Development and Clinical Evaluation of Web-based Upper-limb Home Rehabilitation System using Smartwatch and Machine-learning model for Chronic Stroke Survivors: Development, Usability, and Comparative Study

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Abstract

Background: Human activity recognition (HAR) technology has been advanced with the development of wearable devices and the machine learning (ML) algorithm. Although previous researches have shown the feasibility of HAR technology for home rehabilitation, there has not been enough evidence based on clinical trial.

Objective: We intended to achieve two goals: (1) To develop a home-based rehabilitation (HBR) system, which can figure out the home rehabilitation exercise of patient based on ML algorithm and smartwatch; (2) To evaluate clinical outcomes for patients with chronic stroke using the HBR system.

Methods: We used off-the-shelf smartwatch and the convolution neural network (CNN) of ML algorithm for developing our HBR system. It was designed to be able to share the time data of home exercise of individual patient with physical therapist. To figure out the most accurate way for detecting exercise of chronic stroke patients, we compared accuracy results with dataset of personal/total data and accelerometer only/gyroscope/accelerometer combined with gyroscope data. Using the system, we conducted a preliminary study with two groups of stroke survivors (22 participants in HBR group and 10 participants in a control group). The exercise compliance was periodically checked by phone calls in both groups. To measure clinical outcomes, we assessed the Wolf motor function test (WMFT), Fugl-meyer assessment of upper extremity (FMA-UE), grip power test, Beck's depression index and range of motion (ROM) of the shoulder joint at 0 (baseline), 6 (mid-term), 12 weeks (final) and 18 weeks(6 weeks after the final assessment without HBR system).

Results: The ML model created by personal data(99.9%) showed greater accuracy than total data(95.8%). The movement detection accuracy was the highest in accelerometer combined with gyroscope data (99.9%) compared to gyroscope(96.0%) or accelerometer alone(98.1%). With regards to clinical outcomes, drop-out rates of control and experimental group were 4/10 (40%) and 5/22 (22%) at 12 weeks and 10/10 (100%) and 10/22 (45%) at 18 weeks, respectively. The experimental group (N=17) showed a significant improvement in WMFT score (P=.02) and ROM (P<.01). The control group (N=6) showed a significant change only in shoulder internal rotation (P=.03).

Conclusions: This research found that the homecare system using the commercial smartwatch and ML model can facilitate the participation of home training and improve the functional score of WMFT and shoulder ROM of flexion and internal rotation for the treatment of patients with chronic stroke. We recommend our HBR system strategy as an innovative and cost-effective homecare treatment modality. Clinical Trial: Preliminary study (Phase I)

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Development and Clinical Evaluation of Web-based Upper-limb Home Rehabilitation System using Smartwatch and Machine-learning model for Chronic Stroke Survivors: Development, Usability, and Comparative Study

Abstract

Background: Recent advancement of wearable sensor technology has shown feasibility of remote physical therapy at home. Especially, current crisis of pandemic has revealed the need and opportunity of internet-based wearable technology in the future healthcare system. Previous researches have shown the feasibility of human activity recognition technology for monitoring rehabilitation activities at home environments; however, few comprehensive studies ranging from the development to the clinical evaluation exist.

Objectives: This study aims to 1) develop a home-based rehabilitation (HBR) system which can recognize and record type and frequency of rehabilitation exercises conducted by the user by using smartwatch, smartphone application equipped with machine learning (ML) algorithm, and to 2) evaluate the efficacy of the home-based rehabilitation system through prospective comparative study with chronic stroke survivors.

Methods: The HBR system consisted of off-the-shelf smartwatch, smartphone, and custom developed applications. Convolution neural network (CNN) was used to train the ML algorithm for detecting the home exercises. To figure out the most accurate way for detecting the type of home exercise, we compared accuracy results with the dataset of personal/total data and accelerometer/gyroscope/accelerometer combined with gyroscope data. From March 2018 to February 2019, we conducted a clinical study with two groups of stroke survivors. Totally, 17 and 6 participants were enrolled for statistical analysis in HBR group and control group, respectively. To measure clinical outcomes, we assessed the Wolf motor function test (WMFT), Fugl-meyer assessment of upper extremity (FMA-UE), grip power test, Beck depression inventory and range of motion (ROM) of the shoulder joint at 0, 6, 12, and follow up assessment 6 weeks after retrieving the hbr system.

Results: The ML model created by personal data using the accelerometer combined with gyroscope data (99.9% [5590/5601]) was most accurate compared to accelerometer (98.1% [5496/5601]) or gyroscope (96.0% [5381/5601]). In comparative study, drop-out rates of control and HBR group were 4/10 (40%) and 5/22 (22%) at 12 weeks and 10/10 (100%) and 10/22 (45%) at 18 weeks, respectively. The HBR group (N=17) showed a significant improvement in mean WMFT score (39.7, vs 40.5, vs 42.5, overall P =.02), ROM of flexion (74.5, vs 93.9, P = .004) and internal rotation (50.4, vs 70.3, P = .001). The control group (N=6) showed a significant change only in shoulder internal rotation (50.8, vs 48.5, vs 57.3, P = .03).

Conclusions: This research found that the homecare system using the commercial smartwatch and ML model can facilitate the participation of home training and improve the functional score of WMFT and shoulder ROM of flexion and internal rotation for the treatment of patients with chronic stroke. This strategy can possibly be one of cost-effective tools for homecare treatment of stroke survivors in the future.

