TUGAS REVIEW PAPER PENYAKIT STROKE

Disusun Untuk Memenuhi Tugas Mata Kuliah Sistem Medis Berbasis Komputer

Oleh :

Benediktus Kevin Mulia	205150309111006
Hafid Ilmanu Romadhoni	205150309111001
Imam Pratama Setiady	205150309111002
Irfan Harlim	205150309111005
Muhammad Riza Irfan	205150309111004

Dosen Pengampu:

Rizal Maulana, S.T., M.T., M.Sc.

PROGRAM STUDI TEKNIK KOMPUTER

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1.1 Latar Belakang

Stroke adalah suatu kondisi yang terjadi ketika pasokan darah ke suatu bagian otak tiba-tiba terganggu, karena sebagian sel-sel otak mengalami kematian akibat gangguan aliran darah karena sumbatan atau pecahnya pembuluh darah otak. Dalam jaringan otak, kurangnya aliran darah menyebabkan serangkaian reaksi biokimia yang dapat merusakan atau mematikan sel-sel saraf otak. Kematian jaringan otak dapat menyebabkan hilangnya fungsi yang dikendalikan oleh jaringan itu. Aliran darah yang berhenti membuat suplai oksigen dan zat makanan ke otak berhenti, sehingga sebagian otak tidak bisa berfungsi sebagaimana mestinya (Nabyl, 2012).

Stroke merupakan penyebab kematian ketiga dan kecacatan kedua di dunia setelah penyakit jantung koroner dan kanker baik di negara maju maupun negara berkembang. Satu dari 10 kematian disebabkan oleh stroke (Ennen, 2004; Marsh & Keyrouz, 2010; American Heart Association, 2014; Stroke forum, 2015). Secara global, 15 juta orang terserang stroke setiap tahunnya, satu pertiga meninggal dan sisanya mengalami kecacatan permanen (Stroke forum, 2015). WHO (2010) mendefinisikan stroke adalah manifestasi klinis dari gangguan fungsi otak, baik lokal maupun global (menyeluruh), yang berlangsung cepat, berlangsung lebih dari 24 jam atau sampai menyebabkan kematian, tanpa penyebab lain selain gangguan vaskuler.

Penyakit stroke sebenarnya sudah tidak asing lagi bagi sebagian besar masyarakat. Hal ini diakibatkan oleh cukup tingginya insidensi (jumlah kasus baru) kasus stroke yang terjadi di masyarakat. Menurut WHO, setiap tahun 15 juta orang di seluruh dunia mengalami stroke. Sekitar lima juta menderita kelumpuhan permanen. Di kawasan Asia tenggara terdapat 4,4 juta orang mengalami stroke(WHO, 2010). Pada tahun 2020 diperkirakan 7,6 juta orang akan meninggal dikarenakan penyakit stroke ini (Misbach, 2010). Berdasarkan data yang berhasil dikumpulkan oleh Yayasan Stroke Indonesia (Yastroki), masalah stroke semakin penting dan mendesak karena kini jumlah penderita stroke di Indonesia adalah terbanyak dan menduduki urutan pertama di Asia. Jumlah kematian yang disebabkan oleh stroke menduduki urutan kedua pada usia diatas 60 tahun dan urutan kelima pada usia 15-59 tahun (Yastroki, 2012). Berdasarkan Riset Kesehatan Dasar (Riskesdas) Nasional tahun 2013, prevalensi stroke di Indonesia berdasarkan diagnosis tenaga kesehatan sebesar tujuh per mil dan yang terdiagnosis oleh tenaga kesehatan (nakes) atau gejala sebesar 12,1 per mil. Jadi, sebanyak 57,9 persen penyakit stroke telah terdiagnosis oleh nakes.

Yang melatarbelakangi pengambilan paper dengan fokus pembahasan pada penyakit stroke ini adalah stroke merupakan penyebab kematian ketiga dan kecacatan kedua sehingga akan sangat banyak diperlukan banyak solusi untuk dapat membantu dalam pengembangan alat yang dapat membantu untuk menurunkan angka kematian dan kecacatan. Hal pertama yang dapat dilakukan sebelum terjadinya kejadian tersebut dapat dilakukan deteksi dini serangan stroke sehingga dapat menyelamatkan nyawa. Identifikasi stroke dan deteksi keparahan stroke dapat mempengaruhi angka kematian, rehabilitasi pada pasien yang telah terkena stroke, biaya pengobatan, dan kualitas hidup pasca stroke dengan pengembangan alat nantinya dengan portabel, biaya dapat dijangkau oleh masyarakat luas, dan hasil pengukuran yang dapat dipertanggung jawabkan secara medis.

Judul	Remote Monitoring of Physical Rehabilitation of Stroke Patients using IoT and Virtual Reality
Nama Jurnal	IEEE Journal on Selected Areas in Communications
Volume dan Halaman	Volume: 39, Hal 562 -573
Tahun	2020
Penulis	Ashish Khanna, Deepak Gupta, D. Jude Hemanth, Oana Geman, Octavian Postolache & Ricardo Alexandre
Reviewer	Benediktus Kevin Mulia
Tanggal	24 April 2021

Studi Kasus	Penderita pasca stroke merupakan kelompok masyarakat lain yang membutuhkan layanan rehabilitasi fisik untuk meningkatkan keterampilan motoriknya. Statistik yang dilaporkan menggarisbawahi stroke sebagai penyebab cacat fisik nomor satu di dunia. Jika tren sekuler berlanjut, diperkirakan akan ada 23 juta stroke pertama kali dan antara 7-8 juta kematian akibat stroke pada tahun 2030. Stroke biasanya dapat menyebabkan cacat fisik yang parah, seperti defisit perhatian, nyeri, kelemahan dan kelumpuhan, biasanya di satu sisi. tubuh. Kekurangan tersebut dapat mengakibatkan hilangnya kemampuan untuk melakukan aktivitas sehari-hari. Beberapa metodologi dapat dikembangkan untuk meningkatkan gaya hidup pasien stroke. Pasien perlu melakukan latihan rehabilitasi fisik untuk memperbaiki kondisi motoriknya, latihan ini direkomendasikan di klinik terapi fisik tetapi juga di rumah untuk mengurangi waktu rehabilitasi yang akan membantu pasien untuk meningkatkan kondisi psikologisnya. Selain itu, penelitian terbaru mengungkapkan bahwa rehabilitasi awal dan intensif dapat mengarah pada pemulihan kapasitas fungsi motorik. Proses rehabilitasi tradisional yang dilakukan dengan peralatan rehabilitasi fisik klasik memerlukan latihan berulang yang mungkin mengganggu dan biasa-biasa saja.
Rumusan Masalah	Permasalahan yang terjadi pada pembahasan penelitian ini adalah timbulnya kurangnya minat pasien dan berkurangnya motivasi untuk proses rehabilitasi, yang dapat berdampak serius pada kualitas rehabilitasi dan masa rehabilitasi mereka dengan biaya yang lebih tinggi untuk sistem perawatan kesehatan. Program rehabilitasi fisik harian mengharuskan pasien pergi ke rumah sakit atau pusat rehabilitasi untuk pelatihan. Ini membutuhkan banyak usaha pada pasien yang sudah menderita kesulitan mobilitas. Seringkali, beberapa pasien tidak dapat pergi ke pusat rehabilitasi karena biaya yang dikeluarkan.
Metode penelitian	

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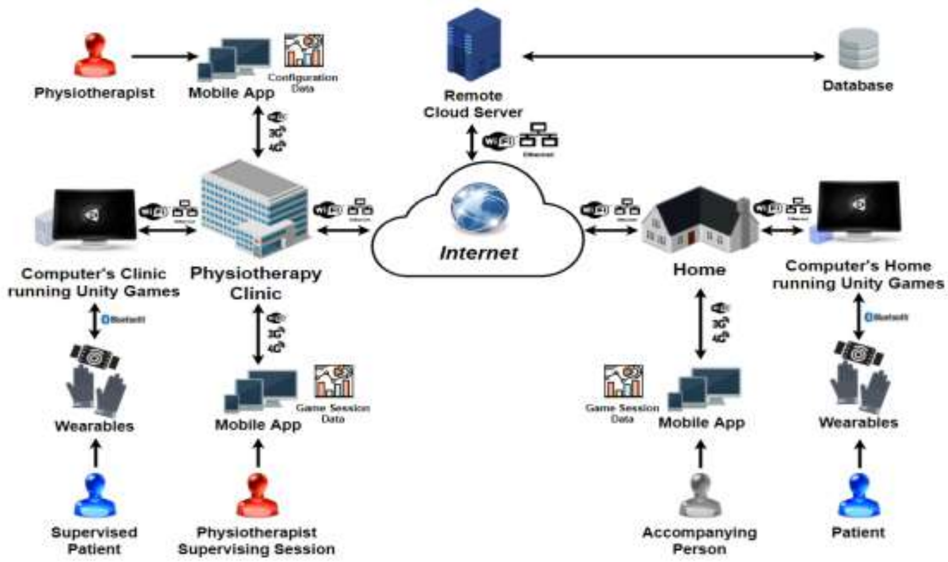

Pendekatan praktis mengenai proses rehabilitasi fisik yang dioptimalkan berdasarkan game serius VR dengan penekanan pada analisis data dari data yang diekstrak selama sesi pelatihan di mana pasien menggunakan perangkat sensor yang dapat dikenakan untuk berinteraksi dengan skenario game VR. Sistem yang diusulkan pada Gambar diekspresikan oleh komponen perangkat keras dan perangkat lunak berbiaya rendah yang menyediakan interaksi Virtual Reality (VR) selama permainan serius terapeutik. Sebagai inti dari sistem dapat disebut sebagai IoT Wearable Sensor Network (WSN) yang diekspresikan oleh seperangkat sensor pintar yang tertanam dalam sepasang sarung tangan dan ikat kepala. Game serius VR diimplementasikan menggunakan perangkat lunak Unity 3D yang juga mencakup modul dan sensor IoT. Sarung tangan pintar mewujudkan antarmuka alami yang diterapkan pada motorik dan rehabilitasi fisik pada pengguna dengan gangguan gerakan tangan dan jari.

Perangkat ikat kepala yang mencakup platform komputasi berbasis AVR Atmel yang terhubung ke IMU bertanggung jawab untuk pengukuran nilai rotasi (Sudut Euler) dan percepatan linier kepala dengan tujuan mengintegrasikan pasien ke Pengontrol Orang Pertama, memungkinkan navigasi di lingkungan VR game serius, dengan cara yang semi-imersif. Pengukuran ini juga dapat digunakan untuk mengevaluasi postur tubuh pengguna selama pelatihan menggunakan permainan serius.

Perangkat yang dapat dikenakan menggunakan komunikasi Bluetooth untuk mengirimkan data dari saluran pengukuran ke komputer klinik atau ke komputer rumah yang terhubung ke Internet. Perangkat seluler menggunakan konektivitas Internet Wi-Fi dan dapat digunakan oleh fisioterapis, pasien, atau orang yang menemani. Manajer klinik melakukan manajemen fisioterapis. Saat memainkan permainan serius, pasien berinteraksi dengan sistem dan karakteristik gerakan yang dilakukan oleh pengguna ini didaftarkan oleh sistem. Sesi pelatihan terapi fisik dilakukan di klinik fisioterapi dimana pasien berada di bawah pengawasan fisioterapis atau di lingkungan rumah tanpa pengawasan khusus, seperti yang ditunjukkan pada gambar. Di rumah pendamping dapat memberikan dukungan dan juga dapat memverifikasi melalui aplikasi mobile. hasil sesi yang dilakukan. Bagaimanapun,

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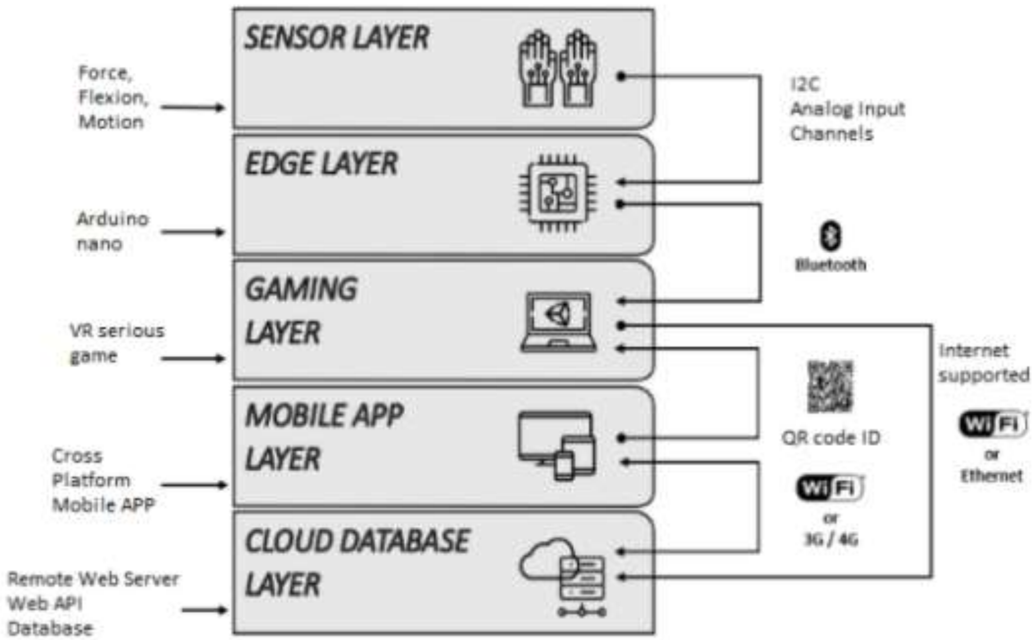
	pengguna pengalamannya sama. Setelah itu, terapis mengakses informasi ini melalui aplikasi seluler, menggunakan komputer, tablet, atau smartphone. Metrik yang dihitung gerakan pasien disajikan melalui representasi grafis. Laporan tekstual dapat dibuat oleh fisioterapis berdasarkan metrik yang dihitung yang juga menjamin umpan balik bagi pasien, meningkatkan komunikasi fisioterapis dan pasien untuk komitmen aktif dalam proses rehabilitasi.
Blok Diagram	 Berikut penjelasan blok diagram dari penelitian ini: 1. Sensor Layer Saluran pengukuran meliputi sensor, sirkuit pengkondisian dan / atau antarmuka komunikasi kabel yang terhubung ke platform komputasi (Arduino nano) yang mewujudkan sensor dan lapisan tepi arsitektur IoT Healthcare untuk rehabilitasi fisik. Seperti yang dapat diamati gaya, fleksi dan pengukuran kualitas inersia dikaitkan dengan lapisan sensor. Jadi, untuk gaya yang diterapkan jari dan fleksi jari, dua set sensor piezo-resistif dianggap sebagai bagian dari sarung tangan pintar. Dengan demikian, satu set 5 sensor piezo-resistif Flexi Force A201 untuk mengekstraksi nilai tekanan yang diberikan pada tip, serta satu set 5 FlexSensors 2.2 "piezo-resistif, untuk mendapatkan nilai fleksi jari dipertimbangkan. Nilai terukur jari fleksi dan gaya yang diterapkan jari oleh ujung jari divisualisasikan dalam skenario VR yang dikembangkan pada platform game Unity 3D. Mengingat input analog mikrokontroler kompatibel dengan tegangan, rangkaian pengkondisian untuk saluran sensor gaya dinyatakan dengan resistansi terhadap konverter tegangan yang diekspresikan oleh pembagi tegangan dan pengikut berdasarkan penguat operasional LM324. 2. Edge Layer Data yang diperoleh dari sensor diproses primer oleh Arduino nano, data yang diproses dikirim secara nirkabel ke platform game. Transmisi nirkabel didasarkan pada protokol Bluetooth yang menggunakan Modul HC-05 yang

	terhubung ke papan Arduino menggunakan port serial. Dengan modul Bluetooth, komunikasi apa pun antara Arduino dan lapisan aplikasi seluler atau lapisan game dapat dilakukan. Lapisan tepi yang mencakup Arduino dengan modul komunikasi Bluetooth didukung oleh paket baterai 3.7V 2050mAh. 3. Gaming Layer Dalam kasus kami, aplikasi yang berisi skenario VR dikembangkan di Unity Game Engine menggunakan bahasa pemrograman melalui skrip C #, untuk membuat ulang semua interaksi oleh pengguna. Aspek utama adalah interaksi fisik antara skenario dan objek saat ini. Komunikasi antara mikrokontroler Arduino dan PC tempat Unity berjalan dimediasi menggunakan port serial yang terkait dengan komunikasi Bluetooth. Kelas SerialPort adalah salah satu yang menengahi komunikasi tersebut dalam bahasa C #. Tes pertama komunikasi antara Arduino dan PC direalisasikan dengan kabel USB, dan kemudian dikonfigurasi koneksi Bluetooth, yang juga didasarkan pada komunikasi serial. Untuk perwujudan tangan virtual, beberapa tekstur objek dipertimbangkan. Sebuah rangkaian perangkat lunak yang disediakan oleh Leap Motion Company digunakan, yang menyediakan proyek Unity 3D yang memiliki beberapa contoh untuk membantu pemrogram membuat aplikasi baru.). Proyek ini tidak hanya memberikan contoh, tetapi juga memiliki objek berbeda yang mewakili tangan dan lengan dengan warna, genre dan ukuran yang berbeda, dan menyediakan beberapa skrip yang sudah diprogram dan siap digunakan. Beberapa metode telah dikembangkan untuk memungkinkan gerakan representasi dari objek virtual yang ditentukan oleh jari. Oleh karena itu, setiap pembacaan yang diperoleh dari Flex Sensor 2.2 ”akan bekerja pada 3 ruas ruas jari, memungkinkan terciptanya gerakan yang mengalir untuk membuka dan menutup setiap jari dalam pemandangan virtual. 4. Mobile App Layer Selama sesi rehabilitasi, data dikumpulkan dan disimpan sebagai bagian dari Catatan Kesehatan Elektronik Rehab Fisik. Data dapat diakses melalui aplikasi seluler, yang berfungsi untuk analisis di masa mendatang pada tingkat fisioterapis. 5. Cloud Database Layer Setelah masuk, dan setelah menerima rencana latihan aktif, adegan permainan untuk setiap rencana latihan dimuat. Setelah koneksi dibuat dengan tiga perangkat, sesi dibuat, dan pengumpulan (melalui proses parallel independen dari utas pembacaan) dari data yang diterima dari tiga perangkat selama pelaksanaan latihan dan pencatatan dalam database dimulai. Proses akuisisi dimulai setelah memastikan bahwa sesi saat ini dibuat untuk rencana yang dimuat. Untuk setiap perangkat, satu set bacaan dibuat, untuk tujuan kami ditentukan dalam 200 baris data, yang setiap kali set ini diisi dikirim ke database. Di akhir setiap sesi, skor untuk setiap permainan juga dikirim ke database bersama dengan parameter gerakan tangan yang sesuai.
Klasifikasi	1. Input

Input fitur pada penelitian ini berupa dua relawan sehat (satu laki-laki, 26 tahun, tinggi 179 cm, dan satu perempuan, 24 tahun, tinggi 170cm) melakukan 5 sesi permainan 3 menit (180 detik) di tantangan Cans Down, menggunakan kedua anggota tubuh untuk mengambil benda virtual (bola tenis muncul di piala emas) untuk menjatuhkan tumpukan 15 kaleng di depan pemain dalam skenario permainan.

2. Proses

Sistem yang diterapkan yang mendukung game serius VR dicirikan oleh berbagai platform komputasi yang terwujud pada lapisan tepi, lapisan aplikasi seluler lapisan game, dan lapisan database cloud. Lapisan komputasi tepi diekspresikan oleh Arduino nano yang didasarkan pada konsumsi daya yang rendah (konsumsi daya: 19 mA) dari mikrokontroler Atmel AVR ATmega328P.

Dalam algoritma ini, posisi baru dihitung dari posisi yang dihitung sebelumnya (persamaan 1), percepatan terukur dan kecepatan sudut, kesalahan ini terakumulasi kira-kira sebanding dengan waktu sejak posisi awal diperkenalkan.

$$Position_{x,y,z}(t_{final}) = Position_{x,y,z}(t_{start}) + Position_{x,y,z}(t) \qquad (1)$$

Integrasi ganda percepatan sisa dari waktu ke waktu untuk mendapatkan perubahan nilai posisi pada awalnya sederhana, tetapi tidak sesederhana itu. Akselerasi dapat diintegrasikan secara matematis sekali untuk perubahan nilai kecepatan dan dua kali untuk perubahan nilai posisi.

Dengan memanfaatkan nilai percepatan, rotasi di sekitar sumbu X (Roll) dan di sekitar sumbu Y (Pitch) dapat dihitung. Jadi, jika AX, AY, dan AZ adalah nilai percepatan untuk sumbu X, Y, dan Z masing-masing, sudut Roll (2) dan Pitch (3) (dalam radian) diberikan oleh:

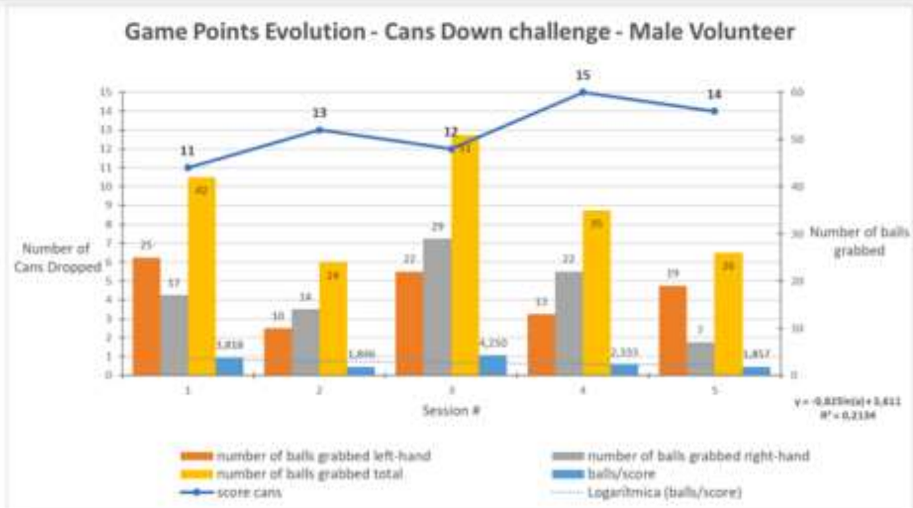
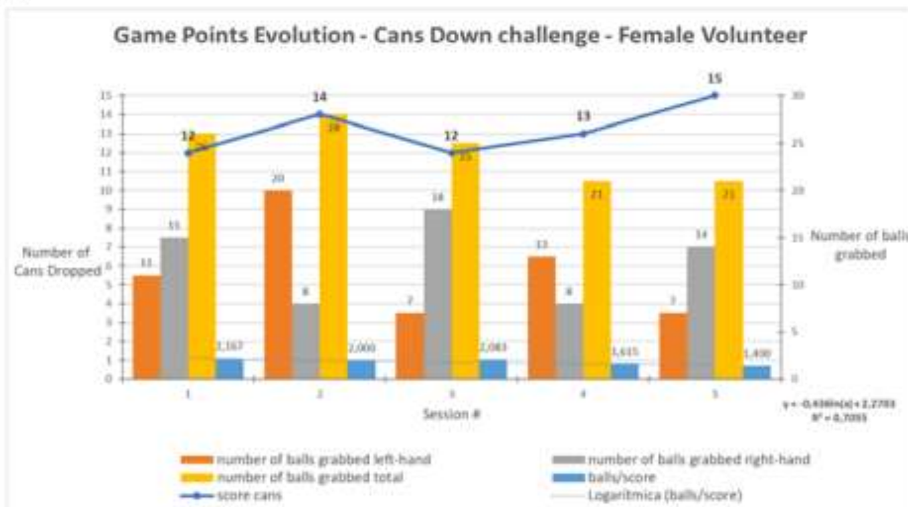
$$Roll = \tan^{-1}\left(\frac{A_Y}{A_Z}\right) \wedge Pitch = \tan^{-1}\left(\frac{-A_X}{\sqrt{((A_Y)^2 + (A_Z)^2)}}\right) \qquad (2)$$

$$Roll = \tan^{-1}\left(\frac{A_Y}{\sqrt{((A_X)^2 + (A_Z)^2)}}\right) \wedge Pitch = \tan^{-1}\left(\frac{-A_X}{A_Z}\right) \qquad (3)$$

Selama permainan, nilai fleksi jari (diekstrak dari FlexSensors 2.2 ") dan gaya ujung jari (diekstraksi dari FlexiForce) divisualisasikan pada VR yang dikembangkan dalam Unity 3D. Dengan kata lain, untuk setiap siklus clock, dua sensor dibaca pada port input analog yang sama. Perintah fungsi Arduino digitalWrite (HIGH) diatur ke 1 nilai input digital yang memberi makan rangkaian listrik sensor analog pertama, kemudian perintah digitalWrite (LOW) menetapkan nilai ini ke 0, penundaan waktu yang sangat singkat (urutan milidetik) diterapkan dan ulangi proses untuk sensor analog kedua. Prosedur ini dilakukan secara bersamaan di masing-masing port analog yang akan melakukan akuisisi data sensor gaya resistif piezo sumbu h.

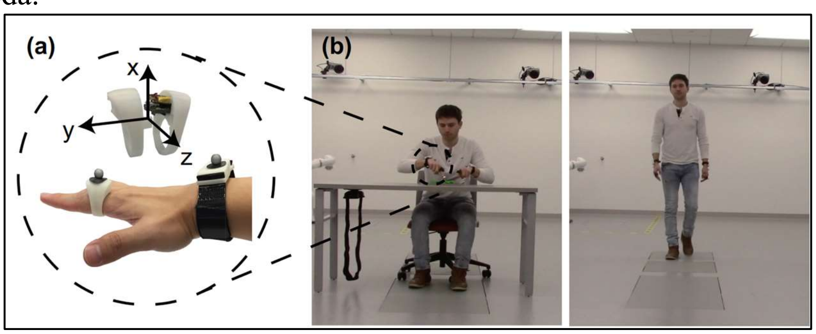
Koreksi dilakukan dengan menggunakan quaternions, untuk mendapatkan nilai sudut Euler yang andal (roll, pitch dan yaw). Filter Kalman, seperti yang disajikan, digunakan untuk melakukan kompensasi kemiringan dari pembacaan yang diperoleh dari akselerometer dan magnetometer. Untuk kegunaan seperti itu, angka empat untuk bergabung dengan pembacaan Giroskop. Dari fusi ini

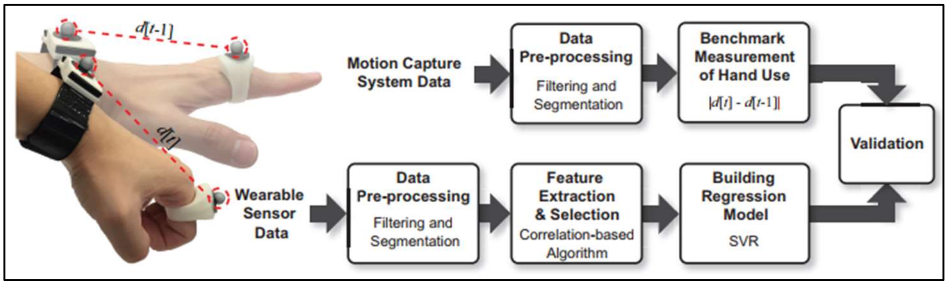
	dihasilkan algoritma AHRS untuk orientasi objek yang handal. Algoritma fusi data dapat ditemukan di perpustakaan RTIMULib-Arduino di file RTFusionRTQF.cpp. 3. Output Dengan menggunakan prototipe yang diterapkan pada penelitian ini, yang biayanya dipertimbangkan untuk adopsi yang mudah, data berikut yang terkait dengan sesi rehabilitasi diperoleh: • Sudut Euler (nilai rotasi kepala dan tungkai atas) • Akselerasi linier terkait dengan karakterisasi dinamis dan kinematik kepala dan tungkai atas. • Fleksi kelima jari (berdasarkan sensor fleksi yang tertanam di perangkat sarung tangan). • Semua nilai gaya kontak lima jari ke jari (berdasarkan sensor gaya yang tertanam di perangkat sarung tangan).
Hasil	
Akuisisi Data	Proses akuisisi dimulai setelah memastikan bahwa sesi saat ini dibuat untuk rencana yang dimuat. Untuk setiap perangkat, satu set bacaan dibuat, untuk tujuan kami ditentukan dalam 200 baris data, yang setiap kali set ini diisi dikirim ke database. Di akhir setiap sesi, skor untuk setiap permainan juga dikirim ke database bersama dengan parameter gerakan tangan yang sesuai.

