 Hz was less than 0.35 or greater than 0.75, at 25 Hz was less than 0.35 or greater than 0.65, and at 30 Hz was less than 0.35 and greater than 0.75. Finally, as explained in section 'Support vector machine regression (SVR)-based classification model,' we diagnosed sarcopenia using thresholds. The thresholds for sarcopenia diagnosis models for males and females were set at 0.57 and 0.58, respectively.

Experimental results

We used complex cepstrum coefficients and body information (BI) such as body weight, height, and age as inputs for the SVR model. Since sarcopenia is more likely to occur with increasing age, age may have a significant impact on model training. Additionally, when sarcopenia occurs, muscle mass decreases, so body weight may also influence it. Therefore, we evaluated the performance by excluding complex cepstrum coefficients extracted from SMCS and using only BI as input to the SVR model. Furthermore, we validated the performance of models using only SMCS, as well as using both SMCS and BI. As described in section 'Support vector machine regression (SVR)-based classification model,' we trained SVR models separately by gender, and the performance of the models is summarized in **Tables 2** and **3**.

Table 2. Support vector machine regression-based sarcopenia classification model performance for male dataset

Input	Precision	Sensitivity	Specificity	Accuracy	F-score	AUC
BI	0.83 (0.68–0.98)	0.71 (0.53–0.89)	0.80 (0.64–0.96)	0.75 (0.58–0.92)	0.77 (0.60–0.94)	0.79 (0.60–0.98)
SMCS	0.93 (0.83–1.00)	1.00 (1.00–1.00)	0.90 (0.78–1.00)	0.96 (0.88–1.00)	0.97 (0.90–1.00)	0.97 (0.89–1.00)
SMCS + BI	0.93 (0.83–1.00)	1.00 (1.00–1.00)	0.90 (0.78–1.00)	0.96 (0.88–1.00)	0.97 (0.90–1.00)	0.97 (0.89–1.00)

Values are presented as 95% confidence interval.
AUC, area under the receiver operating characteristic curve; BI, body information; SMCS, stimulated muscle contraction signal.

Table 3. Support vector machine regression-based sarcopenia classification model performance for female dataset

Input	Precision	Sensitivity	Specificity	Accuracy	F-score	AUC
BI	0.72 (0.53–0.91)	0.67 (0.47–0.87)	0.70 (0.51–0.89)	0.68 (0.49–0.88)	0.70 (0.51–0.89)	0.60 (0.36–0.84)
SMCS	1.00 (1.00–1.00)	0.92 (0.81–1.00)	1.00 (1.00–1.00)	0.95 (0.86–1.00)	0.96 (0.88–1.00)	0.99 (0.94–1.00)
SMCS + BI	1.00 (1.00–1.00)	0.92 (0.81–1.00)	1.00 (1.00–1.00)	0.95 (0.86–1.00)	0.96 (0.88–1.00)	0.98 (0.92–1.00)

Values are presented as 95% confidence interval.
AUC, area under the receiver operating characteristic curve; BI, body information; SMCS, stimulated muscle contraction signal.

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For the sarcopenia classification model trained with the male dataset, when using only BI, precision, sensitivity, specificity, accuracy, and F-score were overall the lowest compared to other models. By contrast, the performance of the model when using only SMCS and when using both SMCS and BI was equivalent. For the sarcopenia classification model trained with the female dataset, using only BI resulted in the lowest diagnostic parameters. Particularly, sensitivity showed very poor performance. Moreover, the performance of the model when using only SMCS and when using both SMCS and BI was similar.

To evaluate the performance of the models, the achieved AUC as shown in **Tables 2** and **3** and the corresponding ROC curve to assess the performance of the algorithms are shown in **Fig. 4**. The ROC curve demonstrated desirable overall performance levels of the models. In the male model, the AUC of the ROC curve when using only BI as input showed the lowest performance level. By contrast the results obtained when using only SMCS and when using both SMCS and BI showed higher performance. For the female classification model, a similar trend was observed with the ROC curve when using only BI as the model input showed poor diagnostic parameters. **Fig. 4**, showed that the sole use of SMCS in the model showed good performance levels in sarcopenia diagnosis (AUC male: 0.97 [95% confidence interval {CI}, 0.89–1.00], AUC female: 0.99 [95% CI, 0.94–1.00]).