Keywords: home-based rehabilitation; artificial intelligence; machine learning; wearable device; smartwatch; chronic stroke

Introduction

Stroke is a major cause of disability in adults. About 13.7 million cases of stroke occur each year globally, but half of them are unable to restore enough upper extremity function required for daily living [1, 2]. The rehabilitation required after stroke has been limited to the first three to six months of hospitalization following the stroke [3]. For the best recovery following stroke and prevention of recurrence, stroke survivors need ongoing home rehabilitation [4-7]. Previous literatures have proven that continued home rehabilitation can activate neuroplasticity in chronic post-stroke patients and result in significantly enhanced clinical outcome [8-10]. In addition, the need for high-quality home healthcare system is drawing greater attention with the recent COVID-19 pandemic.

The major barriers in delivering high-quality home rehabilitation services are high cost and labor-intensiveness [11, 12]. Therefore, socioeconomically deprived people are less likely to receive high-quality rehabilitation care and more likely to suffer from recurrence and poor quality of life [13, 14]. The burdensome labor of home care also puts the care giver and receiver at risk for poor mental health and depression [15, 16].

To overcome the barriers for home rehabilitation, potential technology-enabled solutions have been suggested. For example, there are two kinds of technology used as solutions: the vision-based solution and the wearable-sensor based solution. The vision-based approach (e.g. interactive TV or Kinect) could be easier to use since it does not require any wearing of devices. [17-21]. However, a vision-based system can only be used within a limited range of space while wearable systems can be used in anywhere, which would be advantageous for promoting frequency of use [22, 23].

To promote frequency of use, we developed an upper limb home-based rehabilitation (HBR) system using wearable sensors embedded in a commercial smartwatch. A machine learning (ML) algorithm implemented by convolution neural network (CNN) was used to recognize four kinds of home exercise activities. While the participants are doing these home exercises, the HBR system makes it possible to share the home exercise data of each participant with the therapists at remote locations. It helped the therapists to encourage and communicate with chronic stroke survivors.

We conducted a prospective comparative study to evaluate the effectiveness of our HBR system. As the long-term goal of this study, we intended to investigate the benefits of using AI-based HBR compared to those of a conventional therapy. Herein, we compared the clinical outcomes of the experimental (HBR) group using the HBR system with those of a control group by performing conventional home exercises. We hypothesized that the HBR group would show enhanced clinical outcomes than the control group [24]. This paper elaborates on the technological advancements pertaining to the detection of home exercise activities using a smartwatch, the ML model, and the results from clinical trial.

Methods

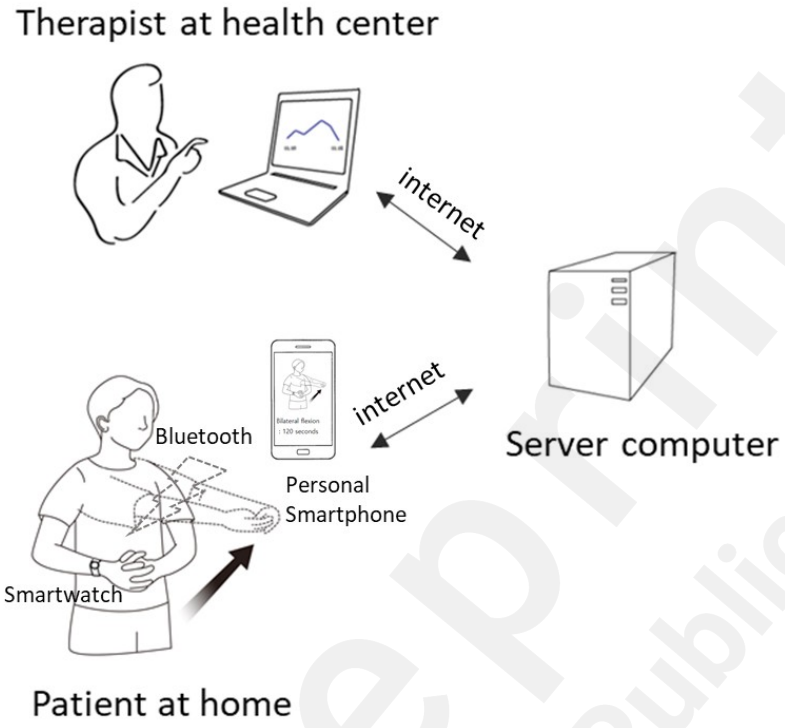
Development of home-based rehabilitation system

System overview of home-based rehabilitation system

We implemented an HBR system which can connect patients and therapists at a distance. Figure 1 represents overview of our HBR system. To make the interface simple and user-friendly, we used a commercial smartwatch (watch style W270, LG, Seoul, South Korea) that can be connected to a personal smartphone after installing the custom programmed application. In our system, the

smartwatch, which includes an inertial measurement unit (IMU) sensor, sent the sensor data to the smartphone via Bluetooth communication while patients were doing exercise. The personal smartphone served as a platform for receiving sensor data, classifying the data, and transmitting the results to a server computer via the internet (Multimedia Appendix 1). The applications for the smartwatch and smartphone were developed using the Android Software Development Kit (Android Studio 2.3, Google, CA, USA).