Hasil Pengujian	 (a)  (b) Pada grafik yang diatas menunjukkan per sesi jumlah bola yang diambil untuk setiap anggota, jumlah total bola yang diambil, skor yang diperoleh dari drop of can, hubungan antara jumlah bola yang digunakan dan skor yang diperoleh serta regresi logaritmiknya. Kemampuan otot umumnya lebih tinggi pada relawan laki-laki dibandingkan relawan perempuan dan dalam konteks ini disajikan hasil komparatif. Jumlah bola yang diraih dapat dianggap sebagai indikator tentang kemampuan gerak tungkai atas tangan kiri dan kanan.
Kelebihan	Kelebihan pada penelitian ini adalah sudah dapat di implementasikan melalui game VR, pasien pun dapat dikontrol dari rumah karena terapis mendapatkan data percobaan dari yang dilakukan pasien nanti melalui database yang dapat dilihat melalui mobile aplikasi. Selain itu juga memiliki kelebihan yaitu menghemat ongkos untuk pasien pasca stroke jika ke rumah sakit jadi dapat mendapatkan rehabilitasi dari rumah.
Kekurangan	Pada penelitian ini memliki kekurangan di bagian pengujian, karena pengujian nya hanya dilakukan oleh dua volunteer, yaitu: 1 pria dan 1 wanita, dimana volunteer ini adalah volunteer yang sehat jadi belum diujikan kepada pasien pasca stroke.

Judul	The Use of A Finger-Worn Accelerometer for Monitoring of Hand Use in Ambulatory Settings
Nama Jurnal	IEEE - JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS
Volume dan Halaman	Vol. X, Hal 2168 - 2194
Tahun	2018
Penulis	Xin Liu, Smita Rajan, Nathan Ramasarma, Paolo Bonato, Sunghoon Ivan Lee
Reviewer	Hafid Ilmanu Romadhoni
Tanggal	24 April 2021

Studi Kasus	Stroke adalah penyebab kematian tertinggi ketiga dan menjadi penyebab utama disabilitas pada orang dewasa di Amerika Serikat. Sekitar 50% dari penderita stroke mengalami gangguan lengan atas pada fase kronis. Gangguan lengan atas setelah stroke sering mengarah ke pengurangan kemampuan untuk kegiatan sehari-hari (ADL) dan secara negatif akan mempengaruhi keseluruhan kualitas hidup mereka. Pada metode konvensional, pasien akan bertemu terapis berdasarkan evaluasi pasien dan menggunakan tes motorik yang tervalidasi medis seperti Fugl-Meyer Assesment, Active Research Arm Test atau Wolf Motor Function Test. Namun, bukti ilmiah menunjukkan bahwa peningkatan fungsional yang diketahui dan dicapai di klinik tidak selalu pengaturan alatnya diterjemahkan sama ke lingkungan kerabat pasien. Dengan kata lain, penderita stroke mungkin menunjukkan peningkatan kapasitas apa yang dapat dilakukan namun tidak memiliki perubahan yang banyak di performa yaitu apa yang sebenarnya dapat mereka lakukan. Maka dari itu, penilaian rawat jalan dari performa motorik dari lengan atas yang terdampak stroke menjadi hal yang penting dalam memperkirakan hasil yang sebenarnya dari rehabilitasi dan untuk mendukung pengendalian terapi pasien dan manajemen kondisi mandiri. Akselerometer yang dipakai di lengan telah menjadi solusi potensial yang tahan gangguan dan kontinyu dalam memonitor performa lengan atas pasien diluar pengaturan klinis untuk waktu yang lama. Sensor pada lengan akan fokus pada kuantisasi durasi dan intensitas dari penggunaan lengan dengan menghitung magnitude akselerasi. Meskipun matrik ini menmberikan kuantisasi yang simpel dan intuitif, sensor ini juga merekam pergerakan lengan utama seperti gerakan pasif lengan saat berjalan yang merupakan data kurang relevan untuk mendeteksi lengan penderita stroke pada saat ADL. Pengukuran ini seringkali menghasilkan kuantifikasi yang kurang akurat terkait performa motorik pasien. Sebagai pendekatan alternatif untuk mengatasi keterbatasan akselerometer pada lengan dan agar dapat menangkap lebih banyak informasi pada lengan

	atas pasien stroke, peneliti memperkenalkan cara untuk dapat memonitor fungsi tangan saat ADL. Berbagai alat seperti sarungtangan dan goniometer telah diperkenalkan untuk mengukur fungsi tangan. Namun alat tersebut kurang nyaman untuk dipakai, lepas pasang, dan kurang diterima pada lingkungan sosial untuk penggunaan jangka panjang. Akhir-akhir ini, Friedman mengajukan alat pada lengan yang dapat memonitor lengan dan sendi jari dengan mengukur perubahan di medan magnet yang diproduksi dari cincin magnet. Meskipun pada penerapan langsung alat tersebut layak, namun sensor tersebut mungkin akan rentan terhadap noise magnet sekitar. Pada paper ini, penulis meneliti penggunaan akselerometer yang diminiaturkan dan dipakai di jari, yang dikombinasikan dengan akselerometer yang dipasang di lengan untuk memonitor performa tangan dengan mengukur jumlah dari aktivitas tangan.
Rumusan Masalah	1. Saat ini belum adanya pengukuran kuantitatif untuk mengukur keseluruhan jumlah pergerakan tangan selama performa ADL pasien dengan sistem sensor yang sudah tervalidasi. 2. Penulis memperkenalkan suatu pengujian baru untuk mengukur keseluruhan jumlah pergereakan tangan dari sistem perekaman pergerakan menggunakan optoelectronic, yang merupakan standar baik untuk analisa pergerakan manusia. 3. Penulis melakukan validasi hasil reliabilitas dari test-retest dan responsifitas pengukuran performa dari kerja 11 motor dari ADL yang melibatkan perbedaan intensitas dari penggunaan tangan dari total 18 utuh secara neurologis kesehatan pribadi. 4. Penulis memperkenalkan suatu machine learning-based analytic pipeline yang memproses data hasil dari sensing system yang dirancang untuk memperkirakan jumlah pergerakan tangan dan memvalidasi akurasi untuk dibandingkan dengan pengujian pengukuran. 5. Penulis juga menyediakan diskusi detail terkait penerapan sistem ini nantinya jika ada di lapangan langsung, seperti kemampuannya untuk dapat beroperasi secara kontinyu meskipun berada di konfigurasi jaringan yang berbeda.  Gambar a adalah sistem sensor yang dirancang untuk jaringan tubuh yang terdiri dari sensor yang digunakan pada jari dan sensor yang digunakan pada lengan. Gambar b merupakan gambaran anggota staf riset sedang mencoba suatu gerakan seperti memotong dan berjalan dengan total ada 11 ADL yang dilakukan selama akuisisi data.

Metode Penelitian	
Blok Diagram	1. Gambar  Gambar tersebut merupakan blok diagram untuk memulai pengujian pengukuran dari total penggunaan tangan selama ADL dari motion capture system dan wearable sensor system. 2.Penjelasan per blok Jumlah keseluruhan penggunaan tangan yang komprehensif didefinisikan sebagai rata-rata perubahan jarak antara proximal phalanx dari indeks jari (dimana sensor pada jari dipasang) dengan sensor yang diletakkan pada lengan (wrist). Titik 3 dimensi dengan basis waktu dari tanda posisi sensor di jari dan lengan dinotasikan dengan ($x_w[t]$; $y_w[t]$; $z_w[t]$) dan ($x_f[t]$; $y_f[t]$; $z_f[t]$) yang difilter dengan low pass filter butterworth orde 6 dengan frekuensi cutoff di 8 Hz untuk menghilangkan frekuensi tinggi dan noise yang dihasilkan selain dari manusia. Kemudian euclidean distance d[t] dihitung diantara dua penanda sensor. Keseluruhan dari penggunaan tangan direpresentasikan m[t] dengan nilai akhir adalah rata-rata m[t] untuk setiap uji motorik dengan satuan cm/s. 1. Pada motion capture system data, data dari sensor diolah pada data pre-processing menggunakan butterworth low-pass filter orde 6 dengan frekuensi cutoff di 8 Hz untuk menghilangkan segala noise dari akselerometer berbasis waktu. Suatu sliding windows selama 9 detik dengan 50% overlap digunakan untuk segmentasi data di setiap uji motorik untuk mendukung komputasi kontinyu dari penggunaan tangan. Dampak dari panjang window pada akurasi estimasi juga dilakukan pengecekan. Setiap sliding window ditetapkan sebagai data point yang memuat: 1. 3-axis akselerometer yang didapatkan dari sensor jari: $a_f[t] =< a^x_f[t]; a^y_f[t]; a^z_f[t] >$ dan sensor pada lengan: $a_w[t] =< a^x_w[t]; a^y_w[t]; a^z_w[t] >$ 2. Pengukuran uji terkait dengan penggunaan tangan seperti nilai rara-rata dari m[t] window.

2. Setelah didapatkan sinyal dari sensor yang bebas dari noise dan telah disegmentasi, data pengukuran penggunaan tangan akan diuji dengan menghitung euclidean distance d[t] diantara dua penanda sensor. Keseluruhan dari penggunaan tangan direperesentasikan dengan penghitungan absolut dari perbedaan jarak d[t] diantara setiap pasang sampel:

$$m[t] = |d[t] - d[t - 1]|.$$

Nilai akhir yang merepresentasikan penggunaan dari tangan didapatkan dari durasi setiap uji motorik dengan menghitung rata-rata nilai dari m[t] dengan satuan cm/s dan siap untuk masuk ke bagian validasi.

3. Pada wearable sensor data, sama halnya dengan proses di motion capture system data, data dari sensor diolah pada data pre-processing menggunakan butterworth low-pass filter orde 6 dengan frekuensi cutoff di 8 Hz untuk menghilangkan segala noise dari akselerometer berbasis waktu. Suatu sliding windows selama 9 detik dengan 50% overlap digunakan untuk segmentasi data di setiap uji motorik untuk mendukung komputasi kontinyu dari penggunaan tangan. Dampak dari panjang window pada akurasi estimasi juga dilakukan pengecekan. Setiap sliding window ditetapkan sebagai data point yang memuat:

   1. 3-axis akselerometer yang didapatkan dari sensor jari:

   $$a_f[t] =< a^x_f[t]; a^y_f[t]; a^z_f[t] >$$

   dan sensor pada lengan:

   $$a_w[t] =< a^x_w[t]; a^y_w[t]; a^z_w[t] >$$

   2. Pengukuran uji terkait dengan penggunaan tangan seperti nilai rara-rata dari m[t] window.

4. Setelah data dari sensor jari difilter dan disegmentasi, maka akan dilakukan ekstraksi fitur. Fitur yang didapatkan dari sensor jari dapat berupa intensitas, kehalusan dan periodesasi dari penggunaan tangan. Lebih spesifiknya, intensitas direpresentasikan oleh fitur berikut:
   1. Rata-rata
   2. Inter-quartile range (IQR)
   3. Minimum dan Maksimum
   4. Root Mean Square dari akselerasi berbasis waktu.

   Kehalusan penggunaan tangan direkam menggunakan:
   5. Standar Deviasi
   6. Perbedaan diantara zero-phase terfilter dan nilai asli akselerometer berbasis waktu yang dihitung.

	Periodesasi dari penggunaan tangan dihitung berdasarkan: 7. Frekuensi dominan 8. Rasio dari energi pada frekuensi dominan terhadap keseluruhan energi sinyal berbasis waktu. Selain fitur yang sudah disebutkan, penulis juga menghitung: 9. Kecondongan/kemiringan sinyal 10. Kurtosis 11. Sinyal Entropi berbasis waktu. Fitur-fitur tersebut diturunkan dari: 1. Magnitude sinyal dari akselerasi berbasis waktu yang dihasilkan dari sensor di jari dan lengan, 2. Perbedaan dari magnitude kedua akselerasi seperti $a_d[t]=\|a_f[t]\|-\|a_w[t]\|$ 3. Setiap sumbu dari akselerasi berbasis waktu dari sensor jari-lengan. Perlu diketahui bahwa fitur tersebut diektraksi dari setiap sumbu sensor jari, bukan dari sensor lengan. Hal ini berawal dari fakta bahwa pergerakan jari konvensional selama pergerakan kasar maupun halus dari tangan timbul dari ruang yang terbatas, dimana lengan lebih sedikit terbatas. Sebagai contoh, pergerakan jari selama penggunaan tangan (menggenggam atau melepas) biasanya dihasilkan dari akselerasi dari sumbu x sensor, dimana pergerakan kasar lengan (seperti gerakan ayun pasif pada lengan saat berjalan) dihasilkan dari sumbu y mengikuti gaya sentripetal dari gerakan ayun pada lengan. Gerakan lengan, dengan kata lain, dapat secara relatif bebas pada setiap sumbunya, dan dengan demikian mengekstraksi fitur dalam sumbu individu sensor jari dapat menyesuaikan model regresi untuk fungsi motorik tertentu yang dipertimbangkan dalam percobaan ini. Secara singkat, terdapat total 271 fitur yang berpotensi relevan dengan jumlah penggunaan tangan telah diekstraksi. 5. Setelah fitur diekstrak, maka fitur tersebut perlu untuk diseleksi (feature selection). Penulis menggunakan algoritma Correlation based Feature Selection (CFS) untuk mengidentifikasi data fitur yang sekiranya relevan dengan jumlah penggunaan tangan. CFS berfokus pada penemuan bagian dari fitur yang relevan berdasarkan evaluasi dari fitur individu yang dapat diprediksi dan derajat dari redundansi dibandingkan dengan yang lain. Pencarian best-first digunakan untuk membentuk ruang pencarian fitur. 6. Setelah fitur diseleksi dengan CFS, fitur akan dibuat model perkiraan regresinya menggunakan Support Vector Regression (SVR). SVR digunakan untuk melatih suatu model data yang memperkirakan pengukuran uji dari penggunaan tangan berdasarkan fitur yang telah diseleksi. SVR adalah algoritma yang dapat dimonitor, nonparametric

	learning algorithm yang mampu menyediakan penghitungan perkiraan yang efisien dari variabel target, yang mana lebih cocok dengan linkungan komputasi dengan resource terbatas seperti wearable device. Penulis juga menggunakan Radial Basis Function (RBF) sebagai kernel fungsi untuk mengubah ruang fitur Performa dari model dievaluasi menggunakan Normalized Root Mean Square Error (NRMSE): $\text{NRMSE} = \frac{\sqrt{\frac{1}{N}\sum_{n=1}^{N}(\hat{\alpha}_n - \alpha_n)^2}}{\max([\alpha_1, \cdots, \alpha_N]) - \min([\alpha_1, \cdots, \alpha_N])},$
Klasifikasi	1.Input Input dari sistem adalah sensor akselerometer yang diletakkan pada dua titik ditangan. Titik pertama adalah di bagian lengan (wrist) dan yang kedua adalah di bagian jari (finger). Pada motion data capture system, data dari sensor akan dilakukan filtering terlebih dahulu menggunakan butterworth low-pass filter orde 8 dengan frekuensi cutoff di 8 Hz untuk menghilangkan noise. Suatu sliding windows selama 9 detik dengan 50% overlap digunakan untuk segmentasi data di setiap uji motorik untuk mendukung komputasi kontinyu dari penggunaan tangan. Setelah filtering dan segmentasi, data akan dibenchmark menggunakan euclidean distance dari jarak antar pasangan titik uji. Pada sensor wearable, sinyal dari sensor akan difilter dan disegmentasi seperti pada motion data capture system dan selanjutnya akan dilakukan ekstraksi fitur. Fitur yang didapatkan dari sensor jari dapat berupa intensitas, kehalusan dan periodesasi dari penggunaan tangan. Lebih spesifiknya, intensitas direpresentasikan oleh fitur berikut: 1. Rata-rata 2. Inter-quartile range (IQR) 3. Minimum dan Maksimum 4. Root Mean Square dari akselerasi berbasis waktu. Kehalusan penggunaan tangan direkam menggunakan: 5. Standar Deviasi 6. Perbedaan diantara zero-phase terfilter dan nilai asli akselerometer berbasis waktu yang dihitung. Periodesasi dari penggunaan tangan dihitung berdasarkan: 7. Frekuensi dominan 8. Rasio dari energi pada frekuensi dominan terhadap keseluruhan energi sinyal berbasis waktu. Selain fitur yang sudah disebutkan, penulis juga menghitung: 9. Kecondongan/kemiringan sinyal 10. Kurtosis 11. Sinyal Entropi berbasis waktu.

Fitur-fitur tersebut diturunkan dari:

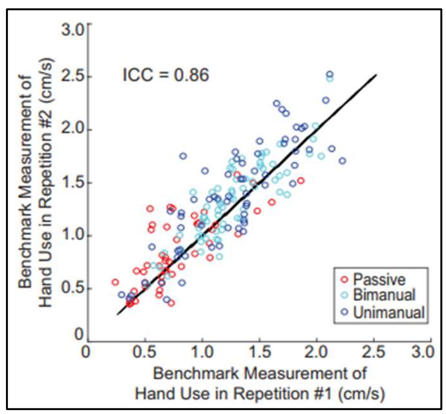
1. Magnitude sinyal dari akselerasi berbasis waktu yang dihasilkan dari sensor di jari dan lengan,
2. Perbedaan dari magnitude kedua akselerasi seperti ad[t]=|af[t]|- |aw[t]|

Task	Description	Type
1	Walking	Passive
2	Sit-to-stand	Passive
3	Stand-to-sit	Passive
4	Buttoning a shirt	Bimanual
5	Typing on a keyboard	Bimanual
6	Folding a towel	Bimanual
7	Tying shoelaces	Bimanual
8	Cutting a putty with a fork and a knife	Unimanual
9	Opening a screw-top jar	Unimanual
10	Taking the cap off of a bottle and drinking	Unimanual
11	Flipping pages of a magazine	Unimanual

3. Setiap sumbu dari akselerasi berbasis waktu dari sensor jari-lengan. Tabel di atas adalah daftar uji motorik dengan level pergerakan bervariasi.

2.Proses

Metode SVR digunakan untuk menetukan rata-rata penggunaan tangan. Berikut ini merupakan plot titik dari rata-rata penggunaan tangan dominan untuk melakukan fungsi motorik dengan 2 kali pengulangan (test-retest reliability.

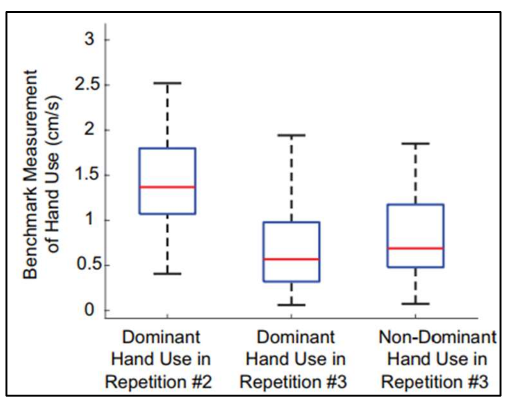


Garis hitam (y=x) di atas menandakan jumlah yang sama dari penggunaan tangan dengan nilai ICC=0,86.

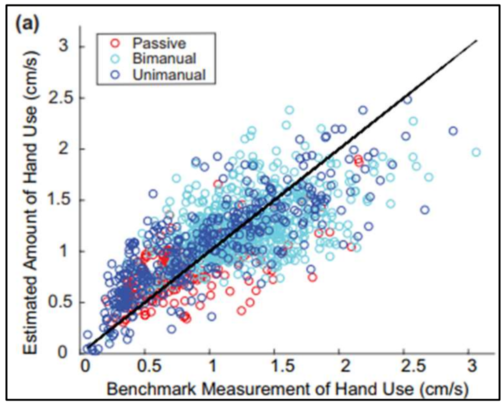
3. Output

Output dari sistem ini adalah jumlah pergerakan tangan dalam satuan cm/s dengan 3 jenis gerakan yaitu pasif, bimanual, dan unimanual. Dengan menggunakan NRMSE yang dihasilkan adalah 0,11 dengan standarnya adalah 0,024 dan koefisien Pearson yang bernilai 0,78 dari standar deviasi adalah 0,10.

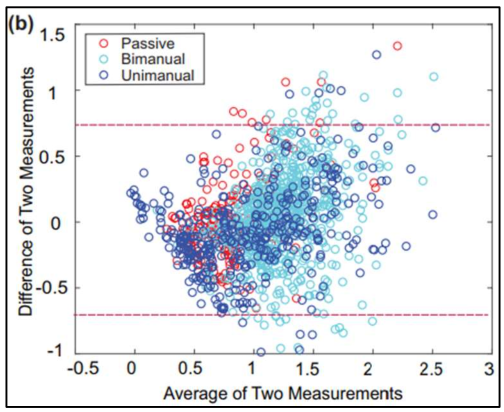
<table>
<tr><td></td><td>Empat konfigurasi jaringan sensor berbeda dari sistem yang diusulkan yang memungkinkan pengoperasian sistem berdasarkan trade-off antara jumlah kemungkinan informasi yang dapat diekstraksi (atau akurasi estimasi) dan throughput data (atau konsumsi daya). Dapat dilihat pada tabel dibawah:

<table>
<tr><th>Konfigurasi</th><th>Deskripsi</th><th>Sensor</th></tr>
<tr><td>#1</td><td>Data deret waktu akselerometer dari node sensor dikirimkan ke gateware seluler secara real-time</td><td>Jari dan lengan</td></tr>
<tr><td>#2</td><td>Data deret waktu akselerometer diproses untuk mengekstrak fitur pada setiap node sensor, dan fitur data yang relevan dikirimkan ke gateware seluler di akhir setiap sliding windows</td><td>Jari dan lengan</td></tr>
<tr><td>#3</td><td>Fitur data dari sensor yang dikenakan jari dikirimkan ke gateware seluler secara real-time</td><td>Jari saja</td></tr>
<tr><td>#4</td><td>Fitur data dari sensor yang dikenakan di pergelangan tangan dikirimkan ke gateware seluler secara real-time</td><td>Lengan saja</td></tr>
</table></td></tr>
<tr><td>Hasil</td><td></td></tr>
<tr><td>Akuisisi Data</td><td>Akuisisi data dilakukan secara langsung yaitu mengambil nilai dari sensor akselerometer dari titik lengan dan titik jari yang kemudian difilter menggunakan butterworth low-pass filter orde 8 dengan 8 Hz frekuensi cutoff.</td></tr>
<tr><td>Hasil Pengujian</td><td>

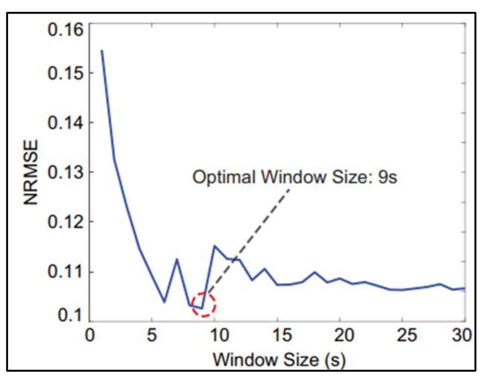
Gambar diatas merupakan hasil dari tingkat responsifitas ketika subjek diminta untuk menggunakan tangan yang tidak dominan untuk melakukan uji motorik unimanual. Grafik tersebut menunjukkan jumlah dari penggunaan tangan dominan selama pengulangan #2 dan jumlah penggunaan tangan dominan/tidak dominan selama pengulangan #3.</td></tr>
</table>



Gambar diatas merupakan plot antara perkiraan total penggunaan tangan dengan satuan cm/s terhadap pengujian pengukuran dari pengggunaan tangan dengan satuan cm/s dengan NRMSE sebesar 0.11 dan koefisien Pearson 0,78.



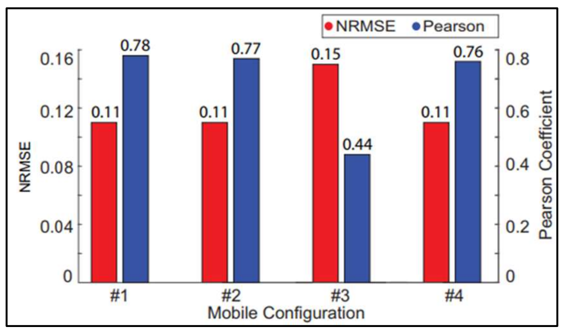
Gambar tersebut merupakan plot korespondensi Bland-Altman dengan bias -8×10^{-3} dan limit agreement sebesar 0,67.



Grafik diatas merupakan hasil dari pencarian ukuran window yang optimal. Plot tersebut menunjukkan bahwa 9s merupakan ukuran window yang memiliki korespondensi dengan akurasi tertinggi dalam hal prakira dengan ketentuan NRMSE.

Feature	Description	Sensor(s)
# 1	Difference in IQR of $\lvert\boldsymbol{a}_w[t]\rvert$ and $\lvert\boldsymbol{a}_f[t]\rvert$	Wrist and Finger
# 2	Difference in Std. Dev. of $\lvert\boldsymbol{a}_w[t]\rvert$ and $\lvert\boldsymbol{a}_f[t]\rvert$	Wrist and Finger
# 3	Dominant frequency of difference between estimated velocity magnitudes of the two sensors	Wrist and Finger
# 4	Ratio of energy associated with high frequency movement to the signal envelope energy	Finger
# 5	Ratio of energy associated with high frequency movement to the entire signal energy	Finger
# 6	IQR of acceleration in the *x*-axis of the finger sensor $(a_f^x[t])$	Finger
# 7	IQR of acceleration in the *y*-axis of the finger sensor $(a_f^y[t])$	Finger
# 8	Ratio of energy associated with high frequency movement to the entire signal energy	Wrist

Tabel tersebut merupakan daftar 8 data fitur yang paling relevan untuk memperkirakan jumlah penggunaan dari tangan. Urutan dari tabel diatas tidak menunjukkan urutan dari tingkat relevansi.



Grafik diatas menunjukkan perkiraan performansi dari algoritma yang dirancang dengan perbedaaan konfigurasi seluler. Konfigurasi #1, #2 dan #4 memberikan perkiraan akurasi yang dapat dikomparasi dimana konfigurasi #3 (sensor lengan saja) menunjukkan performa inferior yang signifikan.

Kelebihan

1. Dari hasil paper diatas menunjukkan bahwa perekaman data menggunakan data dari akselerometer yang ditempatkan pada jari dan lengan dapat digunakan untuk memperkirakan jumlah penggunaan tangan selama ADL dengan rataa-rata error 0,11 dengan ketentuan NRMSE dan dapat dilakukan secara kontinyu.
2. Pada paper ini juga memperkenalkan dan memvalidasi suatu pengujian baru untuk mengukur jumlah penggunaan tangan berdasarkan data yang didapatkan dari optoelectronic motion capture system.
3. Implementasi dan validasi pengukuran ini dapat berfungsi sebagai kebenaran dasar yang kuat untuk studi masa depan yang bertujuan untuk mengukur jumlah penggunaan tangan menggunakan sensor on dan / atau off-body.

	4. Studi yang diusulkan penulis dapat memvalidasi penggunaan sensor yang dipasang di jari untuk memperkirakan jumlah penggunaan tangan berdasarkan serangkaian fungsi motorik yang terkait dengan ADL. 5. Sistem yang diusulkan penulis dapat menyediakan penghitungan aktivitas-independen dari jumlah penggunaan tangan (yaitu, tidak memerlukan klasifikasi aktivitas yang dilakukan). Selain itu, penggunaan algoritma machine learning (SVR dengan kernel RBF) yang mampu menghasilkan estimasi dengan cara yang efisien secara komputasi (dengan sedikitnya 8 fitur) membuat sistem ini cocok untuk pemantauan berkelanjutan di lingkungan dengan sumber daya terbatas, misalnya di unit komputasi dari sensor wearable.
Kekurangan	1. Eksperimen pada jurnal ini melibatkan jumlah subjek yang relatif kecil, yaitu sebanyak 18 orang untuk melakukan 11 set fungsi motorik. 2. Hasil yang disajikan dalam jurnal ini mungkin tidak dapat digeneralisasikan untuk populasi sehat atau stroke secara umum. 3. Metode yang diusulkan untuk memperkirakan jumlah penggunaan tangan ini tidak dapat memberikan informasi mengenai jenis gerakan lengan atas (misalnya, gerakan pasif vs. unimanual vs. bimanual vs. stabilisasi). 4. Teknologi yang diusulkan penulis tidak dapat merekam penggunaan tangan dalam menstabilkan sebuah objek (misalnya, memegang cangkir atau menstabilkan sepotong steak dengan garpu) karena hanya berfokus pada perkiraan jumlah gerakan tangan.