DISCUSSION

For this study, we trained AI models to classify decreased muscle mass index and therefore probable sarcopenia by collecting SMCS data from stroke patients and assessed the diagnostic parameters. The diagnosis of sarcopenia was based on SMI and handgrip strength, with SMI measured through DEXA technique. Nonetheless we attempted to compare the classification performance of each parameter and the performance of the proposed technique, with separate verification undertaken for the SMI and handgrip values. The precision, sensitivity, specificity, accuracy, and F-scores for the SMCS were 0.93, 1.00, 0.90, 0.93, and 0.97 for men and 1.00, 0.92, 1.00, 0.95, and 0.96 for women,

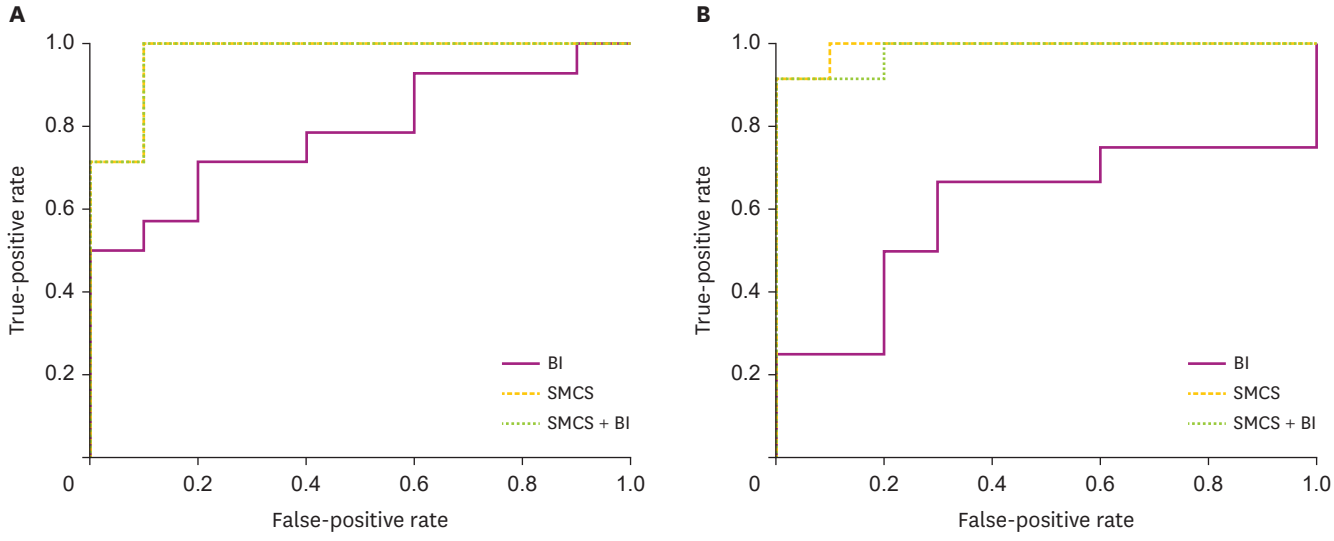

Fig. 4. Receiver operating characteristic curve of the sarcopenia classification model. (A) Model result for male dataset, (B) model result for female dataset. SMCS, stimulated muscle contraction signal; BI, body information.

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respectively. Consequently, the performance of the proposed AI models was overall higher than the classification performance of either the SMI or handgrip parameters. Based on our preliminary results, the proposed techniques may potentially classify sarcopenia with higher accuracy levels than using conventional methods such as DEXA and handgrip strength. This is of particular interest in consideration that some nonsarcopenic stroke patients were unable to fully exert voluntary muscle contraction of the non-hemiplegic hand with lower grip values that were out of proportion with their SMI values.