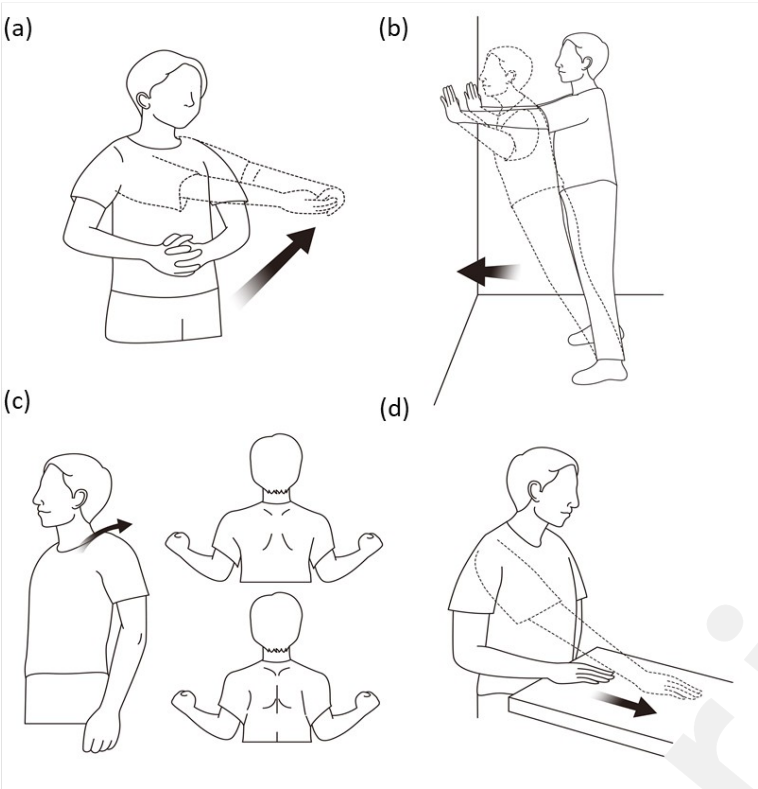
Figure 1. System overview of home-based rehabilitation (HBR) system.



Selection of home rehabilitation exercise tasks

We selected four exercise tasks based on bilateral movement therapy which is called bilateral arm training (BAT) rehabilitation. Previous literature has shown that BAT exercise can induce reorganization in contra-lateral motor networks by interhemispheric crosstalk and evoke a functional recovery of upper extremities in chronic stroke survivors [25, 26]. As shown in Figure 2, the following exercises were selected: (a) bilateral shoulder flexion with both hands interlocked; (b) wall push exercise; (c) active scapular exercise; (d) towel slide exercise.

Figure 2. Home rehabilitation exercise tasks for upper limbs. (a) Bilateral shoulder flexion; (b) wall push exercise; (c) Active scapular exercise; (d) Towel slide exercise.



Machine learning algorithm for home exercise recognition

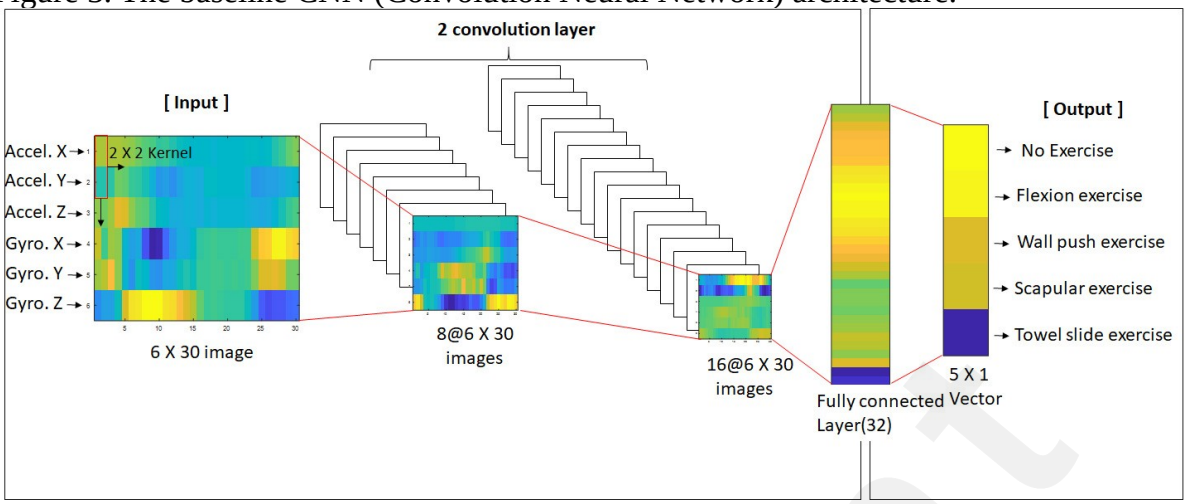
There are various kinds of deep learning algorithms for human activity recognition [27, 28]. Among them, we have selected the convolution neural network (CNN) as it has been reported to be highly accurate in human activity recognition and simpler than other algorithms since it does not need feature extraction[29, 30]. We made a program for building the ML model with Python script (Python 3.5, python software, Netherland) and convolution neural networks (CNNs) in TensorFlow platform (Tensorflow 1.7.0, Google, USA, CA).

The kinematic data structure from the IMU sensor consists of 3-axis (x, y, z) accelerometer and gyroscope data. When a patient is exercising while wearing the smartwatch, the accelerometer and gyroscope of the IMU sensor measure the acceleration and velocity during the exercise. Since all sensor data is in a time-series sampled at 10 Hz, the whole data can be represented by a two-dimensional matrix with the time axis (horizontal) and the sensor axis (vertical) as shown in Figure 3. We used the sliding time window method and applied a three seconds time window according to the experimental results that compared the performance of ML algorithm at various time windows [31].

The training data essential to implementing the ML algorithm was obtained on the first day of the meeting. Since it was difficult to meet chronic patients and patients, we gathered the data just after explain about the four kinds of home exercises above. Participants were asked to repeat them 15 times in 2 sessions wearing a smartwatch.

Figure 3 reflects our baseline CNN architecture. Two convolution layers, which have 8 and 16 feature maps, are followed by a fully connected layer which has 32 nodes. Rectified units are employed as activation functions and SoftMax functions are used for evaluating the final five output node values.

Figure 3. The baseline CNN (Convolution Neural Network) architecture.



We experimented with two types of ML models: a ML model built with the personal dataset and another ML model built with total dataset. The personal dataset was composed of the exercise data of the user himself whereas the total dataset consisted of all participants' exercise data including the user. In order to evaluate the accuracy of each model, we apply for a cross-validation test.