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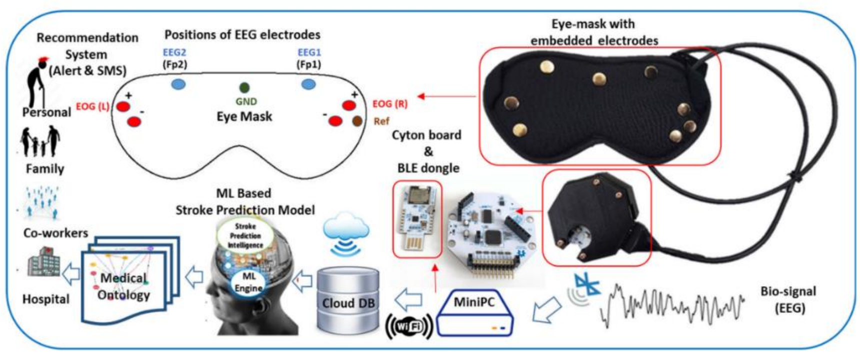
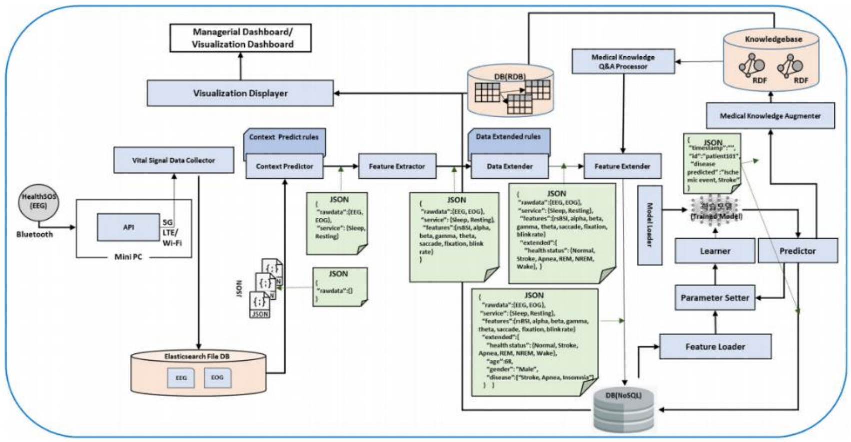
Reviewer	Imam Pratama Setiady
Tanggal	24 April 2021

Studi Kasus	Stroke adalah salah satu gangguan neurologis utama di masa dewasa dan merupakan penyebab kematian dan kecacatan kedua di dunia di antara populasi lansia. Identifikasi stroke dan deteksi keparahan stroke mempengaruhi angka kematian, rehabilitasi, biaya pengobatan, dan kualitas hidup pasca stroke. Salah satunya adalah ischemic stroke dimana ini terjadi ketika aliran darah ke otak tersumbat oleh bekuan darah. Identifikasi yang terlambat dari ischemic stroke dapat menyebabkan gangguan kognitif dan beban ekonomi. Melacak perilaku sistem neuro-kelistrikan adalah kunci untuk memprediksi serangan stroke. Peristiwa ischemic melemahkan aktivitas neuro-elektrik, akhirnya akan menekan gelombang frekuensi tinggi (gelombang gamma atau beta), dan memperkuat pita sinyal saraf frekuensi rendah (alpha, theta, gelombang delta). Sebuah gelombang delta amplitudo tinggi (0,5-4 Hz) adalah tipikal pada ischemic stroke. Stroke juga mempengaruhi simetrisitas gelombang otak kiri dan korteks kanan. Perubahan perilaku simetris dari kekuatan spektral elektroensefalografi kuantitatif (EEG) antara dua belahan otak dapat dijelaskan oleh Revised Brain Symmetry Index (rsBSI) yang mana merupakan penanda penting prediksi awal pada stroke. SOS dikenali sebagai sinyal marabahaya yang mengindikasikan krisis atau kebutuhan untuk bertindak. HealthSOS di kombinasikan dengan elektroda EEG yang disematkan dalam masker mata dan modul kontrol untuk melakukan monitoring aktivitas saraf portable yang efektif. HealthSOS diusulkan sebagai sistem pemantauan kesehatan yang dapat melacak, memberikan status kesehatan dan memberi peringatan waspada jika melebihi nilai ambang batas dan memberikan peringatan darurat bahwa pasien dalam keadaan darurat.
Rumusan Masalah	Timbulnya permasalahan yang terjadi pada pembahasan penelitian ini adalah pada penelitian sebelumnya sistem EEG untuk pengobatan pada pasien rawat jalan dan untuk prediksi kejadian ischemic atau kekurangan suplai darah ke jaringan atau organ tubuh karena permasalahan pada pembuluh darah dalam aplikasinya dalam kehidupan sehari-hari belum diterapkan. Kemudian tidak praktisnya untuk pemantauan terus menerus pada pasien berisiko tinggi untuk penilaian rinci tentang stroke yang ada saat ini kebanyakan menggunakan teknologi MRI atau CT scan dimana ini kurang praktis.

<table>
<tr>
<td>Metode penelitian</td>
<td>Metode yang digunakan dalam penelitian ini adalah metode akusisi data terhadap pasien secara langsung. Akuisisi data EEG dilakukan dari belahan otak kiri dan kanan dilakukan setidaknya selama 15 menit dalam keadaan subjek istirahat dan berbaring di tempat tidur dengan dipasangkan elektroda EEG yang tertanam dalam sebuah masker mata di frontal cortex. Tujuannya adalah untuk mengetahui indeks EEG, termasuk rsBSI, rasio delta alpha, dan untuk mengevaluasi fitur prediktif untuk membedakan kelompok ischemic stroke dan kelompok kontrol yang sehat untuk prediksi ischemic stroke. Subjek penelitian ini adalah pada kelompok pasien stroke dan kelompok kontrol yang sehat terdiri dari laki – laki dan perempuan. Pasien ischemic stroke diverifikasi secara klinis dengan menggunakan MRI atau CT scan. Kelompok kontrol yang sehat didapat dari riwayat kejadian ischemic atau penyakit penyakit yang menyerang pada bagian sistem saraf yang mendasari sebelumnya. kelompok ischemic stroke dan kelompok kontrol yang sehat dipilih dengan rentang usia yang hampir sama untuk mengurangi variasi aktivitas saraf terkait usia. Populasi penelitian terdiri dari pasien yang dirujuk ke Pusat Rehabilitasi Rumah Sakit Universitas Nasional Chungnam, Daejeon, Korea Selatan.</td>
</tr>
<tr>
<td>Blok Diagram</td>
<td>


Alat ini dirancang untuk memperoleh data EEG dalam keadaan subjek ketika istirahat dan berbaring, yang mana terdiri dari sistem elektroda berlapis emas yang disematkan pada masker mata. Alasan disematkannya EEG pada masker mata karena dapat menghilangkan cahaya biru, yang menghambat tidur. Terdapat dua elektroda EEG yang ditempatkan pada frontal Fp1 dan Fp2. Area frontal dipilih karena posisi ini paling cocok untuk mendapatkan gelombang otak dengan menggunakan penutup mata. Alat ini menggunakan OpenBCI Cyton Board open-source untuk memperoleh sinyal EEG. Cyton Board terdiri dari akuisisi bio-sinyal 8 channels, slot MicroSD untuk penyimpanan data, konektor baterai Lipo, dan komunikasi nirkabel ke komputer mini melalui dongle USB BLE berbasis radio RFduino. Sinyal EEG diambil pada sampling 250 Hz melalui modul Cyton Board. Grounding dipilih pada Fpz sesuai sistem 10-20 dan referensi ditempatkan pada posisi dekat dengan telinga kanan. Modul akuisisi memiliki baterai 3,7V dan modul pengisian DC. Hasil dari pemantauan dan prediksi pada subjek tadi melalui masker mata tadi datanya kemudian akan dilakukan
</td>
</tr>
</table>

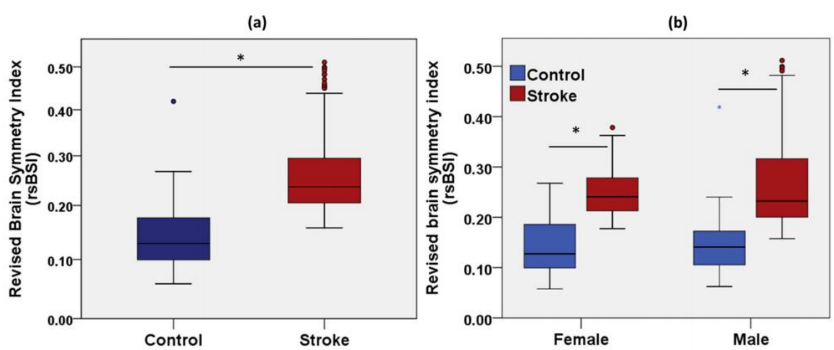
<table>
<tr><td></td><td>penyimpanan pada cloud DB dan dapat memberikan suatu alarm rekomendasi berupa alarm dan pesan sistem yang akan memberi tahu pasien, keluarga, dan petugas medis tentang keadaan pasien secara konkret.</td></tr>
<tr><td>Flowchart</td><td>


Sistem HealthSOS diproses mula mula ketika perangkat akuisisi data EEG mengirimkan data mentah ke aplikasi MiniPC terdekat melalui komunikasi Bluetooth. Kemudian API mengirim data sinyal EEG dan EOG dalam format JSON ke web DB menggunakan protokol ActiveMQ untuk menyimpan data tersebut berupa data gelombang otak dari belahan kanan dan kiri. Feature Extractor digunakan untuk melakukan ekstrak fitur fisiologis yang sensitif pada penyakit baik yang bersifat akut maupun kronis. Rule-based feature extender akan menemukan kemungkinan kelainan kesehatan pada saraf menggunakan feature thresholds dan tingkat status kesehatan yang didapat. Machine learning model akan mempelajari dan memprediksi status kesehatan pada subjek. Basis Pengetahuan Medis dan diketahui kenyataan secara konkret kemudian ditemukan kemungkinan penyebab penyakit, menghasilkan tindakan yang harus dilakukan dan rekomendasi tentang kesehatan. Rekomendasi tersebut diteruskan menuju pengguna, pusat kesehatan, dan departemen darurat terkait untuk mengambil tindakan yang diperlukan data hasil tadi kemudian dilakukan penyimpanan pada DB.</td></tr>
<tr><td>Klasifikasi</td><td>a. Input
Input fitur pada penelitian ini berupa pada penelitian pada kelompok pasien stroke dan kelompok kontrol yang sehat terdiri dari laki – laki dan perempuan. Pada kelompok pasien stroke terdapat 37 pasien (usia rata-rata 71,6 tahun, 61% laki-laki) yang didiagnosis dengan ischemic stroke. Kelompok kontrol yang sehat terdapat 36 pasien (usia rata-rata 76 tahun, 28% laki-laki). Dimana pengambilan data dilakukan dengan cara subjek memakai masker mata dengan kondisi subjek istirahat dan berbaring di tempat tidur.

b. Proses
Dalam penelitian ini data diambil dengan cara subjek memakai masker mata yang terdapat dua elektroda Fp1 pada bagian kiri dan</td></tr>
</table>

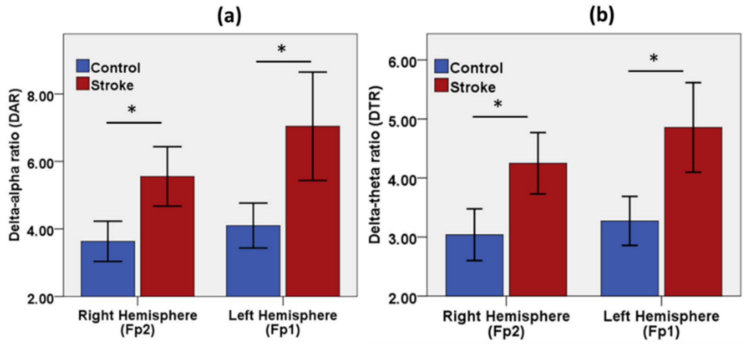
	Fp2 pada bagian kanan dengan kondisi subjek istirahat dan berbaring di tempat tidur. Beberapa algoritma machine-learning digunakan untuk mengklasifikasikan fitur pada saraf dari pasien kelompok ischemic stroke dan kelompok sehat. Discriminant analysis, Support vector machine (SVM), Neural network, QUEST dan algoritma C&R tree telah digunakan untuk mengklasifikasikan fitur gelombang pada otak kelompok ischemic stroke dan kelompok sehat. Secara keseluruhan dimana model support vector machine (SVM) menunjukkan accuracy tertinggi dengan sensitivity, specificity, precision, NPV (Negative predictive value) yang didapatkan dari confusion matrix. Accuracy (ACC) dihitung sebagai rasio prediksi yang benar terhadap total observasi dan dianggap sebagai ukuran kinerja yang paling intuitif untuk mengidentifikasi model terbaik. Precision (positive predictive rate) adalah rasio prediksi positif yang benar terhadap total observasi positif yang diprediksi. Sensitivity (true positive rate) adalah rasio prediksi positif yang benar untuk semua pengamatan aktual. Specificity (true negative rate) adalah rasio prediksi negatif yang benar untuk semua pengamatan aktual. Selain parameter tersebut, terdapat parameter lain seperti negative predictive value, AUC, dan Gini coefficient. $\text{Sensitivity} = \frac{TP}{TP + FN}$ $\text{Specificity} = \frac{TN}{TN + FP}$ $\text{Precision} = \frac{TP}{TP + FP}$ $\text{Negative predictive value (NPV)} = \frac{TN}{TN + FN}$ $\text{Accuracy(ACC)} = \frac{TN + TP}{TN + TP + FN + FP}$ Parameter tersebut dievaluasi dan dihitung menggunakan rumus dimana TP adalah true positive, TN artinya true negative, FP adalah false positive, dan FN artinya false negative. Semua ukuran kinerja untuk dataset training dan dataset testing. c. Output Setelah dilakukan pengambilan data penelitian pada kelompok pasien stroke dan kelompok kontrol yang sehat. Didapat bahwa model support vector machine (SVM) menjadi pilihan terbaik. Dimana dalam pengambilan data sendiri terhadap kelompok pasien ischemic stroke dan kelompok kontrol yang sehat dibagi menjadi beberapa kelas yaitu laki – laki dan perempuan. Dimana nantinya akan didapatkan indeks EEG, kemudian kelas pada Revised Brain Symmetry Index (rsBSI), Delta-Alpha and Delta-Theta Ratio, Correlation Coefficient,Kurtosis, Skewness, Spectral Slope dengan pengambilan data pada gelombang Alpha,Beta,Theta,Delta dan Gamma.
Hasil	Hasil penelitian ini berupa data pada subjek dengan kelompok pasien stroke dan kelompok kontrol yang sehat terdiri dari laki – laki dan perempuan dengan data EEG yang didapat berupa Revised Brain

<table>
<tr><td></td><td>Symmetry Index (rsBSI), Delta-Alpha dan Delta-Theta Ratio, Correlation Coefficient,Kurtosis, Skewness, Spectral Slope dan Pengujian Algoritma Machine-Learning.</td></tr>
<tr><td>Akuisisi Data</td><td>Proses akusisi data dilakukan pada kelompok pasien stroke dan kelompok kontrol yang sehat terdiri dari laki – laki dan perempuan. Pada kelompok pasien stroke terdapat 37 pasien (usia rata-rata 71,6 tahun, 61% laki-laki) yang didiagnosis dengan ischemic stroke. Kelompok kontrol yang sehat terdapat 36 pasien (usia rata-rata 76 tahun, 28% laki-laki). Sinyal EEG diperoleh dengan menggunakan sistem masker mata dengan fokus pada korteks frontal dengan peletakan dua elektroda pada Fp1 pada bagian kiri dan Fp2 pada bagian kanan. Pada kasus populasi stroke, data EEG dilakukan selambat-lambatnya 120 jam setelah masuk ke unit gawat darurat rumah sakit. Dimana subjek disarankan untuk tidak meminum minuman apapun seperti kopi atau alkohol sebelum percobaan dilakukan. Data EEG akan didapatkan dalam keadaan subjek ketika istirahat dan berbaring. Hanya difokuskan mempertimbangkan EEG untuk analisis studi populasi stroke walaupun data EEG dan EOG dapat diperoleh dengan menggunakan alat ini. Suhu ruangan dipertahankan pada 24° dan kelembaban 40%. Subjek disarankan untuk melembabkan kulit bagian dahi untuk mengurangi impedansi elektroda kering. Setelah memakai masker mata, perekaman data ditunda selama 5 menit untuk menenangkan kondisi subjek ke kondisi istirahat, kemudian data EEG direkam setidaknya selama 15 menit dalam kondisi subjek istirahat dan berbaring di tempat tidur.</td></tr>
<tr><td>Hasil Pengujian</td><td>a. Hasil Revised Brain Symmetry Index



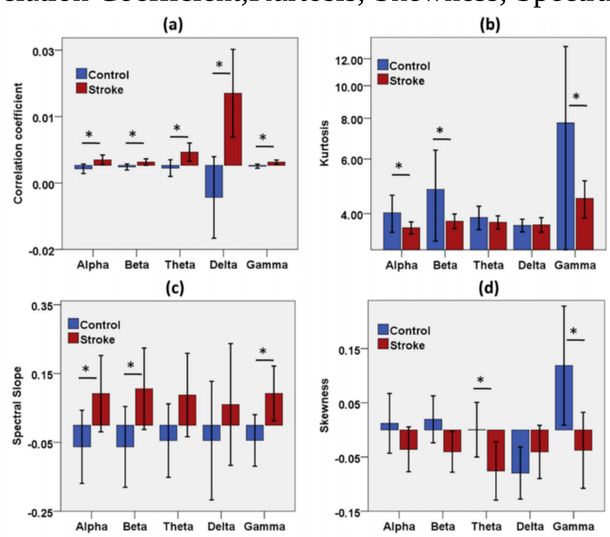
Rentang median dan interkuartil dari rsBSI dihitung di kulit kepala frontal antara kelompok pasien ischemic stroke menunjukan distribusi statistik rsBSI 0.263 dan 0.088 dan kelompok kontrol yang sehat menunjukan distribusi statistik rsBSI 0.143, dan 0.053 ini menunjukkan perbedaan yang signifikan karena $p < 0{,}0001$. Sementara pada pengelompokan pria dan wanita pada rsBSI kelompok stroke laki-laki memiliki jangkauan interkuartil yang lebih luas dibandingkan dengan kelompok stroke perempuan. Disisi lain, median rsBSI (0,23) populasi stroke pria sedikit lebih rendah daripada (0,24) populasi stroke wanita.</td></tr>
</table>

b. Hasil Delta-Alpha Ratio dan Delta-Theta Ratio



Rata-rata DAR (delta-alpha ratio) dan DTR (delta-theta ratio) untuk kelompok ischemic stroke menunjukan nilai 5.556 dan 4.250 masing-masing di Fp1 dan 7.043 dan 4.856 di Fp2. Sementara rata-rata DAR (delta-alpha ratio) dan DTR (delta-theta ratio) untuk kelompok kontrol yang sehat masing-masing 3,634 dan 3,040 di Fp1 dan 4.10 dan 3.273 di Fp2. DAR (delta-alpha ratio) menunjukan nilai p <0,0001 pada posisi Fp1 dan menunjukan nilai p <0,0005 pada posisi Fp2. Sementara pada dari DTR (delta-theta ratio) menunjukan nilai p <0,005 dihitung dalam elektroda frontal Fp1, Fp2 antara populasi kelompok ischemic stroke dan kelompok kontrol yang sehat. Error menunjukkan interval kepercayaan 95%. Dengan demikian dapat disimpulkan bahwa perbedaan mean dan varians DAR, DTR kelompok ischemic stroke kelompok kontrol yang sehat berbeda satu sama lain.

c. Hasil Correlation Coefficient,Kurtosis, Skewness, Spectral Slope



Statistik dari koefisien korelasi pita frekuensi EEG (alfa, beta, theta, delta, gamma) untuk kelompok ischemic stroke dan kelompok kontrol yang sehat menunjukan rata-rata koefisien korelasi pada Fp1 menunjukkan nilai p <0,05 dan tidak ada perbedaan yang signifikan yang diamati dalam varian koefisien korelasi. Rata-rata analisis kurtosis di Fp2 menunjukkan nilai $p < 0{,}05$, dan tidak ada perbedaan yang signifikan yang diamati pada sarana kurtosis. Rata-rata statistik kemiringan spektral pita frekuensi EEG kemiringan spektral di Fp1, hasil kemiringan, perbedaan yang signifikan nilai $p < 0{,}05$ tetapi tidak ada perbedaan yang signifikan yang diamati dalam varian kemiringan. Sementara kemiringan di Fp1 menunjukkan rata-rata statistik kemiringan pita frekuensi EEG. Dalam hasil skewness, perbedaan yang signifikan nilai $p < 0{,}05$ diamati pada rata-rata skewness theta dan gamma. band di Fp1, tetapi tidak ada perbedaan signifikan yang diamati dalam varian kemiringan. Error menunjukkan interval kepercayaan 95%.

d. Hasil Pengujian Algoritma Machine-Learning

TABEL 1. Hasil kinerja klasifikasi model yang berbeda menggunakan dataset training.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	AUC (%)	Gini (%)
SVM	93	98	88	89	98	98	95
Discriminant	88	91	86	86	90	96	92
Neural Network	90	86	94	94	87	96	93
QUEST	93	94	93	93	94	95	91
C&R Tree	92	98	86	87	98	92	84

TABEL 2. Hasil kinerja klasifikasi model yang berbeda menggunakan dataset pengujian.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	AUC (%)	Gini (%)
SVM	89	94	84	84	94	97	95
Discriminant	87	87	86	85	88	94	88
Neural Network	88	88	88	87	89	92	84
QUEST	91	90	93	92	91	94	88
C&R Tree	89	94	84	84	94	89	78

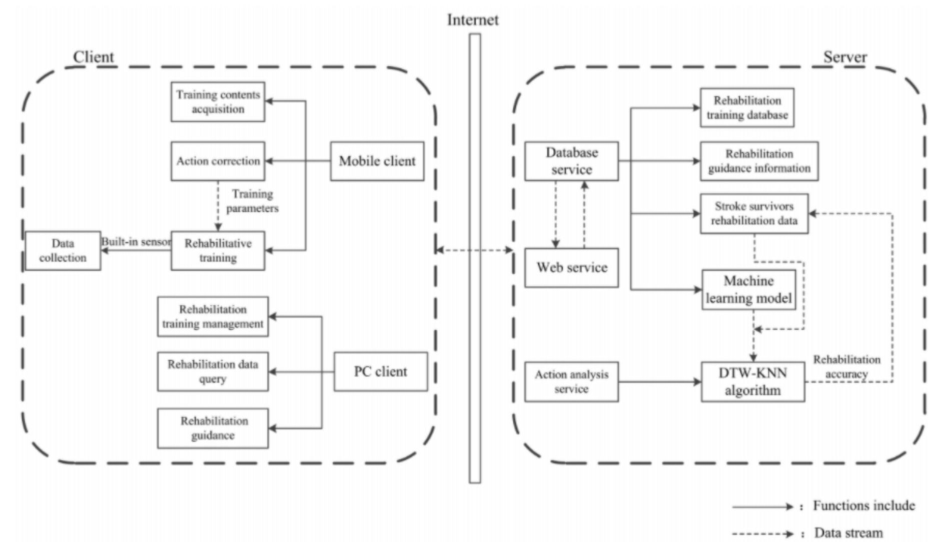
Dalam penelitian beberapa algoritma machine-learning digunakan untuk mengklasifikasikan fitur pada saraf dari pasien kelompok ischemic stroke dan kelompok kontrol yang sehat. Discriminant analysis, Support vector machine (SVM), Neural network, QUEST dan algoritma C&R tree telah digunakan untuk mengklasifikasikan fitur gelombang pada otak kelompok ischemic stroke dan kelompok kontrol yang sehat. Secara keseluruhan dimana model support vector machine (SVM) menunjukkan akurasi tertinggi baik pada dataset training (ACC: 92%), AUC tertinggi (98%), dan koefisien Gini tertinggi (95%) dan pada dataset testing menunjukkan akurasi tertinggi (ACC: 92%), AUC tertinggi (97%), dan koefisien Gini tertinggi (95%) pada kinerja klasifikasi. Secara keseluruhan, statistik antara prediksi stroke dengan 5 algoritma machine-learning digunakan adalah 84%.

Kelebihan	Kelebihan penelitian ini adalah alat yang digunakan dalam penelitian berupa alat pertama yang menggunakan EEG yang dibuat pada masker mata untuk tujuan prediksi pada penyakit ischemic stroke. Dapat di aplikasikan menjadi perangkat portabel alternatif yang baik karena dapat melakukan pemantauan kesehatan real-time dalam aktivitas kehidupan sehari-hari, seperti istirahat, EEG tanpa dengan beberapa kabel dan gel konduktif yang merupakan bukan solusi praktis. Pada alat ini diterapkan juga sistem yang dapat digunakan sebagai memprediksi serangan stroke saat bangun tidur.
Kekurangan	Kekurangan penelitian ini adalah alat yang digunakan dalam penelitian Dalam studi ini, kami fokus hanya pada lobus frontal (bagian otak besar yang terbesar dan terletak di bagian depan otak) untuk memahami perubahan EEG untuk gangguan saraf akibat ischemic stroke belum dapat diterapkan pada seluruh korteks. Alat ini hanya difokuskan mempertimbangkan EEG untuk analisis studi populasi stroke walaupun data EEG dan EOG dapat diperoleh dengan menggunakan alat ini. Pada alat ini belum dapat di aplikasikan sistem yang dapat dilakukan pemantauan selama tidur. Sementara gerakan mata dapat terlihat signifikan dan penting untuk kualitas tidur dan tidur REM (Rapid Eye movement).

Judul	Upper Limb Rehabilitation System for Stroke Survivors Based on Multi-Modal Sensors and Machine Learning
Nama Jurnal	IEEE Access
Volume dan Halaman	Vol. 9, Hal 30283 - 30291
Tahun	2021
Penulis	Sheng Miao, Chen Shen, Xiaochen Feng, Qixiu Zhu, Mohammad Shorfuzzaman, dan Zhihan Lv
Reviewer	Irfan Harlim
Tanggal	27 April 2021

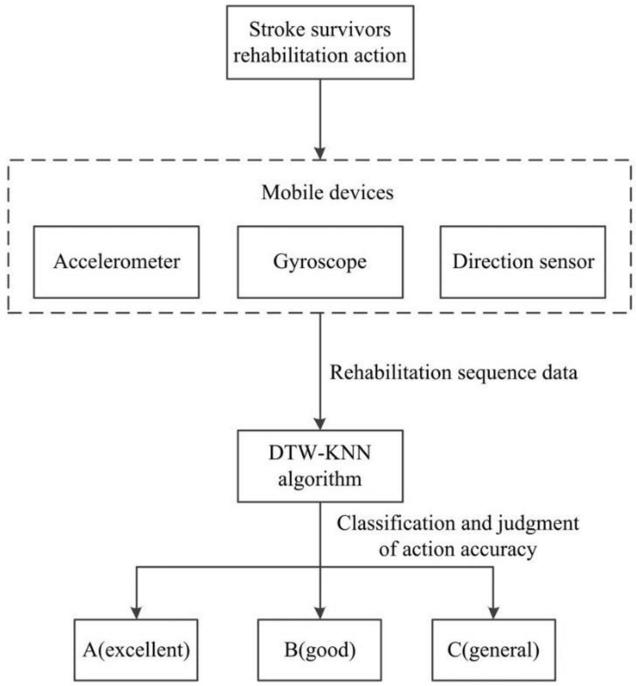
Studi Kasus	Rehabilitasi bagi pasien stroke sebagian besar diselesaikan di bawah bimbingan dokter. Terdapat berbagai cara pengobatan, namun sebagian besar dipengaruhi oleh berbagai faktor seperti pengalaman dokter dan intensitas treatment. Efek dari suatu treatment rehabilitasi stroke tidak bisa mendapatkan feedback-nya secara langsung, selain itu suatu metode treatment sangatlah rumit, mahal dan sangat bergantung terhadap dokternya. Serta inkonsistennya pasien penderita stroke terhadap treatment yang sedang ia jalani, disebabkan karena keterbatasan terhadap biaya. Dengan menggabungkan teknologi Internet-of-Things (IOT), machine learning, dan intelligence system technologies untuk merancang suatu sistem kecerdasan berbasis smartphone guna membantu rehabilitasi pasien stroke lengan bagian atas (Upper Limb Rehabilitation). Pada penelitian paper ini menggunakan sensor multi-modal yang sudah terdapat di smartphone, dengan menggengam smartphone pada saat proses rehabilitasi data-data hasil rehabilitasi dari user atau pasien bisa didapatkan dan kemudian data tersebut di transfer menuju server melalui Internet. Algoritma yang digunakan merupakan gabungan dari DTW dan KNN. Fungsinya untuk mendapatkan nilai keakuratan terhadap tindakan rehabilitasi serta mengklasifikasikannya ke beberapa tingkat penyelesaian treatment. Pada hasil percobaan menunjukkan bahwa algoritma DTW dan KNN dapat menilai tindakan rehabilitasi dengan akurat serta tingkat akurasi klasifikasi yang dibedakan menjadi excellent, good, dan normal dimana masing-masing nilainya adalah 85,7%, 66,7%, dan 80%. intelligence system yang digunakan dalam paper ini dapat membantu penderita stroke untuk melanjutkan treatment rehabilitasi secara mandiri dan pemantauan secara jarak jauh, serta mengurangi biaya rehabilitas dan beban psikologis.
Rumusan Masalah	awal mula terdapat permasalahan yang yaitu pasien stroke rawat jalan yang masih perlu menjalani proses treatment rehabilitasi dirumah. tetapi teknologi untuk treatment penanganan rehabilitasi stroke yang ada pada saat ini masih sangat mahal dan juga tidak kondusif untuk digunakan dirumah. Selain itu pasien masih inkonsisten dalam proses rehabilitasi mandiri membuat data yang diterima oleh dokter sulit untuk membuat

<table>
<tr><td></td><td>keputusan tindak lanjutnya. selain itu juga, Covid-19 membuat kesulitan proses rehabilitasi dengan bimbingan dokter secara langsung di rumah sakit karena memiliki resiko yang tinggi terpaparnya Covid-19 selama menjalankan sesi rehabilitasi yang dijalankan di rumah sakit.</td></tr>
<tr><td>Metode penelitian</td><td></td></tr>
<tr><td>Blok Diagram</td><td>



Client:
Melalui PC client dokter akan membuat perencanaan pelatihan, panduan melakukan rehabilitasi serta menentukan tindakan selanjutnya yang sesuai dengan penyakit stroke yang diderita oleh pasien. Alat ini dirancang untuk membuat suatu treatment rehabilitas pasien rawat jalan stroke agar melakukan rehabilitasinya secara mandiri dirumah. Nantinya pada mobile client, pasien stroke dapat melihat menu latihan yang sudah dibuat oleh dokter sesuai dengan penyakit stroke pasien tersebut.