Previous studies [17,18] have indicated that preexisting sarcopenia may influence functional outcomes following a stroke. Although it is crucial to assess sarcopenia, technical limitations arise due to hemiparesis. In this study, traditional evaluations such as gait parameters or the chair raise test were not utilized. Some even failed to fully reach normal grip strength values despite normal SMI values. Our results have demonstrated that the SMCS can be employed as a potential parameter to address the current challenges in diagnosing sarcopenia. Additionally, results were compared to standard BI measures. Not only did the BI show lower diagnostic parameters with accuracy levels as low as 0.67, but showed different levels of accuracy between male and female. In contrast, the SMCS was easy to perform, required minimal volition from the patient and still showed high diagnostic properties in both genders.

Previous studies have used needle electromyography (EMG) to gather information about motor neurons [19-21]. However, the invasive nature of needle EMG makes it impractical for everyday applications. sEMG has been used as an alternative that records composite signals from multiple motor units [22,23]. The sEMG results can vary depending on the subject's willingness, making it difficult to objectively evaluate the neuromuscular system [24]. To solve these problems, we have conducted research on compound muscle action potentials (CMAP) [25-28]. CMAP are motor neuron response signals recorded through EMG during electrical muscle stimulation. Especially, by recording CMAP using sEMG, response signals from stimulated motor neurons passing through the muscle fiber transverse tubules are recorded by sEMG sensors [29]. Therefore, we can obtain combined response signals from motor neurons and muscle fibers through CMAP.

Compared with conventional methods of assessment, the system proposed in this paper may allow for easy and convenient evaluations, alleviating related cost and time in sarcopenia. In addition, since stroke patients may not fully participate in grip strength assessment or gait speed, due to their motor weakness our new model addresses key issues that may help overcome diagnostic difficulties in sarcopenia diagnosis in stroke patients. One may hypothesize that this novel technique may provide clinical benefits and help to overcome the technical difficulties in sarcopenia diagnosis in stroke patients, however, further larger scale prospective studies are warranted.

Some limiting factors need to be considered. One primary limitation of our study on diagnosing sarcopenia through bio-signals of the neuromuscular system is the restricted range of electrical stimulation frequencies used. While we have limited the maximum frequency of electrical stimulation to 30 Hz to prevent excessively short intervals between stimulations, there are numerous lower frequencies below 30 Hz that were not explored. This limitation is significant because these unexplored frequencies could potentially hold critical information about the neuromuscular system's response to sarcopenia. The decision to increase frequencies in 5 Hz increments, although practical from a data collection standpoint, may have further constrained our ability to capture subtle yet clinically relevant

changes at frequencies not examined. Future studies are necessary to explore these lower frequencies comprehensively, which could lead to more robust findings and improve the diagnostic accuracy of sarcopenia using bio-signals. Additionally, collecting comprehensive data across all possible frequencies in clinical settings presents logistical challenges, suggesting the need for innovative data collection methodologies or advanced simulation techniques to overcome these practical constraints. Second was the inconsistent BI results across gender. To assess the impact of using BI as input for the AI model on performance, we validated the performance when only BI was used as input for the AI model. In the experimental results, males showed an F-score of 0.77, while females showed an F-score of 0.70. To analyze the reasons for these differences, we calculated the Pearson correlation between the major parameter of sarcopenia diagnosis, SMI, and BI. And, the correlation between BMI and SMI measured by DEXA was 0.54 for males, whereas it was 0.31 for females' data. Additionally, the correlation between age and SMI was −0.17 for males and −0.24 for females. Since males' body weight and height have higher correlations with SMI compared to those of females, it is confirmed that the male model showed higher performance.

In this study, we introduced an AI-based technique for classifying sarcopenia using SMCS, a bio-signal indicative of neuromuscular system health. The degeneration of motor neurons and muscle fibers is a hallmark of sarcopenia, making their monitoring essential for accurate diagnosis. We utilized SMCS to capture response signals from these tissues, and upon testing, our AI model demonstrated high accuracy by analyzing feature vectors derived from these signals. Notably, our system's ease of use and convenience make it particularly beneficial for sarcopenia classification in stroke patients, who may encounter difficulties with mobility and hand grip measurements.

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