Cross-validation test for accuracy comparison

A five-fold cross-validation test was performed to test accuracy of the ML model in recognizing exercise tasks. We divided data into one training dataset and four test datasets. The training dataset were used for building ML model and the training dataset was used for finding out the accuracy of ML model built. So, we compared the accuracy of the model made by personal data versus total data. And, we compared the accuracy between models based on each sensor data: accelerometer only, gyroscope only, and accelerometer and gyroscope combined to determine which sensor data is most accurate for exercise prediction. Accuracy was calculated by using the following formula:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Where TP are true positives, TN true negatives, FP false positives, and FN false negatives.

Development of mobile applications

We have implemented three different android applications: (1) Smartwatch application; (2) Smartphone application for patients; (3) Smartphone application for physiotherapists (android studio 2.3, Google, CA, USA). The smartwatch application was designed to transmit sensor data to a smartphone as soon as the exercise button on the smartphone is pressed and to stop transmission when the use of the application on the smartphone ended. There is no start or finish button on the smartwatch. We made the smartphone application automatically finish as soon as the android application of the smartphone shuts down. The smartphone application for patients played as a platform for starting the smartwatch, detecting home rehabilitation, and transmitting exercise time data to the server computer. The personalized ML model embedded in the smartphone application recognized the type of exercise that the subject is doing. After recognition of exercise, smartphone calculated and transmitted the exercise time by internet access. It also showed the personal rehabilitation time of the previous three days by pressing a button in the application. Lastly, the smartphone application for the physiotherapist provided the physiotherapist with the rehabilitation status of all enrolled patients for the past one month to make convenient statistical evaluation.

Clinical trial: prospective comparative study

Experiment design

We performed a clinical trial in two local healthcare centers located in two cities: Cheongju (Control group) and Daejeon (HBR group) in South Korea. In each center, we recruited 12 and 26 patients with chronic stroke, respectively. Inclusion criteria were (i) age 40 to 70 years, (ii) mild to moderate neurologic deficit with hemiplegia, (iii) more than six months after the onset of stroke, (iv) 24 points or more in K-MMSE(Korean version of mini mental state examination) score and (v) possibility to understand the procedures and communicate with the supervisor. Exclusion criteria were: (i) joint arthritis of the glenohumeral joint, (ii) rotator cuff tear, (iii) cervical root syndrome, (iv) subluxation of shoulder joint, (v) reluctance to follow the home exercise regimens of this study, and (vi) do not have a smartphone with android OS.

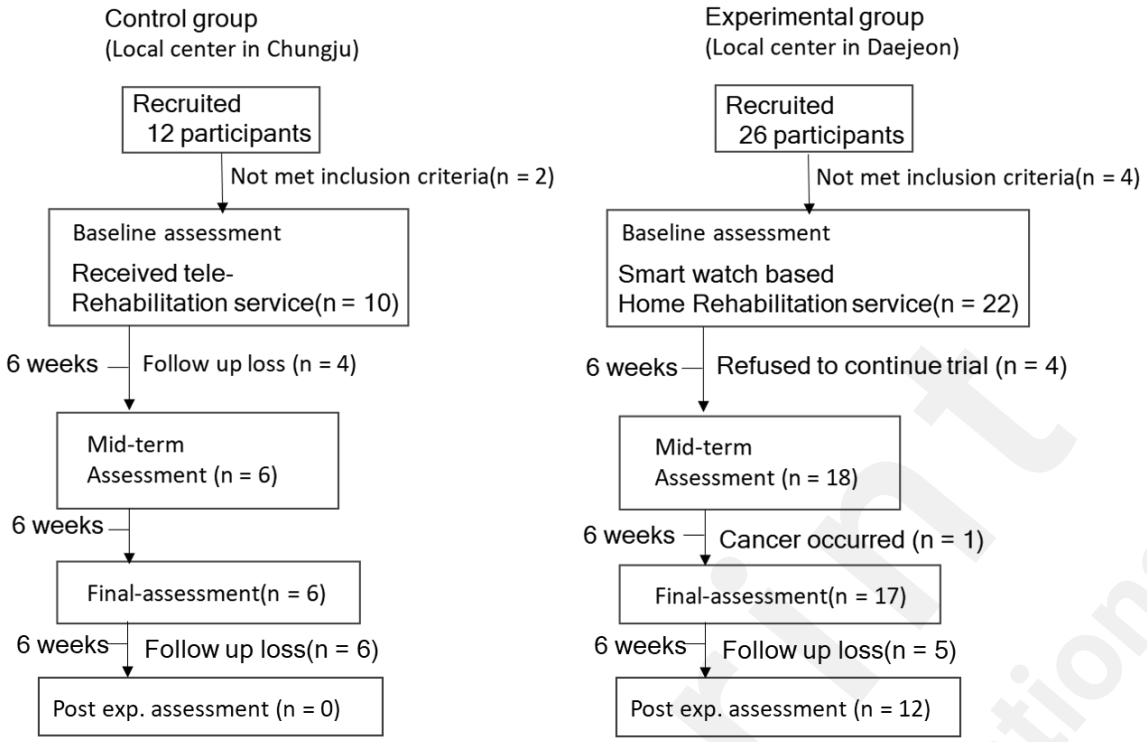
Figure 4 shows time Flow of the study. According to the criteria, we excluded two patients in the control group due to shoulder pain during exercise. In the HBR group, four patients were excluded: one patient had rotator cuff repair surgery before, one had shoulder subluxation, and two had shoulder pain during exercise. After excluding those patients, 10 and 22 patients were initially enrolled in this study. While doing the home rehabilitation program, four patients in the control group dropped out. The drop-out was determined by the therapist who undertook the task of home-based rehabilitation for the participants who did not respond to phone calls. In the HBR group, four patients gave up using our HBR system, as they were unfamiliar with the IT devices and experienced difficulties in their usage. One patient missed it due to the deterioration caused by other underlying diseases. Finally, 6 patients in the control group and 17 patients in the HBR group completed the protocol at 12 weeks. To figure out the changes of clinical scores, we tried to conduct an assessment at 6 weeks after the final assessment (18 weeks). Control group did not reply to our call whereas participants in HBR group cooperated to the requirement for assessment.