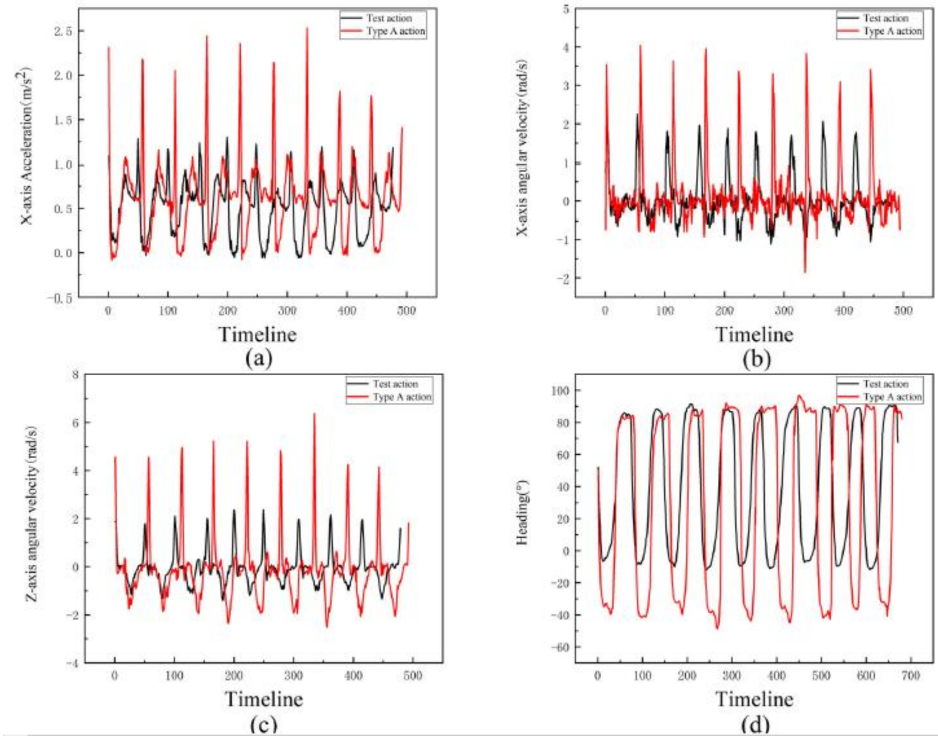
Server:
Setelah melakukan treatment rehabilitasi, data-data dari hasil pembacaan sensor akan disimpan dalam database MySQL, dengan menggunakan protokol HTTP sebagai komunikasi antara Client dan layanan database. Database tidak hanya berisikan data-data hasil pengukuran tetapi terdapat database perencanaan pelatihan pasien, panduan rehabilitasi pasien, serta mechine learning models. Data-data hasil pembacaan sensor akan diolah menggunakan algoritma gabungan antara DTW dan KNN, setelah itu akan diumpan balikan menuju data-data pasien yang melakukan rehabilitasi untuk diupdate datanya. Selanjutnya data hasil rehabilitasi pasien akan ditampilkan pada web service yang bertujuan agar pasien dan juga dokter mengetahui progres setiap latihannya, dan nantinya dokter juga dapat membimbing secara jarak jauh serta menyesuiakan program latihan sesuai dengan kemajuan proses rehabilitasinya dengan tujuan pasien dapat menyelesesaikan treatment rehabilitasi dengan cara yang efisien dan nyaman.</td></tr>
</table>

<table>
<tr><td>Flowchart</td><td>

Mula-mula ketika pasien stroke upper limb melakukan treatment rehabilitasi dengan menggengam perangkat smartphone, pada saat yang bersamaan sensor yang sudah terdapat pada smartphone yaitu accelerometer, Gyroscope dan Direction sensor mengukur setiap gerakan dari proses rehabilitasinya. Dengan kombinasi ketiga sensor tersebut dapat menganalisis dan dapat menggamabarkan situasi pengguna sebenarnya. selanjutnya data yang diperoleh ketiga sensor tersebut akan diolah menggunakan algoritma gabungan antara DTW dan KNN, tujuannya mengklasifikasikan data hasil perkembangan latihan rehabilitasinya dengan tiga kategori A(exellent), B(good), dan C(general).</td></tr>
<tr><td>Klasifikasi</td><td>Input
Input dari penelitian ini yaitu berupa pasien rehabilitasi rawat jalan penderita stroke lengan bagian atas (Upper Limb Rehabilitation) dengan treatment rehabilitasinya menggunakan smartphone yang memanfaatkan sensornya yaitu accelerometer, Gyroscope dan Direction sensor.

Proses
Setelah data-data hasil treatment rehabilitasi disimpan dalam database proses selanjutnya adalah melakukan pengolahan data dengan menggunakan algoritma gabungan antara DTW dan KKN. Pada awalnya data hasil rehabilitasi diolah terlebih dahulu dengan menggunakan algoritma DTW. Inti dari DTW adalah menyelesaikan distortion curve, yaitu correspondence antar poin yang dapat dinyatakan sebagai:
$$\varphi(k) = (\varphi_x(k), \varphi_y(k))$$</td></tr>
</table>

	dalam beberapa situasi untuk mencari cumulative distance nilai distance antar dua urutan (sequence) penyelesaiannya sebagai berikut: $$d_{\phi}(X, Y) = \sum_{k=1}^{T} d(\phi_x(k), \phi_y(k))$$ Maka untuk menentukan output DTW yaitu dengan menemukan distortion curve yang paling sesuai untuk meminimalkan cumulative distance, sehingga menggunakan nilai baris terakhir dan kolom terakhir dari loss matriks, persamaanya sebagai berikut: $$DTW(X, Y) = \min_{\phi} d_{\phi}(X, Y)$$ Setelah didapatkan output dari DTW, nilai tersebut digunakan untuk mengukur kemiripan antara gerakan yang dihasilkan dari pasien rehabilitasi dan gerakan orang normal setelah itu output dari standar distance dimasukan kedalam klasifikasi menggunakan KNN. Pada penelitian paper ini Algoritma DTW digunakan untuk menghitung distance pada 9 atribut antara seluruh data real pengujian dan setiap kelompok data real pengujian, dan jumlah kumulatif dari distance pada 9 atribut digunakan sebagai 2 perbandingan actions, kemudian dilakukan normalisasi pada beberapa distance, setelah itu data distance diproses oleh KNN untuk dilakukan klasifikasi. Output Hasil output treatment rehabilitasi pasien stroke yaitu dapat menilai keakuratan serta mengklasifikasikan menjadi tiga kategori A (excellent), B (good), dan C (general) dengan menggunakan DTW dan KNN yang nantinya akan ditampilkan pada web server untuk dapat dilihat secara real time oleh pasien serta dokter perkembangan dari rehabilitasinya.
Hasil	
Akuisisi Data	Proses akuisisi data dilakukan dengan mengambil contoh kasus stroke pada penderita Brunnstrom staging dan treatment yang dilakukan yaitu elbow flexion sebanyak 18 grup pengujian. Setelah melakukan treatment rehabilitasi selanjutnya data yang hasilkan dibuat klasifikasi penilaian dengan kategori A (excellent), B (good), dan C (general) lalu setelah observasi dan penilaian dari dokter didapatkan hasil klasifikasi yaitu 6 grup pada setiap kategori dengan model keputusan (decision model) pada x-axis acceleration, the x-axis angular velocity, the z-axis angular velocity menghasilkan data yang berbeda-beda. Maka output menghasilkan yaitu Type A 5, Type B 3 dan Type C 3. Sehingga dengan algoritma gabungan DTW dan KNN menilai bahwa type A memiliki nilai yang paling baik dengan kategori Excellent begitupun dengan penilaian dari dokter yang menyatakan hal yang sama bahwa type A memiliki nilai yang paling baik. berikut merupakan data dari kategori A yang dibandingkan dengan pengujian lainnya.



Hasil Pengujian

Actual situation	A			B			C		
Model decision	A	B	C	A	B	C	A	B	C
Number of groups	6	0	0	1	4	1	0	2	4

dapat dilihat meskipun memiliki hasil penilaian pengujian yang rata yaitu 6 setiap kategori tetapi terdapat perbedaan model keputusannya pada x-axis acceleration (A), the x-axis angular velocity (B), dan the z-axis angular velocity(C). Melalui perhitungan confusion matriks dapat dihitung nilai akurasi dari model klasifikasi yaitu sebesar 77,8% dari seluruh kategori klasifikasi.

Indicators	A test action	B test action	C test action
Accuracy	85.7%	66.7%	80%
Recall	100%	66.7%	66.7%
Specificity	91.7%	83.3%	91.7%

Tabel diatas merupakan persentase hasil pengujian treatment elbow flexion yang dilakukan oleh pasien stroke penderita Brunnstrom staging dimana A menunjukan tingkat penyelesaian yang excellent, B menunjukan tingkat penyelesaian yang good, dan C menunjukan tingkat penyelesaian yang general. Dari hasil confusion matriks dapat dilihat bahwa pada pengujian A menghasilkan accuracy, recall dan specificity tertinggi.

Kelebihan

kelebihan treatment rehabilitasi penyakit stroke pada penelitian ini yaitu treatment rehabilitasi secara mandiri pada masa Covid-19 sangat

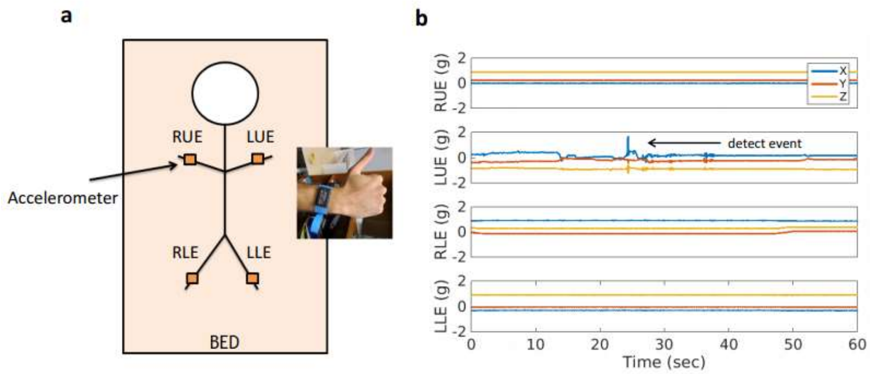
	membantu pasien stroke, karena mengurangi kontak secara langsung dengan dokter maupun pasien lainnya yang ada dirumah sakit. Dibandingan dengan metode treatment tradisional, metode rehabilitasi pada penelitian ini tidak terbatas ruang dan waktu sehingga penderita stroke dapat melakukan rehabilitasi dirumah diwaktu kapanpun dan juga biaya yang dikeluarkan rendah dan dokter dapat secara langsung melihat perkembangan secara real time melalui PC client sehingga dapat memutuskan tindakan yang harus dilakukan selanjutnya atau membuat perencanaan pelatihan yang sesuai selanjutnya dengan baik.
Kekurangan	kekurangan treatment rehabilitasi penyakit stroke pada penelitian ini yaitu dengan menggunakan nilai akselerometer internal yang terdapat pada smartphone digunakan sebagai nilai koordinat ponsel, sangat sulit untuk secara akurat mencerminkan bahwa nilai tersebut merupakan keadaan real dari pergerakan pasien rehabiltas penderita stroke. sehingga mengakibatkan kesalahan-kesalahan tertentu dalam tindakan penentuan konten pelatihan rehabilitasi dan juga penggunaan KNN sebagai klasifikasi algoritma, komputasinya sangat besar sehingga harus menyediakan penyimpanan yang lebih besar.

Judul	Use of Accelerometry for Long Term Monitoring of Stroke Patients
Nama Jurnal	IEEE – Journal Of Translational Engineering in Health and Medicine
Volume dan Halaman	Vol. 7, Hal 2168 - 2372
Tahun	2018
Penulis	Alfredo Lucas , John Hermiz PhD , Jamie LaBuzetta MD , Yevgeniy Arabadzhi , Navaz Karanjia MD , Vikash Gilja PhD
Reviewer	Muhammad Riza Irfan
Tanggal	24 April 2021

Studi Kasus	Stroke adalah salah satu penyakit penyebab kecacatan tertinggi di dunia. Gangguan fungsi syaraf akut pada penderita stroke disebabkan oleh gangguan peredaran darah otak yang timbul secara cepat dalam beberapa jam. Sekitar 80% penderita stroke mempunyai defisit neuromotor, sehingga memberikan gejala kelumpuhan pada tubuh yang bervariasi baik anggota gerak bagian atas maupun bawah. Tindakan pemantauan jangka panjang pada kondisi pasien stroke sangat diperlukan agar penanganan yang cepat dan tepat dapat meminimalkan resiko tingkat kerusakan motorik dan mencegah kemungkinan munculnya komplikasi. Pada penelitian jurnal ini pasien stroke akan dipantau setiap jam baik oleh dokter dan perawat dalam upaya untuk lebih memahami kondisi fisik pasien. Dalam penelitian ini mencoba untuk menemukan korelasi antara nilai motorik pasien dan data akselerometer yang direkam secara kontinyu pada pasien stroke. Penggunaan akselerometer diimplementasikan pada 4 pasien yang mengalami gangguan stroke dan pergerakan mereka akan dipantau terus menerus selama 7 hingga 14 hari.Penempatan akselerometer diletakkan pada kedua pergelangan tangan dan kaki pasein. Fitur yang berkaitan dengan kelancaran gerakan, kekuatan dan karakteristik pola pergerakan pasien diekstraksi dari akselerometer menggunakan analisa frekuensi waktu. Metode pengklasifikasian Support Vector akan mendapatkan data latih dari fitur hasil ekstraksi untuk menguji kemampuan perekaman data jangka panjang akselerometer di dalam memprediksi kerusakan anggota gerak pada pasien dalam sisi dependen dan antigravitasinya dan secara signifikan di atas kinerja dasar diperoleh dalam banyak kasus (P <0,05) . Pendekatan leave one subject out dilakukan untuk menilai generalisasi dari metodologi yang digunakan. Metodologi yang disajikan dalam penelitian ini memberikan pendekatan yang sederhana, namun efektif untuk melakukan penilaian motorik jangka panjang pada pasien perawatan neurokritis.
Rumusan Masalah	Dalam penelitian ini menilai apakah pemantauan jangka panjang selama tujuh hari atau lebih, dengan menggunakan akselerometer pada pasien stroke ICU neurologis dapat efektif dalam menentukan gangguan kerusakan motorik pada anggota gerak atas atau bawah pada pasien.

Metode penelitian	

Gambaran Pengukuran Akselerometer



Pada **gambar a** merupakan ilustrasi pengaturan ekperimental pada pasien dimana empat akslerometer dipasangkan pada anggota gerak atas yaitu pada tangan kanan dan kiri sedangkan pada anggota gerak bawah pada pergelangan kaki kanan dan kiri. Pengukuran akselerometer tri-aksial dilakukan terus menerus di semua 4 ekstremitas.

Jika terdapat perubahan sinyal pada akselerometer seperti pada **gambar b** maka di interpretasikan sebagai terdeteksi adanya pergerakan pada pasien. Penting untuk dicatat bahwa beberapa peristiwa pergerakan yang terdeteksi terkadang bukan murni pergerkan yang dihasilkan oleh subjek, melainkan oleh dokter yang perlu berinteraksi dengan pasien.

Subjek penelitian dari jurnal ini direkrut dari Neurological Intensive Care Unit di UC San Diego Medical Center tepatnya pasien rumah sakit Hillcrest. Sebanyak empat orang dewasa sebagai subjek penelitian dengan gangguan unilateral, dengan demografi subjek disajikan pada tabel berikut:

Tabel 1 Demografi Subjek

Subject Number	Age	Gender	Impaired Side	Length of Data Collection (days)	Minimum Limb Scores (RUE-LUE-RLE-LLE)	Maximum Limb Scores (RUE-LUE-RLE-LLE)
Subject 1	46	M	Right	7	0-1-0-1	2-5-1-5
Subject 2	39	F	Left	7	0-0-0-0	4-2-5-2
Subject 3	48	M	Left	14	1-0-1-0	4-3-4-2
Subject 4	74	M	Left	7	5-3-5-4	5-5-5-5

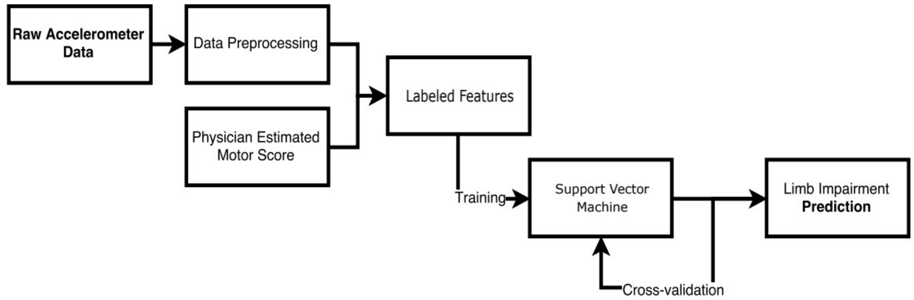
Flowchart	Diagram Flowchart Sistem  Penjelasan Diagram Flowchart: 1. Raw Accelerometer Data Pada bagian awal adalah mendapatkan data mentah yang diperoleh dari sensor akselerometer. Pada bagian ini empat akselerometer tri-aksial (Akselerometer Axtivity AX3) ditempatkan di ekstremitas kiri atas (LUE = lengan kiri), ekstremitas kanan atas (RUE = lengan kanan), ekstremitas kiri bawah (LLE = kaki kiri), dan ekstremitas bawah kanan (RLE = kaki kanan). Semua akselerometer dipasang dan ditempatkan di pergelangan tangan dan pergelangan kaki pada subjek. Data secara kontinyu diperoleh pada frekuensi 100Hz sampai dengan 14 hari atau sampai subjek keluar dari ICU Neurologis. Setelah penelitian selesai, akselerometer dilepas dari tangan dan kaki kemudian datan akan diproses ke komputer. 2. Data Prepocessing Proses selanjutnya merupakan proses untuk mengolah data mentah yang diperoleh dari sensor akselerometer. Data akselerometer mentah diambil sampelnya dari 100Hz ke 50Hz, karena kekuatan sinyal yang signifikan hanya terlihat di bawah 25Hz. Setelah melakukan down sampling, besarnya masing-masing akselerometer dihitung menurut persamaan : $$A[t] = \sqrt{x[t]^2 + y[t]^2 + z[t]^2}$$ Untuk mengklasifikasikan ada tidaknya pergerakan, ambang batas yang dipilih secara empiris diterapkan ke A′[t] dari sinyal. Parameter yang digunakan untuk mendeteksi fitur dipilih secara manual dan ditentukan berdasarkan kemampuan yang memadai untuk mendeteksi kejadian dari contoh data window. 3. Physician Estimated Motor Score Pada tahap ini merupakan penilaian motorik pada pasien yang ditlakuan oleh dokter menggunakan Oxfor Grading Motor Scale dan dicatat setiap jam pada grafis medis subjek.

Table 2: Oxford Motor Grading Scale

Motor Score	Description
Score 0	No muscle movement
Score 1	Muscle movement without joint motion
Score 2	Moves with gravity eliminated
Score 3	Moves against gravity but not resistance
Score 4	Moves against gravity and light resistance
Score 5	Normal strength

Data penilaian motorik diunduh dari rekam medis elektronik setelah menghapus semua identitas informasi. Pada subjek pasien 1 sampai 3 penelitian dicatat selama mereka berada di rumah sakit tanpa adanya gangguan dalam prosedur pengumpulan data dengan penilaian dilakukan setiap jamnya. Sedangkan pada subjek 4 mengalami beberapa gangguan dalam prosedur pengumpulan datanya dan hasil penilaian motorik didapatkan setiap 1 sampai 4 jam untuk mengurangi resiko mengalami delirium pada pasien yang dinyatakan oleh dokter. Selama setiap penilaian ekstremitas, anggota tubuh yang dikategorikan sebagai "dependen" jika memiliki skor motorik 0-2 sedangkan "anti gravitasi" jika skor motorik 3-5. Skor 3 dipilih sebagai ambang batas karena memisahkan gerakan yang dapat dilakukan melawan gravitasi (skor 3, 4, dan 5) dan yang tidak dapat melawan gravitasi (skor 0, 1, dan 2), yang secara efektif memberikan representasi biner dari gangguan .Penilaian dan informasi kerusakan motorik yang terjadi pada setiap pasien ditunjukkan pada Tabel 1.

4. Labeled Feature

Pada bagian labeled feature ini merupakan proses untuk memperoleh fitur-fitur yang akan digunakan dan dilakukan ekstraksi pada setiap fiturnya. Pada penelitian ini terdapat 9 fitur yang diturunkan dari akselerometer. Vektor magnitudo waktu untuk setiap event window data kemudian digunakan untuk membuat 9 fitur bernilai scalar. Fitur-fitur tersebut dipilih berdasarkan kemampuannya untuk mengkarakterisasi gerakan berdasarkan kelancaran, intensitas dan perilaku pola, dan semuanya telah berhasil digunakan untuk mengkarakterisasi aktivitas motorik pada akselerometer yang dikenakan pada pergelangan tangan dan pergelangan kaki.

5. Support Vector Machine

Pada proses pengklasifikasian dilakukan dengan metode Support Vector Machine. Support Vector Classifiers dilatih dengan fitur yang diekstraksi untuk menguji kemampuan perekaman akselerometer dalam jangka panjang dalam memprediksi sisi dependen dan antigravitasi. SVM dilatih untuk setiap subjek penelitian dan secara terpisah untuk ekstremitas atas dan bawah dalam setiap subjek. Data dibagi menggunakan pendekatan 80/20, dimana 80% digunakan untuk pelatihan dan validasi dan 20% digunakan untuk pengujian. Set pengujian dan pelatihan dipastikan memiliki perbandingan yang sama baik dari kelas dependen maupun antigravitasi. Proses ini diulangi untuk setiap pasien dan jenis ekstremitas (atas dan bawah).

6. Limb Impairment Prediction

Pada bagian akhir ini merupakan hasil klasifikasi berupa prediksi kerusakan motorik anggota tubuh pada pasien setelah menggunakan metode penelitian Support Vector Machine. Dimana terdapat 3 kelas prediksi kerusakan yang terjadi yaitu pada anggota gerak bagian atas dan bawah (Combine extremity), anggota gerak atas (Upper Extremity) dan anggota gerak bawah (Lower Extremity).

Klasifikasi

1. INPUT

Pada penelitian ini terdapat 9 fitur yang diturunkan dari akselerometer. Vektor magnitudo waktu untuk setiap event window data kemudian digunakan untuk membuat 9 fitur bernilai skalar. Fitur dipilih berdasarkan kemampuannya untuk mencirikan gerakan berdasarkan kelancaran, intensitas dan pola perilaku, dan semuanya telah digunakan untuk mencirikan aktivitas motorik menggunakan accelerometer yang dikenakan pada pergelangan tangan dan pergelangan kaki pasien.

Name	**Description**
Magnitude Average	- Time average of the magnitude vector
Maximum Magnitude	- Maximum value of the magnitude vector
Minimum Magnitude	- Minimum value of the magnitude vector
NARJ	- Normalized average rectified jerk [30]
Power 1	- Power of the first dominant FFT coefficient
Power 2	- Power of the first dominant FFT coefficient
Frequency 1	- Frequency corresponding to the first dominant FFT coefficient
Frequency 2	- Frequency corresponding to the second dominant FFT coefficient
Movement Count	- Number of events recorded in the hour

Fitur pertama terdiri dari rata-rata waktu dari vektor magnitudo seperti yang ditunjukkan pada persamaan dibawah:

$$A_{avg} = \frac{1}{t_f - t_i} \int_{t_i}^{t_f} A[t]dt$$

Dimana untuk ti dan tf sesuai dengan keadaan titik waktu awal dan akhir. Nilai maksimum dan minimum dari besarnya vektor juga digunakan untuk mencirikan kelancaran pergerakan. Untuk mengubah sinyal jerk menjadi besaran skalar, digunakan Normalized Average Rectified Jerk (NARJ) sebagai pengganti jerk rata-rata waktu karena NARJ telah terbukti menjadi metrik yang konsisten untuk perataan pergerakan yang tidak bergantung pada durasi sinyal. NARJ dihitung dengan persamaan sebagai berikut :

$$NARJ = \frac{1}{t_f - t_i} \int_{t_i}^{t_f} \left| \frac{dA[t]}{dt} \right|$$

	Transformasi FFT dari vektor magnitudo digunakan untuk mendapatkan fitur berbasis frekuensi. Frekuensi dominan pertama dan kedua (tidak termasuk DC) dan daya FFT yang sesuai diekstraksi sebagai fitur. Penggunaan beberapa kombinasi fitur ini juga terbukti berguna, tetapi dengan sedikit perbaikan dapat meningkatkan akurasi pada klasifikasi, oleh karena itu fitur tersebut dikecualikan sebagai cara untuk meminimalkan jumlah fitur. Selain itu, waktu komputasi fitur juga dipertimbangkan dalam proses seleksi untuk memastikan penerapan translasi. Fitur diubah ke dalam sebuah matriks di mana setiap baris sesuai dengan satu jam di mana peristiwa dicatat dan kolom sesuai dengan fitur masing-masing untuk jam itu. Baris tertentu dari matriks fitur diberi label berasal dari ekstremitas dependen jika nilai motorik untuk ekstremitas pada jam tersebut kurang dari 3, dan jika lebih dari 3 maka termasuk ektremitas antigravitasi,sesuai dengan ambang batas yang telah ditentukan sebelumnya. Kolom dari matriks fitur (vektor fitur) diskalakan agar memiliki mean nol dan varian unit, yang diperlukan untuk mencegah penskalaan fitur yang tidak merata yang dapat mempengaruhi hasil. Normalisasi ini dilakukan per subjek dan per hari. Artinya, vektor fitur yang sesuai dengan subjek yang sama untuk hari tertentu dinormalisasi di bawah distribusi yang sama ke zero mean dan variansi unit. 2. PROSES Metode yang digunakan untuk mengklasifikasikan pada penelitian ini adalah metode Support Vector Machine. Support Vector Classifiers dilatih dengan fitur yang diekstraksi untuk menguji kemampuan perekaman akselerometer dalam jangka panjang dalam memprediksi sisi dependen dan antigravitasi. SVM dilatih untuk setiap subjek penelitian dan secara terpisah untuk ekstremitas atas dan bawah dalam setiap subjek. Data dibagi menggunakan pendekatan 80/20, dimana 80% digunakan untuk pelatihan dan validasi dan 20% digunakan untuk pengujian. Proses ini diulangi untuk setiap pasien dan jenis ekstremitas (atas dan bawah). Nilai Cross Validation dihitung untuk pengklasifikasi dasar dan digunakan sebagai akurasi dasar agar sesuai dengan actual classifier. Mengingat jumlah nilai akurasi cross validation hanya 10 untuk setiap actual classifier, normalitas dari data ini tidak dapat ditentukan secara akurat.Karena alasan ini Wilcoxon rank-sum test digunakan untuk membandingkan antara nilai cross validation dari aktual classifier dengan akurasi dasar classifier. Untuk memvalidasi pemilihan fitur, pendekatan pemilihan fitur rekursif digunakan. SVC dilatih menggunakan semua kemungkinan kombinasi fitur dalam rangkaian mulai dari fitur 1 hingga fitur 9. Metode 10 fold Cross validation diterapkan ke setiap kelas dan akurasi rata-rata cross validation untuk semua fold dan semua klasifikasi digunakan sebagai metrik untuk kinerja setiap set fitur.