All patients in the control group received personal education about the four exercise tasks for 30 minutes at the beginning of the study enrollment. In the control group, the participants received a printed handout to remind them about how to do the four exercise tasks. In contrast, the participants in the HBR group received the same education and were given a smartwatch and the HBR applications installed on their own smartphones on the first day of the meeting. During the education, we acquired learning data for the ML algorithm in the HBR group. The physiotherapist taught each individual patient how to do the four exercise tasks and the training data were labeled manually while the patient was practicing each of the four tasks. In other words, with the smartwatch worn, participants were asked to repeat each home exercise 15 times in 2 sessions. In total, 120 exercise data were collected.

In both groups, weekly calls were made by the same therapists[17]. To avoid the bias from the examiner, two therapists divided patients in both groups into half and managed them. They encouraged the participants to do home exercise and answered any questions regarding how to do the home exercise from participants in both groups. Since the control group did not use any sensor at home, one additional question was asked in control group regarding how much time the control subjects spent on home exercise.

In the HBR group, the participants were able to figure out their own home exercise results and it was possible for the therapist get access to the data of all the participants. Thereafter, the physiotherapist communicated with the participants and encouraged them based on the home exercise data collected by the HBR system (Multimedia Appendix 2).

Figure 4. Time Flow of the study.



All participants were asked to come to the local healthcare centers for outcome evaluation, and two physical therapists at each center conducted the clinical assessments at 0 weeks (baseline), 6 weeks (mid-term) and 12 weeks (final). In addition, we conducted one more time at 18 weeks which was 6 week follow up after the completion of home rehabilitation program to examine the change after our home rehabilitation program. For a functional scoring system, the Fugl-Meyer Assessment of Upper Extremity (FMA-UE) and Wolf-Motor Function Test (WMFT) were used. We also evaluated psychologic depression using Beck depression inventory, grip power using a dynamometer (Patterson medical, UK, Nottinghamshire), and shoulder range of motion (ROM) angle using a goniometer.

Statistical analysis

We used descriptive statistics to characterize the demographics and analyzed the difference between control and HBR group on baseline by Mann-Whitney U test. We compared the clinical results of functional recovery (WMFT, FMA-UE), grip power, Beck depression inventory, and range of motion by Friedman test. As a post-hoc analysis, the Wilcoxon signed rank test with Bonferroni correction method was used. SPSS software was utilized for all the statistical analysis (SPSS statistics 25, IBM, NY, USA).

The sample size was determined by a previous study related to the current study using virtual reality home training [32]. Based on the result of the ROM increase of 41.67 ± 22.29 degrees, we calculated the sample size using the G*Power software (two-tailed, alpha error: 0.05, power (1 – beta error): 0.8, effect size: 1.869, loss rate: 10%). This power analysis showed the sample size to be 6.

Results

Accuracy results of home-based rehabilitation system

It was impossible to detect the accuracy of the home exercise activity logs as the ground truth of home exercise motion of the participants was unknown due to matters pertaining to personal privacy.

Instead, we attempted to ascertain what type of sensor data can detect home exercise activities most accurately via a cross-validation test.

The results shown in Table 1 represent the accurate values which were calculated by the cross-validation test with different ML models depending on various input data and sensor data. With regard to the input data, the ML model trained by the accelerometer combined with the gyroscope data had the best accuracy compared to others. Particularly, the ML model developed using the personal data (99.9%) was more accurate than the model developed using the total data (95.8%), although the amount of personal data was much smaller than that of the total data.

Table 1. Per-exercise accuracy for CNN model.

	Personal data (%)			Total data (%)		
	A[a]	G[b]	A+G[c]	A[a]	G[b]	A+G[c]
No exercise	100 (1224/1224)[d]	95.8 (1172/1224)	100 (1224/1224)	97.4 (1192/1224)	97.8 (1197/1224)	100 (1224/1224)
Bilateral flexion	98.5 (1103/1120)	97.8 (1095/1120)	99.0 (1109/1120)	96.1 (1076/1120)	98.1 (1099/1120)	97.2 (1089/1120)
Wall push	99.0 (1014/1024)	93.7 (959/1024)	100 (1024/1024)	93.8 (960/1024)	86.5 (886/1024)	93.2 (954/1024)
Active scapula	93.0 (1030/1108)	97.6 (1081/1108)	100 (1108/1108)	92.2 (1022/1108)	87.0 (964/1108)	93.0 (1030/1108)
Towel slide	100 (1125/1125)	95.5 (1074/1125)	100 (1125/1125)	94.2 (1060/1125)	88.7 (998/1125)	95.5 (1074/1125)
Total	98.1 (5496/5601)	96.0 (5381/5601)	99.9 (5590/5601)	94.8 (5310/5601)	91.8 (5144/5601)	95.8 (5371/5601)

[a] Accelerometer data; [b] Gyroscope data; [c] Accelerometer combined with gyroscope data; [d] Indicates the value of correct samples divided by total samples.

Multimedia Appendix 3 shows the results of cross-validation test.