	3. OUTPUT Ouput hasil klasifikasi dari penelitian ini adalah berupa prediksi gangguan motorik yang terjadi pada penderita stroke yang dibagi ke dalam 3 kelas. Kelas pertama merupakan pasien yang mengalami gangguan pada anggota gerak bagian atas dan bawah (Combined). Kelas kedua merupakan pasien yang mengalami gangguan hanya pada anggota gerak bagian atas (Upper). Dan kelas ketiga merupakan pasien yang mengalami gangguan pada anggota gerak bagian bawah (lower).
Hasil	
Akuisisi Data	Proses akuisisi data dalam penelitian ini adalah sebanyak empat orang dewasa yang berasal dari pasien rumah sakit Hillcrest sebagai subjek penelitian dengan gangguan stroke. Penggunaan empat akselerometer dipasangkan secara langsung pada masing-masing pasien dengan detail tri-aksial (Akselerometer Axtivity AX3) ditempatkan di ekstremitas kiri atas (LUE = lengan kiri), ekstremitas kanan atas (RUE = lengan kanan), ekstremitas kiri bawah (LLE = kaki kiri), dan ekstremitas bawah kanan (RLE = kaki kanan). Semua akselerometer dipasang dan ditempatkan di pergelangan tangan dan pergelangan kaki pada setiap subjek. Data secara kontinyu diperoleh pada frekuensi 100Hz selama 14 hari atau sampai pasien keluar dari ICU Neurologis.
Hasil Pengujian	a. Hasil dari seleksi fitur rekursif  Terlihat bahwa setiap fitur yang digunakan menghasilkan akurasi di atas garis baseline mean cross validation. Akurasi terbesar dicapai dengan klasifikasi yang dilatih menggunakan semua fitur yang tersedia seperti yang ditunjukkan oleh segitiga biru, dan dengan klasifikasi yang menggunakan semua fitur kecuali besaran rata-rata, direpresentasikan oleh lingkaran merah yang letaknya paling atas pada indeks. Tren penurunan umum diamati karena lebih sedikit fitur yang digunakan untuk melatih model, dan terdapat pemisah yang jelas antara serangkaian fitur tertentu, seperti yang ditunjukkan oleh jarak vertikal yang besar pada gambar.

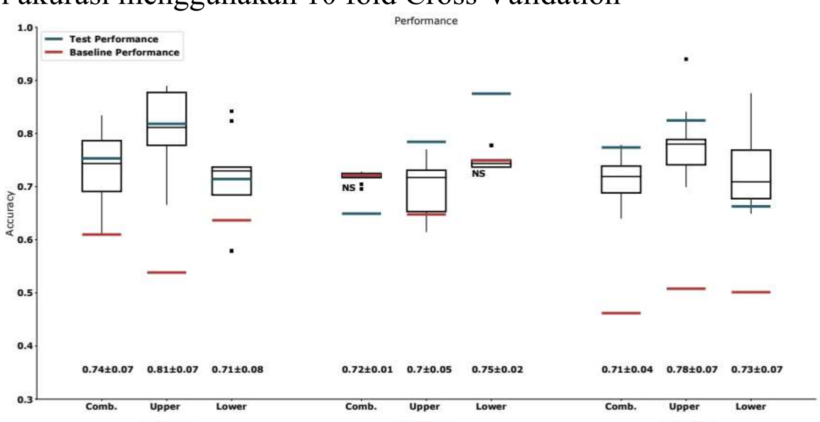
Fitur tunggal dengan akurasi terbesar adalah average magnitude, movement count dan power 2. Lebih detailnya, set fitur berkisar antara fitur 2 dan 7 yang berisi salah satu dari tiga fitur ini selalu muncul di atas jarak vertikal yang menunjukkan kepentingan relatif dari ketiga fitur ini. Masing-masing klasifikasi dilatih menggunakan semua fitur karena perbedaan dalam kinerja cross validation antara antara 8 set fitur berkinerja tertinggi dan set fitur lengkap sebelumnya diabaikan.

b. Hasil dari Support Vector Classifier

	Combined	**Upper**	**Lower**
Subject 1	0.74 (0.61)	0.82 (0.56)	0.72 (0.65)
Subject 2	0.50 (0.35)	0.51 (0.61)	0.47 (0.74)
Subject 3	0.66 (0.51)	0.77 (0.51)	0.73 (0.49)

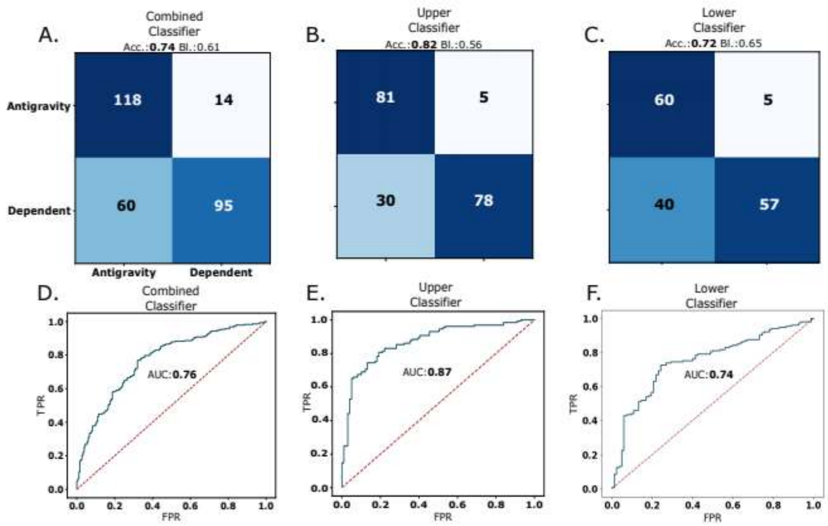
Hasil dari SVC terlatih ditunjukkan pada tabel diatas. Klasifikasi kelas ***combine extremity***, di semua subjek terlatih, rata-rata memiliki akurasi cross validation sebesar 0.72 ± 0,05 dan akurasi set tes 0,73 ± 0,05. Untuk kelas ***upper extremity*** memiliki akurasi cross validation rata-rata 0,76 ± 0,08 dan akurasi set tes 0,81 ± 0,02, dan klasifikasi kelas ***lower extremity*** rata-rata akurasi cross validation sebesar 0,78 ± 0,13 dan akurasi set pengujian 0.80 ± 0,06. Sebagian besar contoh memiliki kinerja cross validation yang secara statistik signifikan (P < 0,05) di atas kelas baseline, dengan pengecualian dari kombinasi (P = 0,25) dan lebih rendah (P = 0.39) klasifikasi ekstremitas untuk subjek 2.

c.Hasil akurasi menggunakan 10 fold Cross Validation



Boxplot diatas mewakili akurasi yang diperoleh setelah melakukan 10 kali cross validation untuk setiap pengklasifikasi ekstremitas dan pengklasifikasi gabungan untuk setiap subjek. Nilai dasar yang diperoleh ditampilkan sebagai garis merah dan akurasi set pengujian ditampilkan sebagai garis biru. Rata-rata ± standar deviasi untuk semua boxplot yang ditampilkan di bawahnya.Tidak ada perbedaan yang signifikan secara statistik antara hasil

<table>
<tr>
<td></td>
<td>cross validation dengan pengklasifikasi dasar yang dilambangkan dengan NS.

d. Hasil akurasi dengan pendekatan Leave One Subject Out


Pada Confusion Matriks diatas gambar A merupakan kelas Combined extremity, gambar B untuk kelas Upper extremity dan C untuk kelas Lower extremity untuk pendekatan leave one subject out yang diuji pada subjek pasien 1. Nilai akurasi pengklasifikasi dan akurasi pengklasifikasi dasar ditampilkan di bagian atas confusion matriks.Pada gambar D merupakan kurva ROC untuk kelas Combined, gambar E untuk kelas Upper dan gambar F untuk kelas Lower. Garis putus-putus mewakili KOP yang ideal untuk pengklasifikasi yang benar-benar acak. Area di bawah kurva KOP (AUC) juga ditampilkan pada gambar.</td>
</tr>
<tr>
<td>Kelebihan</td>
<td>1. Pada paper ini telah menunjukkan bahwa informasi gerakan yang diperoleh dari akselerometer dapat digunakan untuk membuat fitur informatif yang dapat digunakan dalam pengembangan metode pendekatan pemantauan yang baru.
2. Klasifikasi menggunakan metode support vector machine pada paper ini mampu mengklasifikasikan kerusakan anggota gerak pasien pada sisi dependen dan antigravitasi dengan hanya menggunakan informasi gerakan yang diekstraksi dari akselerometer.
3. Waktu komputasi pada penelitian ini termasuk cepat dengan penghitungan seluruh matriks fitur untuk subjek tertentu membutuhkan waktu rata-rata 3 detik, dan menghasilkan sekitar 0,5 milidetik untuk menghitung semua fitur dalam satu peristiwa.
4. Hasil pendekatan leave one subject out pada paper mendapatkan hasil yang menjanjikan dengan akurasi set pengujian maksimum 0,82 pada kelas anggota gerak atas (Upper), dan akurasi rata-rata 0,76 pada semua kelas.</td>
</tr>
</table>

Kekurangan	1. Penggunaan sensor pada penilitian ini memiliki kelemahan karena sensor akselerometer yang dipasangkan pada pasien dalam jangka panjang berisiko menyebabkan iritasi kulit pada pasien. 2. Batasan dari penelitian ini adalah ukuran sampel penelitian yang terbatas hanya pada 4 subjek, ukuran sampel penelitian yang lebih besar diperlukan agar mendapatkan hasil akurasi yang lebih baik. 3. Pada paper ini terdapat keterbatasan yaitu berupa penilaian motorik yang dilakukan pada pasien bersifat subjektif berdasarkan penilaian dari dokter bukan dari hasil rekam medis pasien.

1.3 Kesimpulan Dan Ide

1.3.1 Kesimpulan

Berdasarkan hasil review paper pada penyakit stroke. Maka dapat disimpulkan bahwa:

1. Kondisi pasien stroke dapat dideteksi dengan baik dimana pendeteksian dapat dilakukan pada beberapa bagian seperti bagian kepala (otak), pergelangan tangan bawah, jari tangan, lengan bagian atas dan kaki pasien.
2. Hasil pengujian algoritma yang dapat digunakan dengan hasil yang terbaik dari kelima paper tersebut untuk mengolah data pasien stroke didapat adalah algoritma SVM dan JST.
3. Secara keseluruhan alat dari kelima paper ini berupa alat yang diciptakan secara portabel sehingga akan cukup mudah dalam pengaplikasian nantinya karena tidak terlalu banyak komponen yang cukup memakan ruang.
4. Secara keseluruhan alat dari kelima paper dapat digunakan untuk pengujian berupa alat yang murah dibandingkan dengan alat konvensional yang ada fasilitas kesehatan dimana ini akan membantu masyarakat luas dari segi biaya.

1.3.2 Ide

Secara keseluruhan dari pembahasan review paper ini dapat dibuat suatu alat yang mendukung pendeteksian pada beberapa bagian tubuh dengan menggunakan satu alat saja sehingga pengaplikasian alatnya menjadi portable dan membuat biaya dapat dijangkau oleh masyarakat luas, yang pendeteksiannya tidak hanya berupa data EEG tetapi dapat menggunakan sinyal yang lain seperti EOG dengan pemantauan nantinya dalam keadaan istirahat maupun tidak. Alat ini nantinya dapat diterapkan suatu sistem untuk memberikan pesan yang akan memberi tahu pasien, keluarga, dan petugas medis tentang keadaan pasien secara konkret nantinya. Pada kasus pasien yang tengah rawat jalan untuk treatment rehabilitasi dapat digunakan alat yang portabel yang nantinya data hasil pendeteksian maupun rehabilitasi dapat disimpan secara hardware maupun software serta untuk membantu tenaga medis nantinya dalam pengaplikasiannya sehingga dapat menggunakan teknologi Virtual Reality untuk membantu agar pembacaan perekaman dapat lebih interaktif dan memberikan gambaran secara jelas.

1.4 Link Video

https://drive.google.com/file/d/1HocOKLbyoNggjLp2VXFCQbTKGBn7mgMd/view?usp=sharing

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Remote Monitoring of Physical Rehabilitation of Stroke Patients using IoT and Virtual Reality

Octavian Postolache
ISCTE- Instituto Universitario de Lisboa
Instituto de Telecomunicações
Lisbon, Portugal
opostolache@lx.it.pt

Ricardo Alexandre
ISCTE – Instituto Universitario de Lisboa
Instituto de Telecomunicações
Lisbon, Portugal
rjfae2@gmail.com

Oana Geman
Health and Human Development Department, Stefan cel Mare University(USV)
Suceava, Romania
oana.geman@usm.ro

D. Jude Hemanth
Department of ECE, Karunya Institute of Technology and Sciences
Coimbatore, India
judehemanth@karunya.edu

Deepak Gupta*
Maharaja Agrasen Institute of Technology, Delhi, India
Federal University of Piauí, Teresina – PI, Brazil.
deepakgupta@mait.ac.in

Ashish Khanna
Maharaja Agrasen Institute of Technology, Delhi, India
Federal University of Piauí, Teresina – PI, Brazil.
ashishkhanna@mait.ac.in

***Abstract*—The statistics highlights that physical rehabilitation are required nowadays by increased number of people that are affected by motor impairments caused by accidents or aging. Among the most common causes of disability in adults are strokes or cerebral palsy. To reduce the costs preserving the quality of services new solutions based on current technologies in the area of physiotherapy are emerging. The remote monitoring of physical training sessions could facilitate for physicians and physical therapists' information about training outcome that may be useful to personalize the exercises helping the patients to achieve better rehabilitation results in short period of time process. This research work aims to apply physical rehabilitation monitoring combining Virtual Reality serious games and Wearable Sensor Network to improve the patient engagement during physical rehabilitation and evaluate their evolution. Serious games based on different scenarios of Virtual Reality, allows a patient with motor difficulties to perform exercises in a highly interactive and non-intrusive way, using a set of wearable devices, contributing to their motivational process of rehabilitation. The system implementation, system validation and experimental results are included in the paper.**

Keywords—physical rehabilitation, virtual reality serious games, wearable smart sensors, Internet of Things

I. INTRODUCTION

The changes in the industry of healthcare for some years this part has been one of the most transformative. The industry that was previously restricted between doctors and patients, now has a third-party member attached – Technology. Although the information and communications technology has already found its place in the field of medicine and its operation, nowadays it is an integral part and dominates the market of healthcare at the patient level. The objectives of personalized interactive training with higher motivation from the patient side are nowadays satisfied joining technologies such Virtual Reality (VR) and wearables devices. Both technologies, while impacting, are allowing themselves to create a greater presence and impact in the lives of patients and physicians in partnership with devices that are always with them. Due to technological evolution, healthcare mobile apps becoming an integral part of users' home screens, when mixed with transformative technologies like VR and wearable healthcare devices, they have the immense potential to change the way the health ecosystem interacts with the masses and are increasing in Healthcare domain. The mobile devices together Mobile Apps are used as computation platform, as communication platform and as Graphical User Interface (GUI) for patients and clinical staff. One of the motivations of this research is to improve the quality of physical therapy services and to decrease the costs in the context of the pressure on the services caused by aging phenomena [1]. Ageing as a natural process it is in generally accompanied with degradation of daily motor activity associated with muscle-skeletal impairments that may also occur after stroke events.

The post-stroke patients are another group of the population that requires physical rehabilitation services to improve their motor skills. The reported statistics underline the stroke as the number one cause of severe physical disability in world [2]-[4]. If secular trends continue it is estimated that there will be 23 million first ever strokes and between 7-8 million stroke deaths in 2030 [4]. Strokes can usually cause severe physical disabilities, such as attention deficit, pain, weakness and paralysis, usually on one side of the body. Such deficiencies may result in loss of ability to perform typical day-to-day activities [5-7]. Several methodologies can be developed for improving the lifestyle of stroke patients [5]-[15].

Patients need to practice physical rehabilitation exercises to improve their motor condition, the exercises being recommended in the physical therapy clinics but also at home to reduce the rehabilitation times which will help patients to improve their psychological conditions. In addition, recent studies reveal that early and intensive rehabilitation may lead to recovery of motor function capacity [16], [17]. The traditional rehabilitation process based performed with classical physical rehabilitation equipment requires repetitive exercises that may be annoying and mundane [18]. Consequently, this could lead to patients' lack of interest and reduced motivation for the rehabilitation process, which can have serious consequences for their rehabilitation quality and rehabilitation period with higher costs for the healthcare system. Daily physical rehabilitation program requires that patients go to the hospital or rehabilitation center for training. This requires a lot of effort in patients who are already suffering from mobility difficulties. Often, some of the patients cannot go to rehabilitation centers because of the cost involved [19]. Even if the cost is not the problem, the patient may not have the incentive to go to a rehabilitation center to perform the exercises. The reported research underlines the relation between the improvements of motor functionalities and patients' motivation [20] and good communications based on objective data between the patients and caregivers.

In times of continuous high technological and economic progress, many people are affected by physical and/or motor limitations due to a variety of reasons, as well as depression caused, among other things, by the need to resort to rehabilitation sessions. Scientists are constantly on the lookout for new ways to prevent and treat physical disorders, as well as ways to intervene in diagnosis to make it more prosperous and effective for those in need of permanent care, using the latest achievements in computer science. The health community has shown an increasing interest in therapeutic approaches based on different Virtual Reality scenario applications [21]. Stimulated by the progress in game development and computer graphics hardware, serious games are getting involved in many institutions like military, health, education and entertainments. Virtual reality (VR) has been used in physical rehabilitation to engage patients who suffer from stroke to train upper limb motion. In the literature several VR games are reported regarding the physical rehabilitation [22]. The used games are giving to patients the ability to interact with virtual objects in real-time during physical training sessions improving their particular motor skills. The therapists are responsible for setting the system for patients according with particular prescription.

On the other hand, there has been an exponential increase in the market offer on the level of body measurement sensors available as wearable devices, allowing users to create monitoring applications - starting with a simple heart rate to a limb movement response. These sensors create different datasets available in real time for different data discovery techniques by the researchers, for example, in the feedback process. The big growth of the measurement sensors capabilities and the networking technologies are found to be very useful for healthcare applications [20-35]. The IoT healthcare solutions are already visible on a global scale, where traditional equipment are replaced by new ones IoT compatible devices that provide the possibility to develop and apply new practical methods as part of healthcare services. The wearables solutions are able to revolutionize healthcare services where physiological and motor parameters are monitored to provide personalized healthcare based on information regarding health status, physical activity, behavior and other parameters such air quality that affect the quality of daily life [27].

II. Related Work, Research Challenges and Novelty

Wearable devices have become a very convenient solution to track a patient's health status. There are now reported an increased number of medical wearable devices that not only help monitor but also for treat and rehabilitate chronic diseases, such as devices equipped with ECG and EMG biosensors to detect cardiovascular diseases [19], devices equipped with electro-muscular stimulation to promote muscle activation and recover injuries [20], or pressure and force sensors applied in insoles and connected to software tools (mobile or web apps) to allow the analysis and monitoring of a patient's gait [21].

Several studies are being carried that present new ways to adapt the new technologies from IoT industry [22], [23] and VR gaming tools [24], [25] to create new healthcare solutions with focus on physical rehabilitation. The immersion provided by games and capacity of measuring various types of data with advanced wearable computing technology and miniaturized sensors, has been considered an excellent solution to response to physical rehabilitation challenges. Serious games involve different technologies such as Virtual Reality (VR), Augmented Reality (AR) or Mixed Reality (MR), sensors, telecommunication technologies, computing interfaces and dedicated servers or cloud services, as well as related in [26]. These technologies can support accurate and detailed capture of kinetic and kinematic complex variables during motor rehabilitation (e.g. standing or walking pressure, time and speed of limbs movements).

Virtual Reality (VR) is described in [27] as "a high-end user computer interface that involves real-time simulation and interactions through multiple sensorial channels" has induced a sense of "presence in" and "control over" the simulated environment [28], [29]. In the reported research presented in [30], the authors proposed a platform that might use various devices (such as Microsoft Kinect, Nintendo Wii Remote, Data Glove or CyberGlove, Leap Motion Controller) and open source software to create low-level keyboard and mouse events that most games treat as input from a real peripheral device. In order to approach the physical rehabilitation services with all the technologies reported in the relevant literature presented, this study is conducted with the objective of exploring a viable solution to fill the need for a rehabilitation system that will help patients and physical therapy clinics, whether in the evolutionary process of patient monitoring as well as the points of reduction of costs associated with each rehabilitation process.

We identify that such a system should be able to allow patients to perform remote physiotherapy at home according to some indications which will be provided by the caregivers. This will reduce the number of patients that need to go to the clinics and increase the commitment of the patients with their rehabilitation process. Such a system was designed to perform the physical therapy assessment of the patients analyzing their progress. This publication results from the further development of the studies presented and reported by the authors in [36-50].

III. Materials and Methods

A practical approach regarding optimized physical rehabilitation process based on VR serious game with emphasis on data analyses of the data extracted during the training session where the patients are using wearable sensor devices to interact with VR game scenario. The proposed system in Fig. 1 is expressed by a low-cost hardware and software components that provides Virtual Reality (VR) interaction during therapeutic serious games. As core of the system can be mentioned an IoT Wearable Sensor Network (WSN) expressed by a set of smart sensors embedded in a pair of gloves and a headband.The VR serious games were implemented using Unity 3D software which also includes an IoT module and sensors. The smart gloves materialize a natural interface applied to motor and physical rehabilitation of in users with hands and fingers motion impairments.

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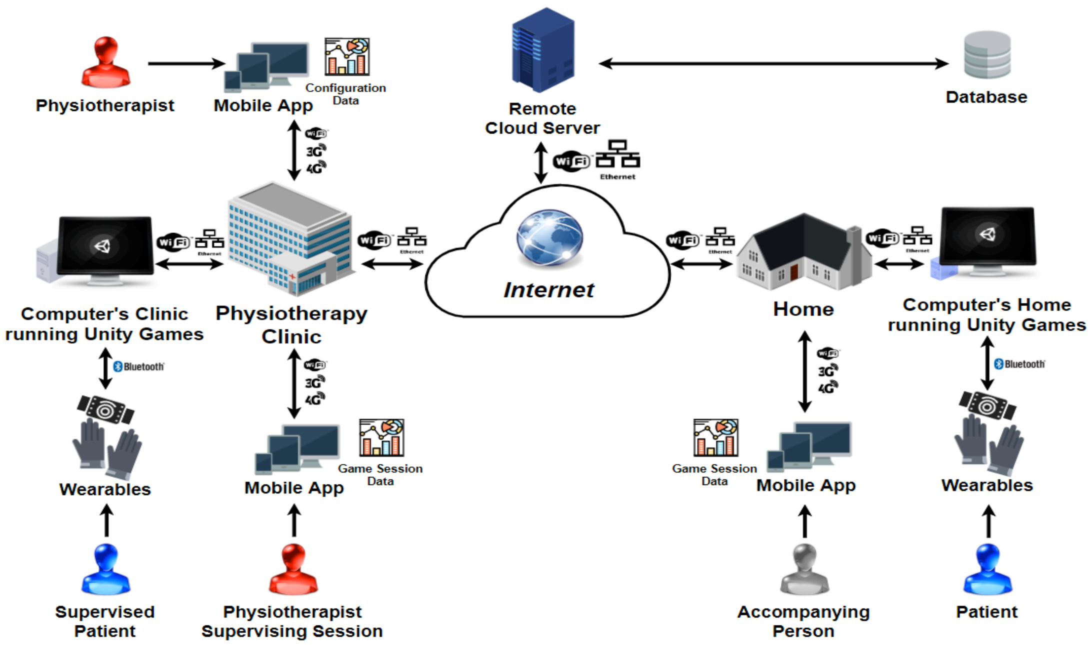

Fig. 1. The VR serious game physical rehabilitation system with wearable user interface

The headband device that includes an Atmel AVR based computation platform connected to an IMU is responsible to the measurement of the rotation values (Euler Angles) and linear accelerations of the head with the aim of integrating the patient into First-Person Controller, allowing the navigation in the VR environments of serious games, in a semi-immersive way. These measurements can be also used to evaluate the posture of the user during the training using the serious games.

The wearable devices are using Bluetooth communication to deliver the data from the measurement channel to clinic computer or to the home computer that it is connected to the Internet. The mobile devices are using Wi-Fi Internet connectivity and can be used by physiotherapist, patient or accompanying person. The clinic manager performs the management of physiotherapists. While playing the serious game the patients interacts with the system and motion characteristics performed by these users are registered by the system. The physical therapy training sessions are performed in physiotherapy clinics where the patient is under physiotherapist supervision or at home environment without specialized supervision, such as it is shown in Figure 1. At home accompanying person may give support and also can verify through the mobile APP the results of the performed sessions. Either way, the user's experience is the same. Following this, the therapists access this information through the mobile application, using a computer, a tablet or a smartphone. The patient's motion calculated metrics are presented through graphical representations. A textual report can be generated by physiotherapists based on calculated metrics that also assure a feedback for the patients, improving communication physiotherapists and patient for active commitment to the rehabilitation process.

System software modules and interactions are:

- **Physio Wear Mobile Application** is developed in Microsoft Xamarin using C# programming language. These are used by the clinical administrators, physicians and the patients.
- **Smart Wearable Devices** (smart gloves and headband) developed with the Arduino Platform for use with therapeutic serious games by patients, connected to host computer with serious games via Bluetooth.
- **Physio Wear Gaming Application** helps the patient to assess the therapeutic virtual games.
- **Web Server** is mainly used to store the large amount of data. It can be both the inputs and the results.

Both the Unity game application and the mobile application require an Internet connection (Wi-Fi, 3G or 4G) as well as the server side itself, to allow the Web API to perform in the processes of reading or writing the data in the database.

A. *System Description: Sensors*

The kinematic and dynamic characterization of the hand usage during the training sessions implies the usage of different measurement channels that are associated with:

- Acceleration (tri-axial acceleration);
- Orientation (tri-axial orientation);
- Force (compression and extension).

The measurement channels are including the sensors, conditioning circuits and/or wired communication interface connected to the computation platform (Arduino nano) that materialize the sensor and edge layer of Healthcare IoT architecture for physical rehabilitation presented in Fig 2. As it can be observed the force, flexion and inertial qualities measurement are associated with sensor layer. Thus, for the finger applied force and finger flexion two sets of piezo-resistive sensors were considered as part of smart gloves (Fig.2). Thus, a set of 5 piezo-resistive Flexi Force A201 sensors to extract the pressure values exerted on the tips, as well as a set of 5 piezo-resistive FlexSensors 2.2", to obtain finger flexion values are considered. The measured values of finger flexion and the finger applied force by fingertips are visualized in the VR scenario developed on Unity 3D gaming platform. Considering that the analog inputs of microcontroller are voltage compatible the conditioning circuits for the force sensor channels are expressed by resistance to voltage converters expressed by voltage divider and a follower based on operational amplifier LM324.

The acquisition of the signals associated with 10 analog sensors for each glove is performed using the Arduino Nano that will be later described. To reduce the number of analog input channels time multiplexing methods was implemented on the level of the microcontroller. So, it was possible to acquire reliable readings from two different analog sensors associated with each finger using a single analog input channel.

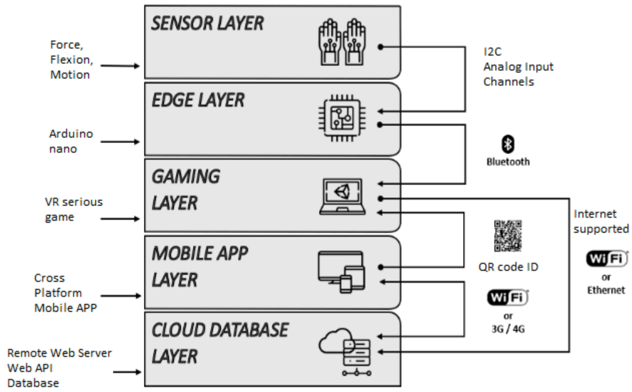

Fig. 2. Healthcare IoT architecture for VR serious game

To extract hand motion information a set of SparkFun MPU-9250 IMU Breakout were used. The MPU-9250 IMU is a 9-axis MEMS sensor that combines two chips: the MPU-6500, which contains a 3-axis gyroscope as well as a 3-axis accelerometer, and the AK8963, which features a 3-axis magnetometer. The acquisition of 9-axis information is performed by 16-bit analog-to-digital converter. By data fusion it is possible to obtain the linear acceleration values and reliable values for the rotational movements.

B. System Description: Computation platforms

The implemented system that supports VR serious games is characterized by different computation platforms materialized on the edge layer, gaming layer mobile APP layer and cloud database layer. The edge computation layer is expressed by Arduino nano that is based on low power consumption (Power Consumption: 19 mA) of Atmel AVR ATmega328P microcontroller, breadboard-friendly board with reduced dimensions (PCB size: 18mm x 45mm), very light (Weight: 7g) and works with a Mini-B USB cable with operating voltage of 5V, that it is characterized by 10bits ADC and 8 multiplexed analog inputs, with built-in input/output support, a standard programming language, which originates from Wiring, and is essentially C/C++.

The acquired data from the sensors are primary processed by an Arduino nano, the processed data is wireless transmitted to the gaming platform. The wireless transmission is based on Bluetooth protocol which use Module HC-05 connected to the Arduino board using serial port. With the Bluetooth Module, any communication between an Arduino and mobile APP layer or gaming layer can be carried out. The edge layer that includes the Arduino with Bluetooth communication module is powered by a battery pack of 3.7V 2050mAh.

The system was designed to be applied in common physical therapy clinics and in these conditions the system costs become critical in regarding system adoption in the large scale. A cost estimative can be considered as one of the starting points of the adoption. In the Table I is presented the cost estimative of the architecture presented in Figure 2.

TABLE I COST ESTIMATIVE OF HEALTHCARE IOT ARCHITECTURE FOR VR SERIOUS GAME

IoT layer	Components	Cost Estimative
Sensor Layer	10xForceS, 10xFlexionS, 3xIMU, Conditioning circuits, gloves, band	350$
Edge layer	3xArduino nano 3xBluetooth HC05	100$
Gaming layer	1xminiPC Gigabyte 1xHDMI monitor	900$
MobileAPP	1xTablet	450$
CloudDatabase Layer – Remote server	Cloud Service for year 128GB, 4GB RAM, dual core Xeon	<100$

Using the implemented prototype, which costs were considered for an easily adoption, the following data associated with the rehabilitation session are obtained:

- Euler Angles (head and upper limbs rotation values);
- Linear acceleration associated with head and upper limbs dynamic and kinematic characterization;
- All five Fingers' flexion (based on flexion sensors embedded in the glove devices);
- All five finger to finger contact force values (based on force sensors embedded in the glove devices).

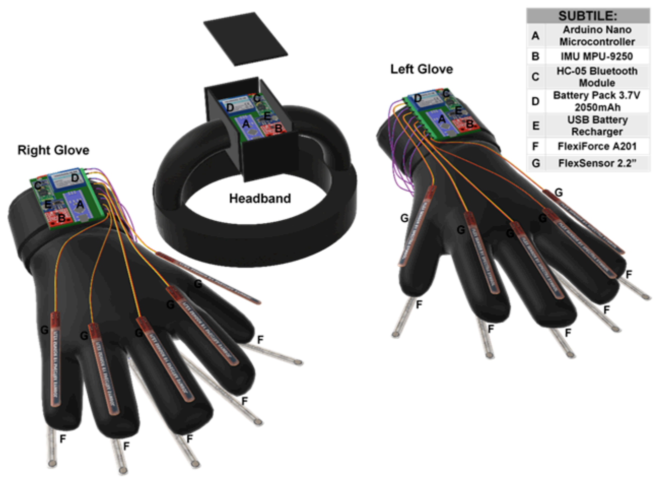

Fig. 3. The final prototypes of wearable devices developed, presented on a 3D object schematic with all smart sensors connected in right places. The green board represents the Printed Circuit Board where are placed all hardware components. The black cover on the headband represents the box of devices and are opened in figure

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Fig. 3 shows the developed final prototypes of wearable devices used for user VR serious game interaction that was already reported by authors in [50].

C. System Description: Embedded Software

The development of new devices that include the use of IMUs, by definition are MEMS (Micro-Electro-Mechanical Systems) [51], can contemplate accelerometers, gyroscopes and magnetometers (and also barometers), allowing accurate measurements on the positioning of the devices themselves through the use of sensor data fusion algorithms. However, MEMS IMUs are vulnerable to various types of noise and errors. An Attitude and Heading Reference System (AHRS) algorithm [52] is necessary for such arrangements. In this algorithm, the new position is calculated from the previous calculated position (equation 1), the measured acceleration and the angular velocity, these errors accumulate approximately in proportion to the time since the initial position was introduced.

$$Position_{x,y,z}(t_{final})=Position_{x,y,z}(t_{start})+Position_{x,y,z}(t) \quad (1)$$

The double integration of residual accelerations over time to obtain a change in position values is simple at first, but not really that simple. Accelerations can be mathematically integrated once for speed value changes and twice for position value changes.

By utilizing the acceleration values, the rotations around the X-axis (Roll) and around the Y-axis (Pitch) can be calculated. Thus, if AX, AY, and AZ are the values of acceleration for X, Y and Z axes respectively, the Roll (2) and Pitch (3) angles (in radians) are given by:

$$Roll = \tan^{-1}\left(\frac{A_Y}{A_Z}\right) \wedge Pitch = \tan^{-1}\left(\frac{-A_X}{\sqrt{(A_Y)^2+(A_Z)^2}}\right) \quad (2)$$

$$Roll = \tan^{-1}\left(\frac{A_Y}{\sqrt{(A_X)^2+(A_Z)^2}}\right) \wedge Pitch = \tan^{-1}\left(\frac{-A_X}{A_Z}\right) \quad (3)$$

In order to measure rotation around the Z-axis (Yaw), the other sensors data need to be considered together the accelerations' data. The following flowchart (Fig. 4) shows the same process using quaternions [53]:

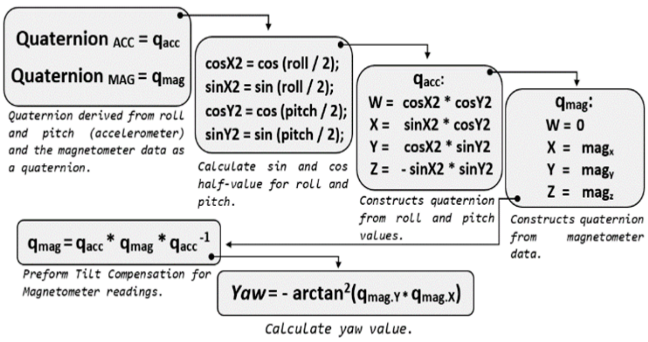

Fig. 4. Flowchart showing calculation of yaw using quaternions based on RTIMULib-Arduino [53]

In our case, for the implementation of an AHRS algorithm, we base the sketches on the available libraries in github public repository to perform the set of many IMUs, as the case of RTIMULib-Arduino from richardstechnotes' github [53], and MPU9250 library from the kriswiner' github [54].

During the game, the finger flexion values (extracted from FlexSensors 2.2''[55]) and tips finger force (extracted from FlexiForce) are visualized on the VR developed in Unity 3D. In other words, for each clock cycle, two sensors are read on the same analogue input port. The Arduino function digitalWrite(HIGH) command sets to 1 the digital input value that feeds the electrical circuit of the first analog sensor, then the digitalWrite(LOW) command sets this value to 0, a very short time delay (order of milliseconds) is applied and repeat the process for the second analog sensor. This procedure is performed simultaneously in each of the analog ports that will make the data acquisition of piezo-resistive force sensors.h axis.

The corrections are done using quaternions, to obtain reliable values of the Euler angles (roll, pitch and yaw). A Kalman Filter, as it is presented in [54], is used to perform the tilt compensation of the readings obtained from the accelerometer and the magnetometer. For such uses the quaternions to merge with the Gyroscope readings. From this fusion results the AHRS algorithm for reliable object orientation. The data fusion algorithm can be found in the RTIMULib-Arduino library in the RTFusionRTQF.cpp file. In Figure 11 is demonstrated how create AHRS algorithm in different stages using quaternions based RTIMULib-Arduino [56].

IV. System Description: Virtual Reality Serious Game

The gaming mechanism is a fundamental component in the development of a video game. It is a computer program or a set of libraries that helps to simplify the development of video games or other type of applications with real-time graphics. There are several gaming mechanisms that can be used to develop 2D or 3D video games, each with certain features to assist the developer in developing. In our case, the application that contains the VR scenarios was developed in Unity Game Engine using programming language over C# scripts, to re-create all interactions by users. The main aspects are the physical interactions between the scenario and the present objects. The communication between Arduino microcontroller and the PC where Unity is running is mediated using the serial port associated to the Bluetooth communication. The class SerialPort is the one that mediates such communication in C# language. The first tests of communication between the Arduino and the PC were realized with USB cable, and later it was configured the Bluetooth connection, that also is based on a serial communication.

For virtual hands materialization some object textures were considered. A software suite provided by the Leap Motion Company was used, which provides a Unity 3D project that has several examples [53] to help the programmer create new applications (Figure 4). These project does not just provide examples, it also has different objects representing hands and arms of different colors, genres and sizes, and provides several scripts already programmed and ready for use. Figure 4 (a) shows the hand (and forearm) object textures for a male avatar, placed in the correct positioning. Some methods have been developed to allow the representation movements of the virtual objects defined by the fingers. Therefore, each reading obtained

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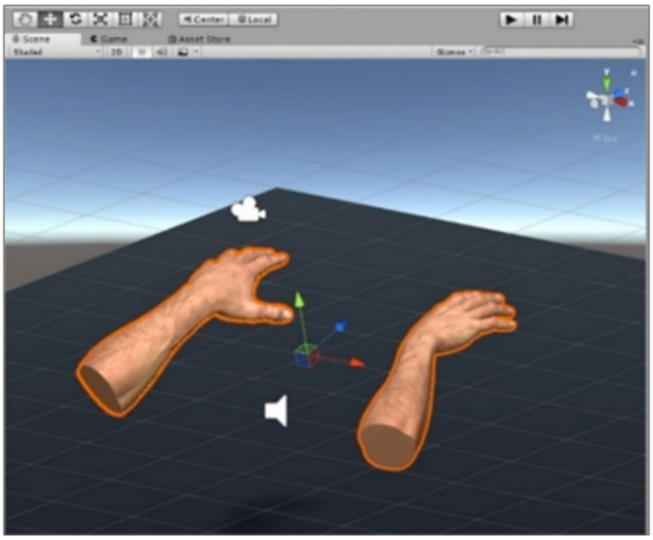
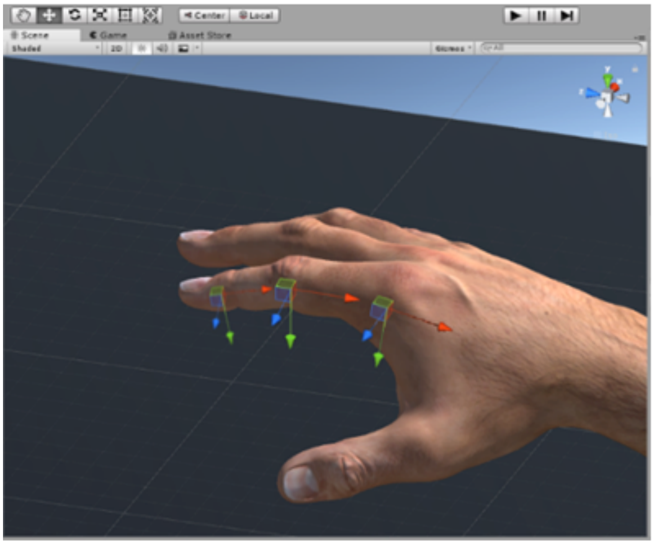
from the Flex Sensors 2.2" will act on 3 finger segment joints, allowing the creation of fluid movements to open and close each finger in the virtual scene. These values, then multiplied by a constant scale factor, are placed with a rotation input value at the junction between two segments of each finger (which has 4 segments per finger). The combination of these methods to act simultaneously in each of the fingers, allows creating interactive virtual movements of the hands and fingers. Figure 4 (b) shows the fingers object textures with points were the flexion readings obtained from gloves will be applied.



(a)

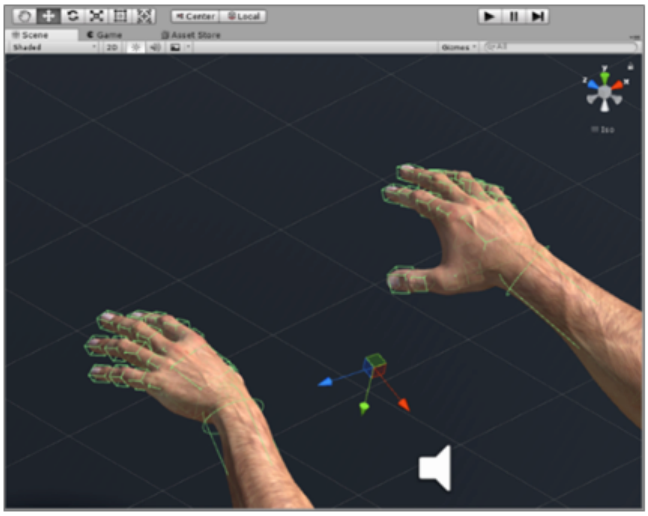


(b)

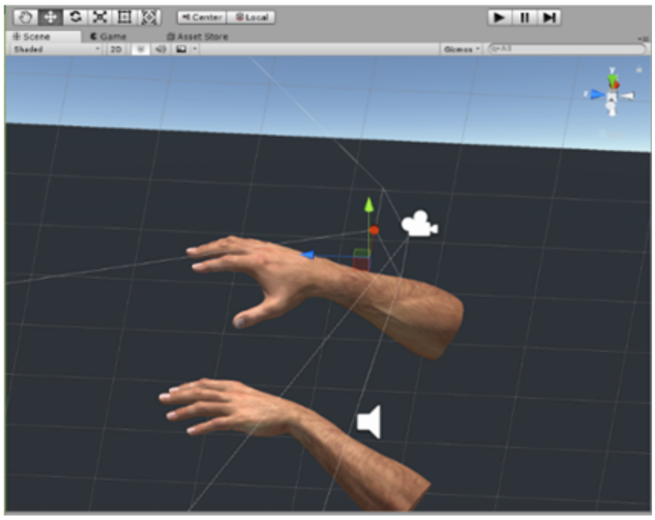
Figure 4. (a) Hand (and forearm) object textures for a male avatar imported from Leap Motion project [55]; (b) Finger object textures with points were the flexion readings obtained from gloves will be applied

The possibility of interacting with virtual scenario, such as grabbing and dropping virtual objects, implied the inclusion of some Collider components in the hands, that define the shape of an object for the purposes of physical collisions (Figure 5). A collider, which is invisible game component, don't need to be the exact same shape as the object's mesh, and in fact, an approximation is often more efficient in data processing time and indistinguishable in gameplay. The Figure 5 (a) shows all collider components (Green Shape Lines) included in both hands texture objects.

The smart headband will be responsible for collecting the head rotation value of the patient, which will be used as the rotation input of the player's avatar head that is the scene camera. Figure 5 (b) shows the scene camera placed on the avatar's head in the game. The remaining elements of the scenarios were created from simple objects (cubes, spheres, capsules ...) and colored with their own textures, such as tennis balls or beverage cans, or imported as whole 3D objects from tools available on the web, such as ping pong paddles or table tennis. Considering the exercising in physical rehabilitation and the main goal to recreate a virtual environment that enhances the physical performance of some people with motor disabilities on upper limbs, two games were developed: The Cans Down challenge and the Coffee Pong challenge.



(a)



(b)

Figure 5. (a) Set of collider components attached on hands texture objects; (b) Scene camera placed on the avatar's head position

Both games are played by direct user interaction with the VR scenario using the smart devices created (smart gloves and smart headband) described above. The main goals of

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our serious games are performing movement of the fingers and arms grabbing virtual objects and throw them in a certain direction, training in this condition also the posture of the body.

In the first developed game, the goal is to knock down the stack of cans by throwing the tennis balls that appear in the golden goblets (Figure 6 (a)). A virtual ball will be grasped if two fingers of a virtual hand touch it simultaneously (the thumb and the other finger of the hand). The ball will be thrown if the fingers of the hand are open and without contact with the virtual object at the end of the arm movements. The user can earn points if he can hit the cans (one point for each can knocked down).

Considering the customization of the game for the users, a second VR serious game was developed (Figure 6 (b)). The second game focusses on accurate measurements of flexion, extension, adduction and abduction of the metacarpophalangeal, proximal interphalangeal and distal interphalangeal joints of the tiny finger motion. The aim is to promote combined movements of both members. The IMU modules required frequently calibration. Thus, the IMU's magnetometer is calibrated at the place where the exercises will occur before any type of data acquisition is performed. This is necessary because exist variations of magnetic field verified from place to place. It is a little demanding on a technical level since it involves placing in the Arduino devices a script (from a library) to acquire magnetic field readings while the devices are rotated in all directions. When there were no variations in the readings, the data is written to the internal memory of the devices, in order to construct reliable values of the rotational movements using the merge algorithms of the raw data. This process involves running a script on the Arduino before start gaming session to access the IMU's magnetic calibration data and rotate the devices in all directions to record the magnetic field mapping.

Figure 6. Therapeutic Serious Games in Unity3D: (a) Cans Down challenge; (b) Coffee Pong challenge, respectively

In order to be able to play the games on any Monitor / TV screen, at the beginning of each training session in the virtual reality scenarios, it is necessary to establish a reference for the wearable devices of the position where the monitor will be located in front of them. The user must be oriented with Monitor.

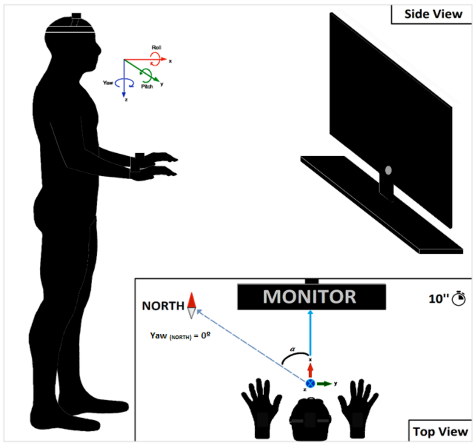

Figure 7. IMU reference calibration to Monitor. The α angle represents the difference of the calculated angle (in degrees) between magnetic NORTH and TV/Monitor where the game runs

This process is performed automatically within the game software at the first 10 seconds of each session. The difference of the position of the monitor is calculated, against the reference of the magnetic NORTH provided by the IMUs as Yaw = 0 degrees. This process allows you to provide correctly orientation of devices to the monitor where the interaction exercises will be performed. Figure 7 represents how the process of IMU reference calibration is done on the gaming start. After the process is completed all rotation data for both limbs and head are collected based on the recorded yaw value for the monitor. This will correspond to the direction in which you want the user to direct their movements.

Figure 8 shows a sequence of moments of a movement in the Cans Down game, where the user uses his left hand to grab the virtual object (represented by the tennis ball) with his fingers closed (a), then flexes his forearm to simulate a movement of applying kinematic force to the object (b), and finally performs the movement of throwing the virtual object towards the Monitor, where is the objective of the game (represented by the stack of cans to be dropped), ending its movement with their fingers extended (c). Some considerations related to adaptability were included in the development of serious games. One of the points to be mentioned is the adaptability to the patient's gender, where for a male patient, the scene initiates the avatar of the player with a kit of masculine textures, and if the patient is female the textures to load refer to male / female hands. The feedback of the game is one of the most important components to encourage the patient to continue playing the game. In any game whether it is video game or a serious game, it must have a mechanism to respond to the actions performed by the user, for example, whenever the user correctly performs a goal a feedback must be given.

Figure 8. Sequence of moments of a movement in the Cans Down game, to grab a tennis ball and hit the cans: (a) grab the ball; (b) flex arm to apply kinematic force; (c) throwing to the cans

The feedback can be divided into two aspects, visual and auditory. With respect to the visual aspect this can be used to show a message indicating that you have performed a sequence of objectives or even to indicate how many points the patient won or lost by performing a certain task. As for the auditory aspect, this can be used as background music, or in the case of performing a positive or negative task, for example, releasing a sound clip that conveys a sense of success in the case of a positive task, or a clip sound that conveys a sense of failure in the case of an unfinished or failed task. Developed application games provide feedbacks, both visual and auditory. In the case of the Cans Down game, auditory feedback is used when the patient throws a ball to stack of cans and the background music is used during play so as not to make the game monotonous if the patient cannot hit the cans with ball. Visual feedbacks are used in several situations:

- To indicate whether the patient gained points hitting the cans with balls;
- To indicate the patient how many balls are picked up.
- The timer present in all games informs the remaining time.

In Both games have visual feedback about Force measurements acquired from FlexiForce Sensors from each fingertip in real time are presented to the user for biofeedback purpose in lower corners.

V. Data Analysis

During rehabilitation sessions, data are collected and stored as part of Physical Rehab Electronic Health Record. The data is accessible through the mobile application, that serve for future analysis on the physiotherapists' level. After being logged in, and after receiving the active exercise plan, the game scene for each exercise plan is loaded. After the connection is established with the three devices, the session is created, and the collection (through a parallel process independent of the reading thread) of the data received from the three devices during the execution of the exercises and recording in the database is initiated. The acquisition process starts after ensuring that the current session was created for the loaded plan. For each of the devices a set of readings is created, for our purpose defined in 200 rows of data, which each time this set is filled is sent to the database. At the end of each session, the scores for each game are also sent to the database together the corresponding parameters of hand motion. For each hand, the collected measured parameters are described below:

- The rotation (Euler Angles) values and linear accelerations of the forearms are obtained and validated by the IMU module. The values of rotations are stored in degrees (-180º to 180º) and linear accelerations are stored in m/s^2.
- The flexion sensors (FlexSensors 2.2") capture the angular flexion and extension values exerted by each finger on each hand. The values are stored in degrees (0 to 90º) of bending according previous calibration in local variables of the embedded software (Arduino Platform).
- The Force Sensors (FlexiForce A201) capture the pressure force values exerted by each fingertip on each hand. The values are stored in percentage of measured force according previous calibration in local variables of embedded software (Arduino Platform) where 0 % corresponds to no readings measured and 100 % to maximum value measured.

The measured collected data associated with head are:

- The rotation (Euler Angles) values and linear accelerations are obtained and validated by the IMU module (-180º to 180º). The values of rotations are stored in degrees (-180º to 180º) and linear accelerations are stored in m/s^2.

The data is stored in a .CSV format to facilitate future analysis and exported to a folder in Game directory. It was created one file for each hand (LEFT and RIGHT) and other to the HEAD. Specific organization of the data was considered and following described. The data to be stored in independent files provides an extra analysis tool so that physiotherapists can perform other types of analysis through the mobile application.

VI. System Description: Mobile App

At the end of each training session, the physiotherapist has the possibility to visualize the results as well as the score obtained by the patient during the rehabilitation performance based on serious games, extracting information about the upper limb motor capabilities and their fingers using a developed Mobile Application which main navigation screens are presented in Fig. 9.

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The data patient data management and data visualization APP was carried out using Microsoft Xamarin using programming language over C# using .NET on Visual Studio 2017 IDE. Xamarin allows developers to program a cross-platform application that can run over Android OS, iOS and Universal Windows Platform, with the same shared code. To run the application, the device (can be a smartphone, tablet or computer) must have access to the Internet, either through a mobile network (3G, 4G) or Wi-Fi.

The navigation screens provide to the physiotherapists possibility to perform login and visualize different information about patient as to add new patient and patient electronic health record. The APP permit to consider new training plan selecting the serious game (e.g. Cans Down) start date-stop date, training duration, hand selection. The physiotherapist can visualize in details kinematic and dynamic values (e.g. forces) associated with executed training plan previously imposed according with the patient needs.

Figure 10 illustrates the sequential diagram of the Pages in the application.

From left top to right bottom

1.1 - Login Page.
1.2 - Master Menu Page
1.3 - Home Page
2.1 - Add Patient Profile Page
2.2. Exercise Plans List Page
2.3 - Add Exercise Plan Page
2.4. Exercise Plan Page
2.5 - Results / Charts Page
2.6 – Obs. Report Page

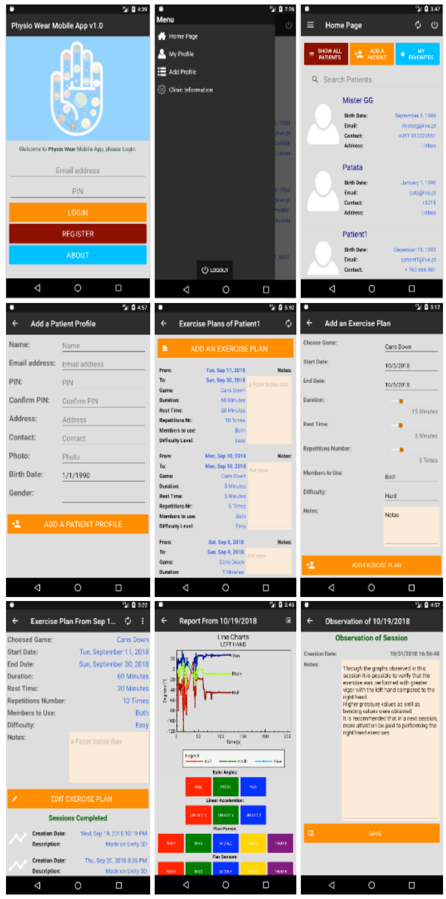

Fig. 9. Mobile APP navigation screens

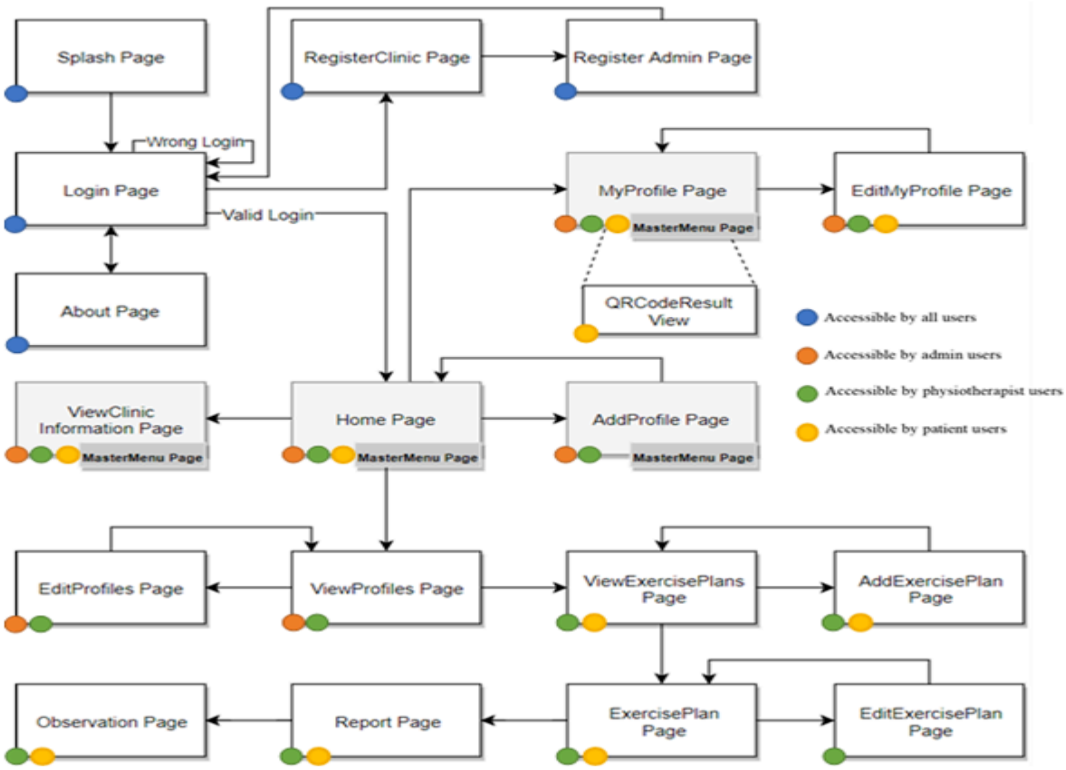

Fig.10. Sequential diagram of the Pages in the Mobile application, for all type of users

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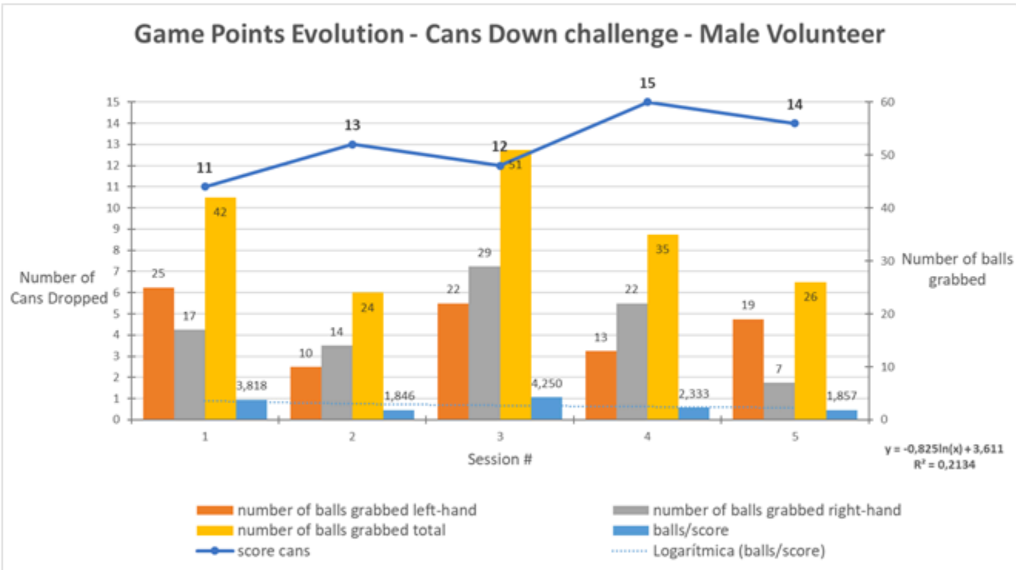
VII. Results

In order to obtain results of usability evaluation of the system developed in the area of physical rehabilitation, several tests to the games and underlying hardware devices were performed.