Results of Clinical Trial

The study was approved by the Institutional Review Board (IRB No.: [redacted]). Informed consent was given to all participants. This study was supported by KAIST-funded Global Singularity Research Program. Patients were recruited from March 2018 to September 2018 and home exercise data were collected until February 2019. As of March 2019, we enrolled 23 stroke survivors for data analysis. Drop-out rates of control and HBR group were 4/10 (40%) and 5/22 (22%) at 12 weeks and 10/10 (100%) and 10/22 (45%) at 18 weeks, respectively.

Table 2 represents the demographics and baseline assessment with no significant differences between the two groups.

Table 2. Patient demographics and baseline assessment in both groups.

	Control group (n=6), Mean(SD)	HBR group (n=17), Mean(SD)	*P* value[e]
Age in years	64.5(9.6)	58.3(9.3)	.25
Functional assessment test			
WMFT[a]	38.8(25.6)	39.7(22.2)	.91
FMA-UE[b]	29.0(14.2)	36.6(18.6)	.35

Grip power (Kg)	11.7(11.6)	13.3(12.7)	.75
BDI[c]	24.2(11.2)	17.88(14.7)	.28
Shoulder ROM[d]			
Flexion	82.0(59.07)	74.5(45.3)	.91
Extension	40.8(19.6)	28.7(21.0)	.11
Internal rotation	50.8(31.2)	50.43(24.5)	.51
External rotation	23.4(28.1)	16.84(17.69)	.97

[a]Wolf Motor Function Test; [b]Fugl-Meyer Assessment for upper extremity;
[c]Beck Depression Inventory; [d]Range of Motion;
[e]*P* value were calculated with Mann-Whitney U test.

To evaluate exercise compliance at home, in control group, telephone survey was the only way to figure out the home exercise activities of participants. So, we called them and asked how much time they exercised at home and encouraged exercise. And we found they did home exercise for about 13.6 (±4.85) minutes per day. However, the numbers obtained for the control group might not be accurate due to the limitations of a verbal survey. In contrast, in the HBR group, the home exercise results of all the participants were provided by the smartphone application. So, we encouraged participants to do home exercise based on the data.
As a result, Figure 5 shows the results of HBR group. In average, participants in HBR group did the bilateral flexion exercise 7.27 (±10.1) min/day, wall push exercise 3.76(±9.01) min/day, active scapula exercise 4.82(±9.62) min/day, and towel slide 6.70(±11.87) min/day. In total, an average of 22.57 (±37.69) min/day of home exercise was done.

Figure 5. Total exercise time of each home exercise for 12 weeks in HBR group.

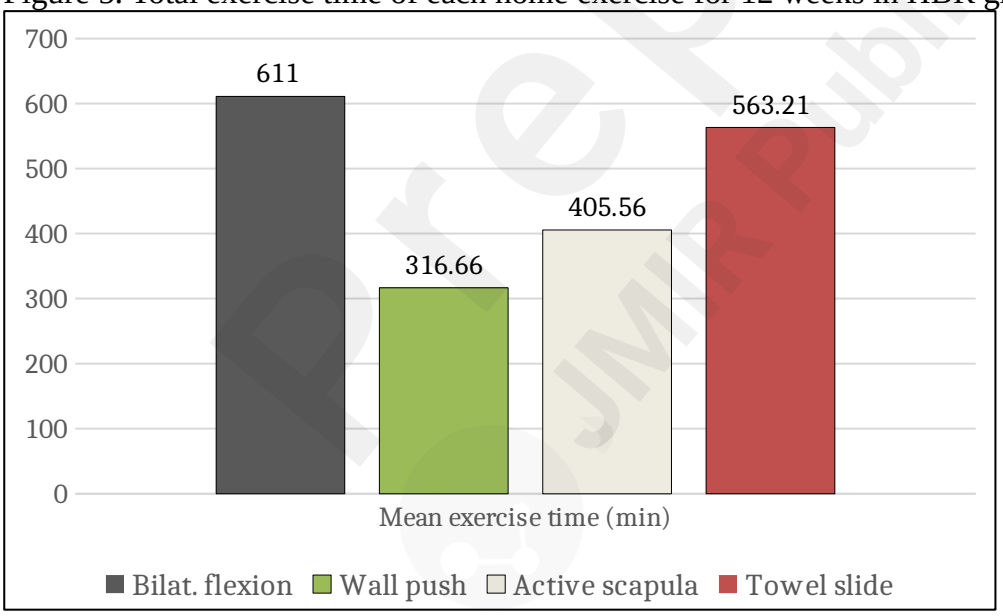


Table 3 presents the clinical results at the baseline, mid-term (6 weeks), and final assessment (12 weeks). In total, 23 individuals with chronic stroke completed this research (Control: 6; HBR: 17). In the HBR group, the Wolf-motor function test, Beck depression inventory, Shoulder ROM of flexion and internal rotation showed significant progression (Multimedia Appendix 4). However, FMA-UE showed no significant difference (*P*=.46). In the control group, there was no significant difference except for the ROM of internal rotation (*P*=.03). In both groups, there was no significant difference in the grip power test.

Table 3. Clinical results in control and HBR Group during experiment.