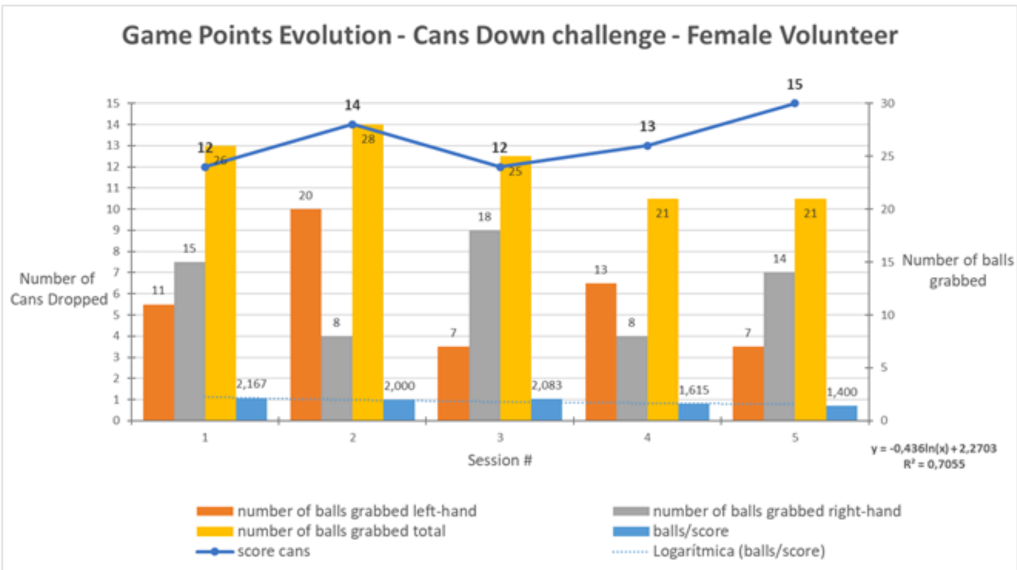
Two healthy volunteers (one male, 26 years old, 179cm tall, and one female, 24 years old, 170cm tall) performed 5 sessions of 3-minute play (180 seconds) at Cans Down challenge, using both limbs to grab the virtual objects (tennis balls appearing in the golden cups) in order to knock down the 15-can stack in front of the player in the game scenario.

The data collected from the sessions were analyzed and are presented in the following graphs of Figure 11.

These graphs show per session the number of balls grabbed for each member, the total number of balls grabbed, the score obtained from the drop of cans, the relationship between the number of balls used and the score obtained and their logarithmic regression. The muscular capabilities are generally higher for male volunteers than for female volunteers and in this context were presented the comparative results. The number of balls grabbed can be considered an indicator about the upper limb motion capabilities for left and right hand.



(a)



(b)

Fig. 11. Game Points Evolution at Cans Down challenge in 5 sessions of 3-minute play: (a) Male Volunteer; (b) Female Volunteer

VIII. Conclusions

The remote monitoring of physical training sessions could facilitate physicians and physical therapists with the information about training outcome that may be useful to personalize the exercises. This will also help the patients to achieve better rehabilitation results in short period of time process.

This research work aims to apply physical rehabilitation monitoring combining IoT, Virtual Reality serious games and Wearable Sensor Network to improve the patient engagement during physical rehabilitation and evaluate their evolution. Serious games based on different scenarios of Virtual Reality, allows a patient with motor difficulties to perform exercises in a highly interactive and non-intrusive way, using a set of wearable devices, contributing to their motivational process of rehabilitation. This methodology can be implemented in real-time situations for stroke and other neurological disorder patients. As a future scope, different methodologies can be incorporated within the IoT set-up to improve the performance of the overall system.

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The Use of A Finger-Worn Accelerometer for Monitoring of Hand Use in Ambulatory Settings

Xin Liu, *Student Member, IEEE,* Smita Rajan, Nathan Ramasarma, *Member, IEEE,* Paolo Bonato, *Senior Member, IEEE,* and Sunghoon Ivan Lee, *Member, IEEE*

***Abstract*—Objective assessment of stroke survivors' upper limb movements in ambulatory settings can provide clinicians with important information regarding the real impact of rehabilitation outside the clinic and help establish individually-tailored therapeutic programs. This paper explores a novel approach to monitor the amount of hand use, which is relevant to the purposeful, goal-directed use of the limbs, based on a body networked sensor system composed of miniaturized finger- and wrist-worn accelerometers. The main contributions of this paper are two-fold. First, this paper introduces and validates a new benchmark measurement of the amount of hand use based on data recorded by a motion capture system, the gold standard for human movement analysis. Second, this paper introduces a machine learning-based analytic pipeline that estimates the amount of hand use using data obtained from the wearable sensors and validates its estimation performance against the aforementioned benchmark measurement. Based on data collected from 18 neurologically intact individuals performing 11 motor tasks resembling various activities of daily living, the analytic results presented herein that our new benchmark measure is reliable and responsive, and that the proposed wearable system can yield an accurate estimation of the amount of hand use (normalized root mean square error of 0.11 and average Pearson correlation of 0.78). This study has the potential to open up new research and clinical opportunities for monitoring hand function in ambulatory settings, ultimately enabling evidence-based, patient-centered rehabilitation and healthcare.**

***Keywords*—Finger-worn ring sensor, Upper Limb Function, Hand Function, Stroke, Rehabilitation, Remote monitoring**

I. Introduction

Stroke is the third most frequent cause of death and a leading cause of disability in adults in the United States [1]. Approximately 50% of stroke survivors suffer from upper limb impairments in the chronic phase, which can be more prominent in one of the two limbs (affected vs. less affected limbs) [2]. Upper limb impairments after stroke often lead to limited ability to perform activities of daily living (ADL) and negatively impact the overall quality of life [3].

In conventional clinical settings, therapists periodically meet with patients in the clinic and prescribe appropriate rehabilitation exercise programs based on their evaluation of patients' functional capacity using clinically validated motor tests, such as Fugl-Meyer Assessment, Active Research Arm Test, or Wolf Motor Function Test [4], [5]. Unfortunately, scientific evidence shows that functional improvements observed and achieved in the clinic do not always translate to patients' home and community settings [6]. In other words, stroke survivors may show improvement in *capacity* (i.e., what they are capable of doing) without much change in *performance* (i.e., what they actually do) [6], [7]. Therefore, objective, ambulatory assessment of motor performance of the stroke-affected upper limb has been of paramount importance in estimating the real impact of rehabilitation, and to support patient-driven therapy and self-management of conditions [8].

Wrist-worn accelerometers have emerged as a potential solution to unobtrusively and continuously monitor patients' upper limb performance outside clinical settings for a long-term period [9]–[11]. Wrist-worn sensors focus on quantifying the duration and intensity (i.e., amount) of arm use based on the counts of the acceleration magnitude [12]. Although these metrics provide simple and intuitive quantification, they capture primarily gross arm movements, such as passive arm swings during walking, which are less relevant to the goal-directed use of the stroke-affected upper limb as part of patients' essential ADL [13]. Consequently, these measurements often result in inaccurate quantification of motor performance [8], [13]. This is considered as a major obstacle to translating research findings into clinically meaningful information and facilitating their widespread use in the therapeutic setting [8].

As an alternate approach to address this limitation of wrist-worn accelerometers and capture more goal-directed use of the upper limbs, researchers have proposed to monitor the hand function during ADL. Various wearable devices, such as instrumented gloves and goniometers, have been introduced to assess the hand function (i.e., amount of hand use) [14], [15]. However, these devices are usually difficult to don and doff, uncomfortable to wear, and socially unacceptable for long-term and continuous daily use, and thus, were mainly restricted to laboratory settings [16]. More recently, Friedman *et al.* proposed a wrist-worn device that can monitor daily use of the wrist and finger joints by measuring changes in the magnetic field produced by a magnetic ring [16]. Despite its feasibility of use in real-world settings, this sensor might be susceptible to ambient magnetic noise.

In this paper, we investigate the use of a miniaturized finger-worn accelerometer, combined with a wrist-worn accelerometer, to monitor hand performance in remote settings

X. Liu, S. Rajan, and S.I. Lee are with the College of Information and Computer Sciences, University of Massachusetts, Amherst, MA, 01002 USA e-mails: {xliu0,srajan}@umass.edu and silee@cs.umass.edu.

N. Ramasarma is with ArcSecond Inc., San Diego, CA, 92131 USA e-mail: nathan@arcsecond.co.

P. Bonato is with the Motion Analysis Laboratory at Spaulding Rehabilitation Hospital, Charlestown, MA 02129 and the Department of Physical Medicine and Rehabilitation, Harvard Medical School, Boston, MA, 02215 USA (e-mail: pbonato@mgh.harvard.edu).

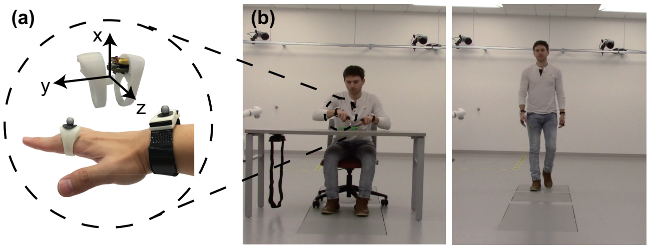

Fig. 1: (a) The proposed body-networked sensor system composed of a finger-worn and a wrist-worn sensor. (b) A research staff member demonstrating a subset (e.g. cutting-putty and walking) of the 11 ADL that was performed during our data collection.

by measuring the amount of hand use. Our main contributions are two-fold. First, there exists no established quantitative measurement for the true amount of hand use during the performance of ADL, against which our sensing system needs to be validated. Hence, we introduce a new benchmark measure of the amount of hand use based on data obtained from an optoelectronic motion capture system, the gold standard for human movement analysis. We validate the test-retest reliability and responsiveness of the measurement during the performance of 11 motor tasks of ADL involving different intensity of hand use in a total of 18 neurologically intact, healthy individuals. Second, we introduce a machine learning-based analytic pipeline that processes the data obtained from the proposed sensing system to estimate the amount of hand use, and validate the accuracy against the benchmark measurement. We also provide a detailed discussion regarding the real-world deployment of the system, such as its ability to enable continuous operation under different network configurations.

II. Sensor System and Data Collection

A. Networked Wearable Sensor System

This study employed a body-networked sensor system composed of a miniaturized finger-worn sensor and a wrist-worn sensor developed by our research team (Arcus, ArcSecond Inc., USA) (see Fig. 1a). The finger-worn sensor contained a nine-axis inertial measurement unit (IMU) that sampled data at 63 Hz, a Bluetooth communication module, a 40mAh battery, and an ultra-low power 32-bit microcontroller. The wrist-worn sensor shared the same system architecture but in a different enclosure for its placement on the wrist.

We hypothesized that the wrist-worn sensor would mainly capture gross arm movements (e.g., arm swing or reaching for an object), whereas the finger-worn sensor would capture both gross arm and fine hand movements (e.g., object manipulation). Thus, we further hypothesized that we could extract information that is specifically relevant to hand use by analytically subtracting the wrist-worn sensor data from the finger-worn sensor data.

This work only leveraged the three-axis acceleration data while disabling the gyroscope and magnetometer because previous studies support that accelerometer data can provide accurate assessment of the amount of human upper limb movements [9], [17], [18], and the use of a gyroscope requires approximately 10 times more power than an accelerometer. For example, our finger-worn sensor with a 40mAh battery would support approximately 5 hours of continuous operation with a gyroscope. This is not practical for continuous monitoring of stroke individuals throughout their daily living. Thus, our work focuses on processing the imperfect data obtained from the two accelerometers within their own coordinate frames (i.e., the orientation of each sensor) using machine learning algorithms.

B. Data Collection

A total of 18 healthy individuals between the ages of 18 and 40 years were recruited from the University of Massachusetts Amherst. All subjects had no major health issues that neglected their ability to follow instructions or independently perform motor tasks involving hand use. Once subjects arrived at the laboratory, they were bilaterally equipped with wearable sensors on the wrist and index finger as shown in Fig. 1. A reflective marker was placed on each sensor for a comparative analysis and to compute the benchmark measurement of the true amount of hand use by using an optoelectronic motion capture system (Miqus, Qualisys, Sweden).

Eleven motor tasks with varying levels of hand and gross arm motor involvement (e.g., passive, unimanual, and bimanual movements) were carefully selected to reflect ADL in real-world environments [19], [20] (see Table I). The motor tasks considered in our work can be categorized into two broad categories: motor tasks that mainly involved passive vs. goal-directed upper limb movements. Furthermore, this work considered two types of motor tasks involving goal-directed movements: movements that mainly involve bimanual vs. unimanual movements. Specifically, unimanual motor tasks were included in order to validate the proposed technology's responsiveness towards changes in the amount of hand use due to a manual intervention (i.e., asking subjects to make use of their non-dominant and to complete the unimanual tasks). Subjects were asked to repeat each motor task three times in their most natural manner (i.e., as if they were to perform in their daily living). For the unimanual motor tasks specifically (Tasks #8-11), they were asked to perform the first two repetitions in a natural manner using their dominant hand (Repetition #1 and #2), and the last repetition by making their best efforts to use the non-dominant hand in order to validate our measurement's responsiveness to an intervention (Repetition #3).

III. Methods

A. Overview of Data Analysis

This section introduces analytic methods to 1) construct a new benchmark measurement of the amount of hand use based on data obtained from the motion capture system and validate its test-retest reliability and responsiveness to an intervention, and 2) to estimate the validated benchmark measurement using data obtained from the wearable sensors (see Fig. 2).

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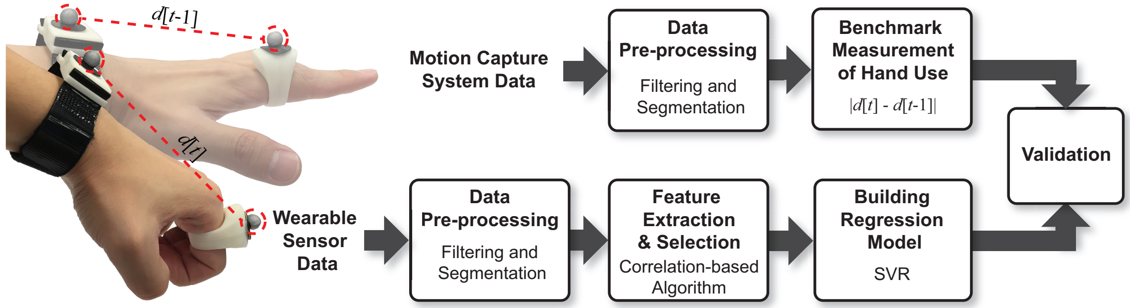

Fig. 2: Analytic pipelines to establish the benchmark measurement of the amount of hand use during the performance of ADL based on data obtained from a motion capture system, and to estimate the established benchmark measurement using data obtained from the proposed wearable sensor system.

TABLE I: A list of motor tasks with varying levels of fine hand and gross arm motor involvement that were used in the experiment.

Task	Description	Type
1	Walking	Passive
2	Sit-to-stand	Passive
3	Stand-to-sit	Passive
4	Buttoning a shirt	Bimanual
5	Typing on a keyboard	Bimanual
6	Folding a towel	Bimanual
7	Tying shoelaces	Bimanual
8	Cutting a putty with a fork and a knife	Unimanual
9	Opening a screw-top jar	Unimanual
10	Taking the cap off of a bottle and drinking	Unimanual
11	Flipping pages of a magazine	Unimanual

B. Establishment of the Benchmark Measure of Hand Use

The amount of comprehensive hand use (i.e., general use of the fingers and the palm) was defined as the average change in the distance between the proximal phalanx of the index finger (where the finger-worn sensor was placed) and the wrist. The three dimensional (3D) position time-series of the markers located at the wrist and finger, denoted as $\langle x_w[t], y_w[t], z_w[t]\rangle$ and $\langle x_f[t], y_f[t], z_f[t]\rangle$ respectively, were filtered using the sixth order Butterworth low-pass filter at a cutoff frequency of 8 Hz to remove high frequency and non-human generated noise. Then, the Euclidean distance $d[t]$ was computed between the two markers. The amount of hand use was then represented by computing the absolute difference of the distance $d[t]$ between each pair of adjacent samples:

$$m[t] = |d[t] - d[t-1]|. \tag{1}$$

A single representative value of the amount of hand use over the duration of each motor task was derived by computing the mean value of $m[t]$. The unit of the measurement is *cm/s*.

C. Validation of the Benchmark Measure: Reliability and Responsiveness

Test-retest reliability evaluates the ability of a metric to measure consistency in two tests under the same conditions [21]. In our study, the two tests were the first two repetitions of the motor tasks performed in a natural manner by the same subject (Repetition #1 and #2). This work hypothesized the observation of similar patterns of measurement. The level of test-retest reliability was quantified by using the intra-class correlation coefficient (ICC), whose value ranges from 0 to 1 [21]. The type of ICC used in this work was ICC (3,1). An ICC < 0.4 indicates poor, $0.4 \leq$ ICC < 0.75 indicates fair to good, and ICC ≥ 0.75 indicates excellent test-retest reliability [21].

Responsiveness examines the ability of a measurement to detect changes that are caused by a specific intervention [22]. In our study, the intervention was to make the best efforts to use the non-dominant hand to perform the unimanual motor tasks during Repetition #3 as discussed in Section II-B. The benchmark measurement of the dominant hand during Repetition #2 was compared against the following two measures using *two-sided Wilcoxon rank sum test* [23]: 1) the amount of the dominant hand use during Repetition #3 and 2) that of the non-dominant hand during Repetition #3. This work hypothesized to observe a statistically significant difference for the amount of the dominant hand use during Repetition #2 and #3, whereas the difference between the dominant hand use during Repetition #2 and the non-dominant hand use during Repetition #3 may depend on how differently (or similarly) subjects performed the same tasks with the two limbs.

D. Estimation of Amount of Hand Use using Wearable Sensor

Fig. 2 shows the machine learning-based analytic pipeline that estimated the *validated* benchmark measurement of the amount of hand use using the accelerometer data obtained from the finger-worn and wrist-worn sensors. We also evaluated the estimation performance in different mobile network configurations that require different data throughputs.

1) Data Pre-processing: A sixth order Butterworth low-pass filter with a cutoff frequency at 8 Hz was again applied to remove any noise in the accelerometer time-series. A sliding window of 9s with 50% overlap was used to segment the data in each motor task to support continuous computation of the amount of hand use; the impact of the length of the window on the estimation accuracy was also investigated. Each sliding window was considered as a data point containing 1) the three-axis accelerometer data obtained from the finger-worn $\boldsymbol{a}_f[t] =< a_f^x[t], a_f^y[t], a_f^z[t] >$ and wrist-worn sensors $\boldsymbol{a}_w[t] =< a_w^x[t], a_w^y[t], a_w^z[t] >$, and 2) the corresponding benchmark measurement of the amount of hand use (i.e., the mean value of $m[t]$ within the window).

2) Feature Extraction: Features were extracted from the filtered and segmented accelerometer data to capture the intensity, smoothness, and periodicity of hand use [24]. More specifically, the intensity was represented by the following features: 1) mean, 2) inter-quartile range (IQR), 3) minimum and maximum, and 4) root mean square of the acceleration time-series. The smoothness of hand use was captured by using 5) standard deviation and 6) the difference between the zero-phase filtered and original accelerometer time-series was computed. The periodicity of hand use was assessed based on 7) the dominant frequency and 8) ratio of the energy at the dominant frequency to the entire signal energy of the time-series. Besides the features mentioned above, we also computed the 9) skewness, 10) kurtosis, and 11) signal entropy of the time-series. The aforementioned features were derived from 1) signal magnitudes of acceleration time-series that were generated by both the finger- and wrist-worn sensors, 2) the difference of the two acceleration magnitudes, i.e., $a_d[t] = |\boldsymbol{a}_f[t]| - |\boldsymbol{a}_w[t]|$, 3) each axis of the acceleration time-series of the finger-worn sensor, and 4) signal envelopes of all the aforementioned time-series. Note that features were extracted from each axis of the finger-worn sensor but not from the wrist-worn sensor. This is due to the fact that conventional finger movements during both gross arm and/or fine hand movements are made within a confined space, whereas those of the wrist are less constricted. For example, finger movements during hand use (e.g., grasping or releasing) usually generated acceleration in the *x*-axis of the sensor, whereas gross arm movements (e.g., passive arm swing while walking) generated acceleration in the *y*-axis due to the centripetal force from pendulum-like arm swing behaviors [25]. Wrist movements, on the other hand, could be made relatively freely in all directions, and thus extracting features in individual axes of the wrist-worn sensor may overfit the regression model for the specific motor tasks considered in our experiment. In sum, a total of 271 features potentially relevant to the amount of hand use were extracted.

3) Feature Selection: Our study employed a Correlation-based Feature Selection (CFS) algorithm to identify data features that were particularly relevant to the amount of hand use [26]. CFS focuses on finding a subset of relevant features based on the evaluation of individual features' predictability and the degree of redundancy compared to others. The best-first search was used to construct the feature search space.

4) Regression Estimation: Support Vector Regression (SVR) was utilized to train a model that estimated the benchmark measurement of the amount of hand use based on the selected features. SVR is a supervised, nonparametric learning algorithm that could provide a computationally efficient estimation of the target variable [27], which is more suitable for resource-constrained computing environments such as our miniaturized wearable devices. We employed Radial Basis Function (RBF) as the kernel function to transform the feature space [28]. The hyperparameters were optimized based on work by Shevade *et al.* [29]. The performance of the model was evaluated using Normalized Root Mean Square Error (NRMSE):

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{N}\sum_{n=1}^{N}(\hat{\alpha}_n - \alpha_n)^2}}{\max([\alpha_1, \cdots, \alpha_N]) - \min([\alpha_1, \cdots, \alpha_N])},$$

where $\hat{\alpha}_n$ and α_n respectively represent the estimated and benchmark measurements of the amount of hand use within a sliding window of index n. N represents the total number of windows (data points) within the testing dataset. Note that $\alpha_n = (1/T)\sum_t^T m_n[t]$, where T is the length of the sliding window, and $m_n[t]$ represents the measurement in (1). All the analyses were performed using leave-one-subject-out cross validation (LOSOCV) to provide a fair evaluation without individual bias and/or over-fitting.

TABLE II: Four different sensor network configurations of the proposed system that allow the operation of the system based on a trade-off between the amount of possible information that can be extracted (or estimation accuracy) and data throughput (or power consumption).

Configuration	Description	Sensor(s)
#1	Accelerometer time-series data of the sensor nodes are transmitted to the mobile gateware in real-time	Finger and wrist sensors
#2	Accelerometer time-series data are processed to extract features on each sensor node, and relevant data features are transmitted to the mobile gateware at the end of each sliding window	Finger and wrist sensors
#3	Data features of the finger-worn sensor are transmitted to the mobile gateware in real-time	Finger sensor only
#4	Data features of the wrist-worn sensor are transmitted to the mobile gateware in real-time	Wrist sensor only

5) Network Configurations: The proposed body sensor system can support different network configurations allowing the operation of the system based on a trade-off between the amount of possible information that can be extracted (or estimation accuracy) and data throughput (or power consumption). This study considered four different network configurations, which are summarized in Table II.

Configuration #1 investigated a network structure where raw accelerometer time-series from the two sensors were transmitted to the mobile gateware of our sensor network. The mobile gateware (e.g., smartphone or smartwatch) represents a node within the body network that collects data from the sensor nodes and pushes them to the cloud. This configuration would allow the maximum flexibility in sensor data processing and feature engineering as it provides access to the raw accelerometer time-series of both sensors. Configuration #2 investigated a more constrained network structure where the features were computed locally on the sensing node and then transmitted to the gateware at the end of each sliding window. This would substantially reduce the power consumption on the sensor nodes by eliminating the need for real-time data streaming. On the other hand, it may also diminish the estimation accuracy

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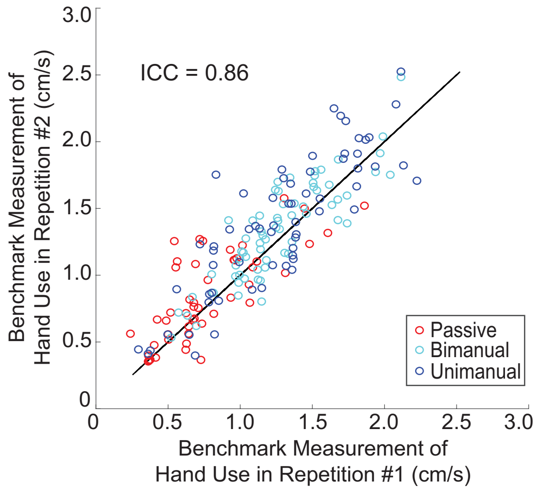

Fig. 3: Scatter plot for the average amount of dominant hand use during two repetitions of motor tasks (test-retest reliability). The black line ($y = x$) indicates the perfectly identical amount of hand use.

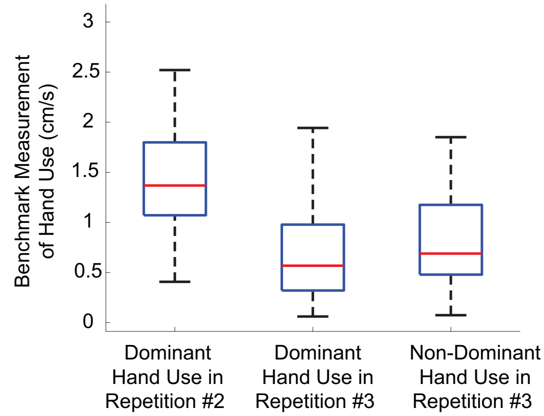

Fig. 4: Results of responsiveness when subjects were asked to use their non dominant hand to perform unimanual motor tasks. The plot shows the amount of dominant hand use during Repetition #2 and the amount of dominant/non-dominant hand use during Repetition #3

as it prohibits the extraction of potentially important data features, e.g., features extracted from $a_d[t]$. Configurations #3 and #4 employ only a single sensor node (either the finger- or wrist-worn sensor) to estimate the amount of hand use. We investigated the estimation performance of these network configurations by eliminating features that were not possible within the corresponding configuration while keeping the rest of the analytic pipeline identical.