	Control group (N = 6)				HBR group (N = 17)			
Evaluation time (weeks)	0 week, Mean (SD)	6 week, Mean (SD)	12week ,Mean (SD)	*P* value[e]	0week, Mean (SD)	6week, Mean (SD)	12week , Mean (SD)	*P* value[e]
Functional assessment test								
WMFT[a]	38.8 (25.6)	40.3 (25.7)	42.2 (22.8)	.69	39.7 (22.7)	40.5 (23.6)	42.5 (23.7)	.02
FMA-UE[b]	29.0 (14.2)	30.0 (14.2)	28.5 (16.1	.72	36.6 (18.7)	37.5 (18.4)	38.5 (18.3)	.46
Grip power (Kg)	11.7 (11.6)	11.0 (10.4)	10.9 (10.3)	.47	13.3 (12.7)	12.9 (12.0)	14.8 (12.1)	.34
BDI[c]	24.2 (11.2)	10.0 (8.6)	8.8 (7.2)	.11	17.9 (14.7)	10.0 (8.8)	8.0 (9.9)	.06
Shoulder ROM[d]								
Flexion	82.0 (59.1)	90.6 (65.3)	87.5 (61.0)	.21	74.5 (45.3)	93.9 (52.3)	94.7 (48.9)	<.001
Extension	40.8 (19.6)	29.5 (18.9)	32.8 (20.4)	.38	28.7 (21.0)	31.5 (16.2)	34.7 (19.9)	.16
Internal rotation	50.8 (31.2)	48.5 (28.6)	57.3 (32.0)	.03	50.4 (24.5)	70.3 (28.3)	63.5 (26.9)	.001
External rotation	23.4 (28.1)	23.6 (30.0)	26.6 (27.7)	.76	16.8 (17.7)	15.4 (18.1)	16.9 (18.4)	.20

[a] Wolf Motor Function Test; [b] Fugl-Meyer Assessment for upper extremity; [c] Beck's Depression Inventory; [d] Range of Motion
[e] Overall *P* value were calculated with Friedman test.

We tried to find out the change of clinical results after the completion of home rehabilitation program which was a course of 12 weeks. So, we compared the clinical outcomes of final assessment (12 weeks) with that of 6 weeks after removing HBR system (18 weeks). There was no significant difference (Multimedia Appendix 5).

Discussion

Principal Results

In this study, we performed comprehensive study based on ML algorithm and wearable device. So, we developed the HBR system using a commercial smartwatch with the ML model, and evaluated the effectiveness of the HBR system via a clinical trial. The machine learning model based on CNN algorithm showed good to excellent accuracy results ranging from 86.5% to 100% and the clinical trial showed a significant increase in terms of ROM and WMFT function score.

While developing an HBR system using commercial smartwatch, determining the type of sensors that provides maximal accuracy was an important issue. According to the previous researches which used IMU sensor for activity recognition, the accelerometer was the most accurate sensor used for activity recognition [29, 30, 33-36]. Based on the results of the cross-validation test in our study, accelerometer signal combined with gyroscope showed the most accurate result. It is consistent with the result in Hyunh et al [37], which tried to detect fall-down by wearing IMU sensor at the chest. It reported that adding a gyroscope can reduce the false-positive and increase specificity from 82.72% to 96.2%. However, in our study, the difference in the accuracy of the results obtained when using an

accelerometer and an accelerometer combined with a gyroscope was relatively small (1.1~1.8%) and in the case of active scapular exercises, the accuracy of the gyroscope was even higher than that of others. Thus, we believe that the choice of the most accurate sensor may depend on the type of exercises and the location of a sensor. Our research, which detected repetitive and slow home exercise tasks by a smartwatch, supports that the use of accelerometer combined with gyroscope was the most accurate signal. However, considering the improvement of accuracy by adding gyroscope was relatively small with the doubled computation and battery loading needed for adding gyroscope, we believe accelerometer only signal could be an alternative choice.

Since the learning data is a decisive factor in optimizing the ML algorithm, we compared the accuracy of the ML model built with personal data versus that with total data. The ML model based on total data was built with data from all participants and the ML model based on personal data was implemented by using the participants' own data. Although the amount of total data was larger than that of the personal data, each exercise motion in the total data represents a mix of different motions of all participants. Therefore, through this comparison, attempted to determine whether the quantity or the quality of data is important. According to the results, the quality was more important. The ML model built only with personal data (99.9%), which represents the quality of data, was more accurate than the ML model with total data (95.4%), which represents the quantity of data. This means that, especially for chronic stroke patients who had various disabilities and individual motion characteristics, data personalization is more important than the total amount of data. We think the different exercise motion of other patients contaminated the data consistency and had a bad influence on the ML model [38].

With regards to the clinical trial, the HBR group showed a significant functional recovery (mean difference = 2.8, P=.02) by WMFT. But, FMA-UE (mean difference = 1.9 point, P=.46) did not show significant results. We think it is related to the different traits of both functional assessment methods. FMA-UE (total 66 scores) is an assessment tool for finding motor impairment, which is composed of reflex activity(6); flexor synergy(12), extensor synergy(6); combining synergy(6); movement out of synergy(6); wrist (10); hand(14); coordination/speed(6) on an ordinal scale of 0(none), 1(partial), 2(complete). In contrast, WMFT (total 75 scores) is a test for assessing functional performance providing insight into joint-specific and integrative limb movements grading from 0 to 5 with 15 function based task [39]. According to the study performed by SL Wolf et al [40], WMFT was more sensitive for assessing the functional improvement in less affected stroke patients than FMA-UE. So the different results of two functional test implies that the home rehabilitation exercise for 12 weeks had beneficial effect in functional recovery, but it was not enough to change synergic movement or hand and wrist function.

In terms of shoulder range of motion, we found a significant increase in shoulder flexion and internal rotation ROM in the HBR group by the Friedman test (P <.01). According to the post-hoc analysis of the Wilcoxon-signed rank test with the Bonferroni correction, shoulder joint ROM with flexion (P =.004) and internal rotation (P =.001) showed a significant increase in the first 6 weeks of home exercise. However, there was no change in external rotation and extension ROM. Regarding the reasons for ROM increase, we think it is associated with the exercise protocol of our study. Among the four kinds of home exercises in our study protocol, bilateral flexion, wall push, and towel slide exercise required wide movement of shoulder flexion and internal rotation. The exercise time records from our HBR system support it since patients did the shoulder bilateral flexion exercise longest time than other exercises. The shoulder extension ROM exercise was not included in our home exercise protocol. Although the shoulder external rotation is required to do the active scapular exercise, the external rotation ROM was not increased. This result would be associated with the fact that chronic stroke patients usually have internally rotated joint contractures which is caused by the impaired motor synergy [41, 42]. We consider the reason why hand grip test did not show significant change

also related with the fact that our home exercise protocol required wide exercise of shoulder joint, but less motion of wrist and hand joint.

Not only the clinical improvement but also a decrease of drop-out rate was another benefit of the HBR system which might encourage the application of wearable system for HBR. We found that the HBR group showed less drop-out rate than the control group at 12 weeks (5/22, 22% vs. 4/10, 40%) and 18 weeks (10/22, 45% vs. 10/10, 100%). After this study was over, we interviewed two participants who dropped out to ask why they decided not to continue the study. They said that they became less interested in conventional home rehabilitation program because weekly phone calls did not help showing any visible improvement but bothered them. We think the HBR system had a good influenced on the motivation of home exercise and relationship with physical therapist. According to the self-determination theory which refers to each person's ability to make choices and manage their own life [24], people need to experience a sense of belonging and attachment with others, which is called ‘connection or relatedness’. In addition, people need to feel in control of their own behaviors and goals, which is called ‘autonomy’. Our HBR system would assist patients to record an exercise time (autonomy) and to communicate with a clinician (connection or relatedness).

Regarding the depression index, previous randomized controlled trials (RCT) reported home rehabilitation can reduce the incidence of depression [43, 44]. Yet, Beck depression inventory in our study did not show a statistically significant difference. It only showed a trend of positive effects (P=.064). It might be significant with a greater number of participants or a longer period because our protocol was relatively shorter than the literature [43, 44].

Lastly, there was no significant difference in HBR group between 12 weeks and 18 weeks (6 weeks after the final assessment without HBR system). However, we believe that the HBR system is more effective when used consistently in home care because most of clinical outcomes at 18 weeks showed a decreasing trend compared to 12 weeks.

Comparison with Prior Work

Previously, Wide has emphasized that enabling self-directed practice is critical for stroke rehabilitation [45]. Regarding the strategy of self-directed practice, it has been shown that verbal encouragement does not have an impact on increasing rehabilitation activity after stroke [46]. Therefore, various methods of self-management training modality for upper limb rehabilitation have been suggested, including robot-assisted therapy. For example, Markopoulos et al [47] and Holden et al [48] developed a watch-like device. They used a visual feedback system as a self-management tool, but they had no remote supervision with the therapist. The mobile Health (mHealth) system proposed by Dobkin [17] uses a similar strategy as that of ours which is called the Rehabilitation Internet-of-Things (RIoT) devices. However, we applied the ML model for home exercise detection and used a commercial smartwatch to simplify the user device interface, which has been regarded by previous researchers as the most important factor for use in clinical practice [17, 49].
When we compare our results with robot-assisted therapy, Albert C. Lo et al [50] reported that robot-assisted therapy showed no significant difference at 12 weeks but only showed improvement over 36 weeks compared with typical care. It costed 15,562 $ for 36 weeks program [50]. In contrast, our HBR system increased flexion ROM at 6 weeks and showed improvement of the WMFT score at 12 weeks. Considering the treatment cost of robot-assisted therapy, our HBR system strategy could be a better treatment modality with similar clinical improvement.

Limitations

There are several limitations to this study. First, the total number of patients who completed our research was relatively small to derive statistically strong evidence, particularly in the control group. Further work with larger sample size would be helpful for more confirmative conclusion. Second, there was a discrepancy in the number of subjects in the control and HBR group. Only six participants of the control group data were enrolled in a data analysis process. However, while carrying out our research, losing subjects was inevitable in the control group because they were tired of receiving calls of management without any benefit, indicating the limitation of a conventional method. Third, there could be a loss of time measurement in the HBR group since some patients appealed that they sometimes did home exercise without the smartwatch due to the inconvenience of wearing smartwatch. Therefore, we think the exercise time stored in the database was underestimated than the real value of home exercise time. Fourth, the actual accuracy of exercise detection at home was not assessed. Although some researchers have attempted to address the privacy preservation of sensitive personal data based on deep learning algorithm [51], we did not implement it and only calculated the accuracy based on a five-fold cross-validation test. Therefore, the actual accuracy, which is the correct prediction rate of exercise detection at home, was not able to be assessed because all the patients wanted to protect their privacy. Fifth, there could have been a selection bias that arose from the local health centers being positioned at different locations. Although we cannot quantify the difference, we think the bias was not significant enough because both centers are closely located (50 Km away) and the socioeconomic status are similar.

Conclusions

This research found that the homecare system using the commercial smartwatch and ML model can facilitate the participation of home training and improve the functional score of WMFT and shoulder ROM of flexion and internal rotation for the treatment of patients with chronic stroke. We recommend our HBR system strategy as an innovative and cost-effective homecare treatment modality.

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Conflicts of Interest

None declared.

Abbreviations

CNN: Convolution Neural Network
FMA-UE: Fugl-meyer Assessment of Upper Extremity
HBR: Home-Based Rehabilitation
IMU: Inertial Measurement Unit
ML: Machine Learning
mHealth: Mobile Health
ROM: Range of Motion

WMFT: Wolf Motor Function Test

Multimedia Appendix Captions

Multimedia Appendix 1: Home-Based Rehabilitation (HBR) system application video

Multimedia Appendix 2: Application view of home exercise results for user and supervisor

Multimedia Appendix 3: Accuracy calculation by cross-validation test

Multimedia Appendix 4: Video representing the clinical results in HBR system

Multimedia Appendix 5: Comparison between 12 weeks and 18 weeks in HBR Group.

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