IV. Results

A. Validation of the Benchmark Measure of Hand Use

Fig. 3 shows a scatter plot of the proposed benchmark measure when subjects were asked to repeat the entire motor tasks in their natural manner (Repetitions #1 and #2). This yielded an ICC of 0.86, which indicates excellent test-retest reliability [21].

Fig. 4 graphically summarizes the responsiveness of the benchmark measurement when subjects were asked to perform the unimanual motor tasks 1) in a natural manner (Repetition #2) and 2) under an intervention to use their non-dominant hand (Repetition #3). The amount of the dominant hand use during Repetition #2 was compared against the amount of the dominant as well as the non-dominant hand use during Repetition #3. Two-sided Wilcoxon rank sum test showed statistically significant differences for the two comparisons: $p < 1.74 \times 10^{-13}$ for the amount of dominant hand use in Repetition #2 and #3, and $p < 2.91 \times 10^{-9}$ for the amount of dominant hand use in Repetition #2 and non-dominant hand use in Repetition #3. The significant difference between the amount of dominant hand use in Repetition #2 and the non-dominant hand use in Repetition #3 was caused by patients not performing the unimanual motor tasks naturally with their non-dominant hand. We observed that subjects used their dominant hand more actively in Repetition #2, with which they were more comfortable executing the motor task.

B. Estimation of the Amount of Hand use

Fig. 5a compares the amount of hand use estimated by the proposed algorithm (y-axis) to the validated benchmark measurement (x-axis). A sliding window of 9s was used to generate the data points in this figure; the effect of the window size on the estimation accuracy will be discussed later in this section. The average value of NRMSE computed over the LOSOCV (across all subjects' data) was 0.11 with a standard deviation of 0.024. The average Pearson coefficient was 0.78 with a standard deviation of 0.10. The estimated amount of hand use for all subjects showed statistically significant correlations to the benchmark measurement with the overall p-value $< 5.6 \times 10^{-204}$. The bias and limit of agreement of the Bland-Altman plot (Fig. 5b) were -8.7×10^{-3} and 0.67, respectively. The results presented herein support that our wearable system can produce a reliable and accurate estimation of the amount of hand use during ADL.

The size of the sliding window could affect the accuracy of the estimation algorithm based on SVR (see Fig. 6). A relatively short window size (e.g., 1s - 5s) could provide estimations in near real-time, but the quality of data features extracted from such a short duration may not be sufficient to make an accurate estimation. For example, the estimation of the benchmark measure (i.e., a measure of changes in distance over a window, whose unit is in cm/s) by using the sensor data (i.e., a measure of acceleration in m/s^2) could not be performed effectively as the conversion from an acceleration to a distance measure fundamentally requires a sufficiently large number of data points – a process that resembles double integration. On the other end, a relatively long window (e.g., $>$ 15s) may contain multiple activities of varying intensity of hand use, which makes it difficult to find unique patterns in data features that are associated with the amount of hand use, resulting in a lower estimation accuracy. Fig. 6 shows that a window size of 9s could minimize the overall estimation error in terms of NRMSE computed over the LOSOCV, i.e., an average NRMSE of 0.11 and an average Pearson's coefficient

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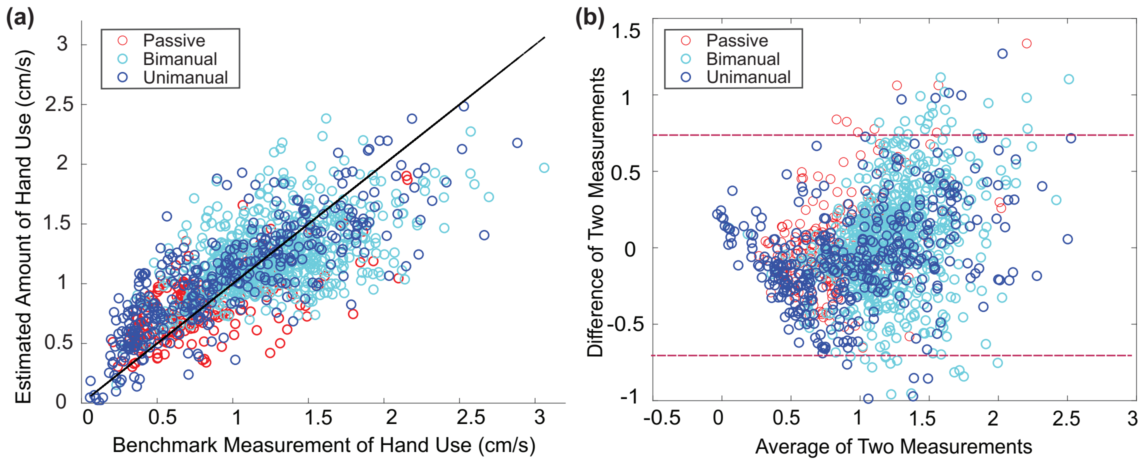

Fig. 5: a) A scatter plot between the estimated amount of hand use based on our proposed work and the benchmark measurement (NRMSE of 0.11 and Pearson coefficient of 0.78), and b) the corresponding Bland-Altman plot (bias of -8.7×10^{-3} and limit of agreement of 0.67).

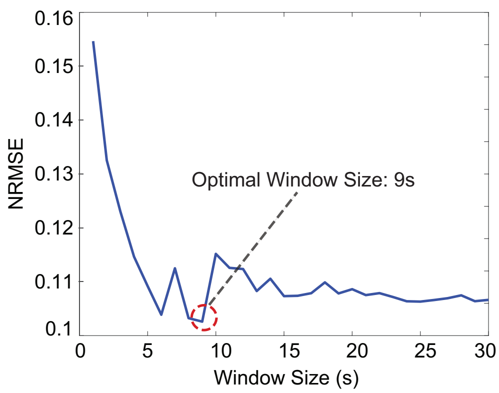

Fig. 6: Results of searching for the optimal window size. The plot shows that 9s is the window size corresponding with the highest accuracy of estimation in terms of NRMSE

TABLE III: A list of eight data features that are most relevant to estimating the amount of hand use. Note that these features are not listed in the order of their importance.

Feature	Description	Sensor(s)
# 1	Difference in IQR of $\|\boldsymbol{a}_w[t]\|$ and $\|\boldsymbol{a}_f[t]\|$	Wrist and Finger
# 2	Difference in Std. Dev. of $\|\boldsymbol{a}_w[t]\|$ and $\|\boldsymbol{a}_f[t]\|$	Wrist and Finger
# 3	Dominant frequency of difference between estimated velocity magnitudes of the two sensors	Wrist and Finger
# 4	Ratio of energy associated with high frequency movement to the signal envelope energy	Finger
# 5	Ratio of energy associated with high frequency movement to the entire signal energy	Finger
# 6	IQR of acceleration in the x-axis of the finger sensor ($a_f^x[t]$)	Finger
# 7	IQR of acceleration in the y-axis of the finger sensor ($a_f^y[t]$)	Finger
# 8	Ratio of energy associated with high frequency movement to the entire signal energy	Wrist

of 0.78.

Table III summarizes the eight most important features relevant to the amount of hand use. Since the evaluation was performed using the LOSOCV technique, the feature selection algorithm was performed on different training data and selected different feature subsets throughout the iterations of the LOSOCV. For example, in our analysis, 20 to 30 different features were selected (out of 271 features) in different iterations. Thus, we report the most frequently selected features from the iterations of the LOSOCV in order to summarize the important features [30]. The eight features in Table III were selected 100% in all iterations. It is not surprising that most of these features were derived directly from or partially involved the finger-worn sensor data, as we hypothesized that the finger sensor could capture information regarding the use of the hand. When we constructed the estimation model with these eight features, we obtained an NRMSE of 0.12 and Pearson coefficient of 0.74. This result shows that we can achieve near-optimal regression performance using only eight features when compared to using the entire feature set selected by the CFS algorithm (i.e., NRMSE of 0.11 and Pearson coefficient of 0.78). This is particularly important for the system's ability to support continuous monitoring – these features need to be computed for every sliding window.

Fig. 7 summarizes the estimation performance for the four sensor network configurations investigated in this work. Configurations #1 and #2 produced similar estimation accuracy (i.e., NRMSE and Pearson coefficient of $\langle 0.11$ and $0.78\rangle$vs. $\langle 0.11$ and $0.77\rangle$, respectively). This result supports that the features extracted from the difference time-series of the finger and wrist accelerations $a_d[t]$ make minimal contributions to the overall estimation accuracy, which was also reflected on the feature selection results in Table III. Configuration #3, which employed only the wrist-worn sensor, showed significantly inferior performance compared to the other configurations. The achieved NRMSE and Pearson coefficient were 0.15 and 0.44, respectively. This observation suggests that wrist-worn accelerometers alone cannot capture important information regarding hand performance during ADL. On the other hand,

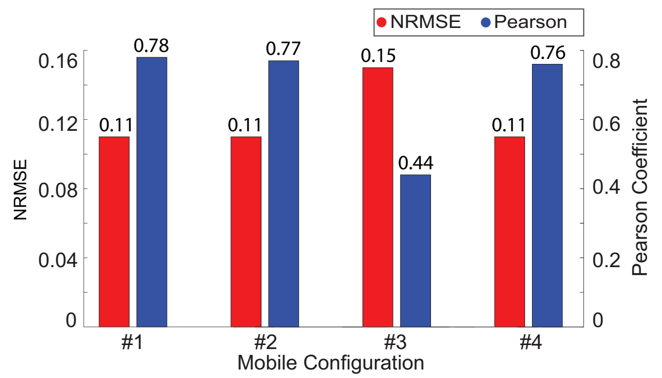

Fig. 7: The estimation performance of the proposed algorithm under different mobile configurations. Configuration #1, #2, and #4 provided a comparable estimation accuracy whereas Configuration #3 (wrist sensor only) showed significantly inferior performance.

Configuration #3, which employed only the finger-worn sensor, produced comparable estimation accuracy to Configurations #1 and #2. This result concurs with our feature selection summary (Table III) that shows important features contributing to the estimation involved data obtained from the finger-worn sensor.

V. Discussion and Conclusions

The results presented in this paper show that accelerometer recordings obtained from the proposed body-networked sensor system composed of a finger-worn and a wrist-worn sensor can be used to estimate the amount of hand use during ADL. The proposed machine learning-based analytic pipeline could provide an average error rate of 0.11 in terms of NRMSE and support continuous monitoring (e.g., producing estimations every 9s). This paper also introduced and validated a new benchmark measurement of the amount of hand use based on data obtained from an optoelectronic motion capture system. The implementation and validation of this measurement can serve as robust ground truth for future studies that aim to quantify the amount of hand use using on- and/or off-body sensors.

A machine learning algorithm was necessary to process the body sensor data and make an accurate estimation of the amount of hand use. The most straightforward approach to estimate the amount of hand use without utilizing machine learning algorithms may be the computation of counts of the difference in acceleration magnitudes of the two sensors – a conventional approach to convert accelerometer data into a measurement of activity intensity in clinical research [11], [12]. This is intuitive since the wrist-worn sensor is assumed to capture mainly gross arm movement whereas the finger-worn sensor would capture both gross arm and fine hand movements. However, the estimation results based on this approach produced a poor estimation accuracy (NRMSE of 0.16) compared to the proposed machine learning-based mechanism. We believe that this is due the non-linear relationship between the accelerations measured by the finger- and the wrist-worn sensors during pendulum-like arm movement [25]. The sensor on the finger is more distal compared to the wrist and thus, the acceleration measured by the two sensors may vary significantly.

The proposed study validated the use of finger-worn sensors to estimate the amount of hand use based on a series of motor tasks associated with ADL. Thus, it is conceivable that the presented technologies could be translated to individuals' home settings to continuously monitor their abilities to function in daily life. The proposed system provides activity-independent quantification of the amount of hand use (i.e., does not require the classification of performed activities). Furthermore, the use of a machine learning algorithm (SVR with RBF kernel) capable of generating the estimations in a computationally efficient manner (with as few as 8 features) makes the system suitable for continuous monitoring in an environment with constrained resources, e.g., on the computing unit of our wearable sensors.

This study contains some limitations worth noting. First, our experiment involved a relatively small number of subjects (18 subjects) performing a set of 11 motor tasks. Thus, the results presented in this paper may not be generalized to the general healthy or stroke populations. However, all the analyses were performed in a LOSOCV manner, which produced an unbiased, fair evaluation rather an optimistic one. Second, the proposed method that estimates the amount of hand use does not provide information regarding the type of upper limb movements (e.g., passive vs. unimanual vs. bimanual vs. stabilization movements). Although accurate classification of upper limb movements based on machine learning algorithms could provide clinically relevant information regarding the functional level of patients with motor impairments (e.g., stroke survivors) [9], it is technically challenging to realize in practice. It is especially difficult to define the perfect classes of upper limb movements that could be performed in free living conditions based on a number of factors, such as the goal-directedness or whether it is unimanual or bimanual [8]. For example, the acceleration of the arm during sit-to-stand is mainly generated by the lower limb (standing up) and could be considered as a passive movement. However, reaching out both arms to balance on the armrest, could be considered an active (bimanual) movement. This also indicates that accurate classification would necessitate the understanding of the context of activities such that the accelerometer data could be properly segmented. Thus, the proposed work focused on quantifying the hand function (i.e., amount of hand use) that could capture relevant information regarding the goal-directed use of the upper limb, which also has been suggested by other work in the field [14], [15]. Lastly, the proposed technology cannot capture the use of the hands for stabilizing objects (e.g., holding a cup or stabilizing a piece of steak with a fork) as it focuses on estimating the amount of hand movement. Stabilization is an important category of hand function, however, we assume that capturing hand movements during ADL could provide more accurate information regarding the goal-directed use of the hands, especially for individuals with hemiparesis, when compared to conventional wrist-worn accelerometers.

We ultimately envision future scenarios in which stroke survivors can be continuously monitored in the free-living setting using the proposed wearable technology. The proposed technology supports a minimally obtrusive means to understand patients' functionality, which may reflect individual responses to rehabilitation. This would allow clinicians the opportunity to provide individually-tailored rehabilitation and therapeutic programs – potentially transforming the current stroke healthcare into evidence-based, person-centered care.

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HealthSOS: Real-Time Health Monitoring System for Stroke Prognostics

IQRAM HUSSAIN AND SE JIN PARK
Korea Research Institute of Standards and Science, Daejeon 34113, South Korea
Electronics and Telecommunication Research Institute, Daejeon 34129, South Korea
Department of Medical Physics, University of Science and Technology, Daejeon 34113, South Korea
Corresponding author: Se Jin Park (sjpark@kriss.re.kr)

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ABSTRACT Electroencephalography (EEG) is immediate and sensitive to cortical impairment resulting from ischemic stroke and is considered as the potential predictive tool of stroke onset, and post-stroke clinical management. Brainwave monitoring outside the heavily equipped clinical environment demands a low-cost, portable, and wearable EEG system. This study aims to assess the feasibility of using an ambulatory EEG system to classify the stroke patient group with neurological changes due to ischemic stroke and the control healthy adult group. HealthSOS, a real-time health monitoring system for stroke prognostics, is proposed here, which consists of an eye-mask embedded portable EEG device, data analytics, and medical ontology based health advisor service. This system was investigated with 37 stroke patients (mean age 71.6 years, 61% male) admitted in the emergency unit of a hospital and 36 healthy elderly volunteers (mean age 76 years, 28% male). EEG was recorded in resting-state using the portable device with frontal cortical electrodes (Fp1, Fp2) embedded in an eye-mask within 120 h after the onset of symptoms of ischemic stroke (confirmed clinically). The EEG data acquisition of the left and right brain hemispheres was done for at least 15 minutes in the awake resting state while subjects laid down on the bed. The statistical result shows that the revised brain symmetry index (rsBSI), the delta-alpha ratio, and the delta-theta ratio of the stroke group differ significantly from those of the healthy control group. In the machine learning analysis, the support vector machine (SVM) model shows the highest accuracy (Overall accuracy: 92%) and the highest Gini coefficient (95%) in classification performance. This study will be useful for early stroke prognostics and the management of post-stroke treatment.

INDEX TERMS Sensor systems and applications, brain–computer interfaces, neuroscience, biomedical monitoring.

I. INTRODUCTION

Stroke is one of the leading neurological disorders in adulthood and it is the second leading cause of death and disability in the world among the elderly population [1]. Early detection of stroke onset is life-saving [2]. Stroke identification and detection of stroke severity affect mortality rate, rehabilitation, medical cost, and quality of post-stroke life. In many cases, stroke symptoms are not visible at the early level of ischemic events. So, the decision of referral to a clinical diagnostic center and detail neural and pathological assessment may be delayed [3]. Late identification of ischemic stroke may lead to cognitive impairment and the economic burden of stroke care with a mental impairment is three times greater than those without cognitive damage [4].

Tracking the behavior of the neuro-electrical system is key for prognostics of stroke. As ischemic events, such as hemorrhage stroke onset happen due to rupture of blood cells, hampers the supply of oxygen to the brain tissue of the lesion area, which leads the brain cells to death. This damage to brain tissue affects the electrical activity of the corresponding local hemisphere and unstabilize the overall central nervous system. Ischemic events weaken the neuro-electrical activities, eventually, suppresses high-frequency waves (gamma or beta waves), and strengthen the low-frequency neural signal bands (alpha, theta, delta wave). A high amplitude delta wave (0.5-4 Hz) is typical in ischemic stroke [5]. Stroke also affects the symmetricity of brain waves across the left and

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right cortex. Changes in symmetric behavior of the spectral power of quantitative electroencephalography (EEG) between the two cerebral hemispheres can be described by the Revised Brain Symmetry Index (rsBSI) [6]. Studies showed that rsBSI is an important marker early prediction of stroke [3], [7].

For a detailed assessment of stroke, computed tomography (CT) and magnetic resonance imaging (MRI) are used to understand brain anatomy and to the diagnostic extent of severity of stroke of both kinds (thrombosis or hemorrhage) [8]. CT and MRI are not practical for continuous monitoring of a high-risk patient with a history of acute stroke or transient ischemic attack (Mini stroke) [9]. For the prognostics of stroke, changes in EEG can be useful in both daily life and clinical setup [10]. The real-time tracking of neural activity is the most practical way of predicting stroke onset. Studies have shown that EEG pattern changes immediately with the onset of an ischemic attack.

Numerous EEG studies have been reported where quantitative EEG measures were studied in clinical applications to evaluate the association between the EEG and the neurologic and functional outcome from ischemic stroke [7], [9], [11]–[14]. In acute stroke patients, quantitative EEG observations improve the prediction of functional outcomes in the acute stage of cerebral ischemia [15]. Delta activity and depression of alpha or beta activity are observed as a predictive marker of poor functional outcomes in the ischemic hemisphere, whereas the absence of these phenomena is observed as the case of good outcomes. In another study, it was reported that global delta power often changed over time, depending on the severity of the ischemic event [9]. In most of the earlier studies, EEG data acquisition is done with a traditional standard 10-20 EEG system with multiple electrodes. Highly trained medical staff and clinical setup are also necessary for those EEG studies. Although traditional EEG offers a noise-free brain signal, long experimental preparation time also delays the prognostics of ischemic stroke.

In summary, an ambulatory EEG system is necessary for continuous EEG monitoring in daily life setup. EEG electrodes were embedded in an eye-mask and a control module alongside would be an effective technique for portable neural activity tracking. As light affects the circadian rhythms and an eye-mask maintains a balance of light and darkness by obstructing lights, an eye-mask is generally used as a sleep wearable device for resting and sleep quality improvement. In a pilot study, Muse EEG wearables were used for the identification of stroke [3]. The rsBSI was only investigated as the marker of prognostics of stroke, other features were not explored. Neural activity monitoring using a portable EEG system was not extensively studied yet for prognostics of stroke.

SOS is recognized as a distress signal that indicates a crisis or the need for action. HealthSOS is proposed as a health monitoring system, which tracks the physiological signal of the user and provides the health status as feedback and an alert to the emergency rescue services if stroke-predictive physiological features exceed the threshold value. HealthSOS consists of an eye-mask based ambulatory EEG, capable of emergency alert as feedback if the stroke prediction occurs.

We hypothesized that changes in the electrical activity of the central nervous system would be instantaneously detected by the portable EEG device. The signal processing and the mathematical analysis based feature extraction, the statistical analysis based feature selection, and the widely applied machine learning techniques would be a reliable method for the early prediction of stroke.

This study aims to develop the HealthSOS, an ambulatory EEG system for ischemic event prediction in daily life setup. This system was developed based on wearable EEG suitable for daily life setting, continuous data messaging to an ActiveMQ cloud server, the time-domain, and frequency-domain features extractor, Pearson correlation method for feature selection, rule-based feature extender, support vector machine (SVM) for the prediction of the stroke onset. The EEG data acquisition of the left and right brain hemispheres was done for at least 15 minutes in the awake resting state while subjects laid down on the bed attaching EEG electrodes embedded in an eye-mask on the frontal cortex. Our objective is to explore EEG indices, including rsBSI, the delta-alpha ratio, the delta-theta ratio and to evaluate the predictive features to differentiate the ischemic stroke group and the healthy control group for prognostics of ischemic stroke.

The rest of this paper is structured into six sections. Section II describes the proposed health monitoring system, followed by the experimental protocol, and the methodology used to validate the prognostic capabilities of the system. Afterward, the results are presented in Section IV, followed by the discussion. Finally, the conclusions are presented in Section VI.

II. PROPOSED HEALTH MONITORING SYSTEM

HealthSOS, a novel health monitoring system consists of a wearable EEG device, the application programming interface (API), the networking module, the signal processing module, the machine learning module, knowledgebase, the medical ontology, and the recommendation system. Details about the EEG data acquisition system, system architecture, and the health advisor system are presented in the next subsections.

A. SENSOR AND HARDWARE DETAILS

An ambulatory EEG device, designed to acquire EEG data in the resting state, consists of an eye-mask embedded electrode system and an EEG control module. As shown in Figure 1, an eye-mask has been designed with fabricated EEG and EOG (electrooculogram) electrodes. In the eye-mask, two dry gold-plated convex EEG electrodes are positioned in Frontal Fp1, Fp2 points as per EEG 10-20 system. The frontal cortex is the best-suited position for brainwave acquisition using eye-mask. The traditional 10-20 EEG system is not practical and convenient for real-time monitoring. The entire system is very light in weight and portable.

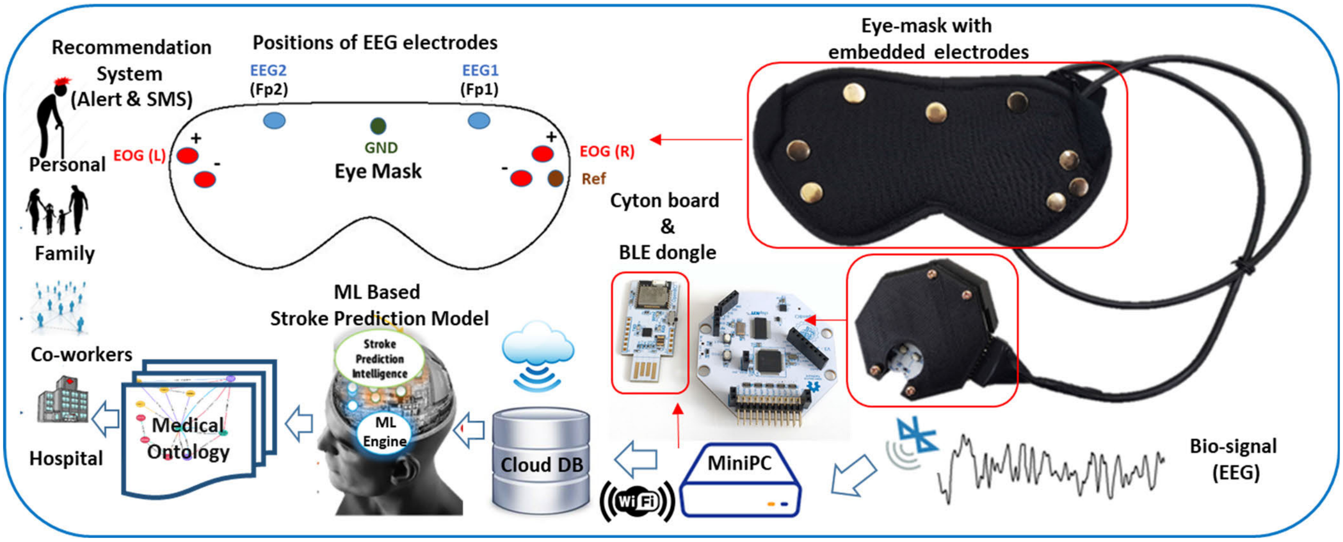

FIGURE 1. Overview of the HealthSOS system. EEG and EOG electrodes are embedded in an eye-mask. This amulatory system is developed to identify the changes in brainwave features due to ischemic stroke or other illnesses and generate recommedations and messages to rescue the patients. Electrode positions, channel descriptions and image of the newly developed portable data acquisition system are shown.

An eye-mask can be a good alternative for user-friendly brainwave acquisition. Using an eye-mask is a comparatively cheap technique with significant sleep improvements for several critical patients [16]. Eye-mask cuts off blue light, which hampers sleep. Additionally, Frontal EEG and two EOG channels can be easily fabricated in an eye-mask. The dry electrode also has limited sleep intervention compared with the wet gold-cap electrode.

B. SIGNAL ACQUISITION MODULE

A newly developed portable EEG device uses the open-source OpenBCI Cyton Board to acquire EEG signals. Cyton board consists of 8-channels bio-signal acquisition, a MicroSD slot for data storage, a Lipo battery connector, and wireless communication to a mini-computer via an RFduino radio-based USB dongle. A 3D printed enclosure was made for ease of handling of the EEG data acquisition module. EEG signals are sampled at 250 Hz sampling rate through the Cyton module. The ground was chosen on Fpz location as per 10-20 system and reference was placed a position close to the right ear. The acquisition module possesses a 3.7V battery and a DC charging module.

C. SYSTEM ARCHITECTURE AND DATAFLOW

HealthSOS, the proposed health monitoring system consists of the body-area wearable physiological sensors, the feature extraction package, feature extension package, the machine learning (ML) model, the knowledge base, the medical ontology, and the health advisor framework during sleeping and resting state. The data acquisition module sends data to the nearest mini computer (miniPC) through the Bluetooth low energy (BLE) network. A java based API was developed to read and sent EEG in JSON (JavaScript Object Notation) format. Details Specification of system architecture and dataflow for automated stroke prediction system using HealthSOS has been shown in Figure 2. All data is sampled and sent at a sampling rate of 250 Hz. The Apache ActiveMQ protocol is used for the messaging of JSON data. The raw-data API sent brainwaves of the right and left hemisphere to web server Elasticsearch NoSQL DB through the Wi-Fi network. The context predictor predicts the user's state of activity (Resting, Sleep, Active), event information, and so on. Then, the feature extraction package is employed to extract important features, which are correlated with ischemic events, such as, Stroke. The neuro-electrical asymmetry of two hemispheres is an important predictive marker of a brain hemorrhage. The rule-based feature extender package categorizes brainwave features according to the ischemic stroke predictive features, such as the symmetry of the left and right cortexes, the ratios of spectral power. The selected brainwave features are feed to the machine learning model for training and testing of the ML model respectively. The past health records, the emergency contact information, personal details, the insurance records can be included in the profile of subscribers of the health monitoring service. The disease ontology and health advisor can recommend possible health advice to assist the patients. In the case of ischemic events such as stroke, a recommendation will be generated to attend the patient to the emergency department of the hospital for further testing, like, CT, MFI, and so on. Messages will be sent to the emergency rescue department, relatives of the patient to assist the patient to move to the nearest healthcare center.

D. FEATURE EXTRACTION AND FEATURE SELECTION

The feature extractor package comprises important neuro features both in the time domain and frequency domain. All feature extraction algorithms are implemented in java. Fast Fourier Transforms (FFT) is performed on artifact-free EEG signal with 10% hamming and extracted absolute power

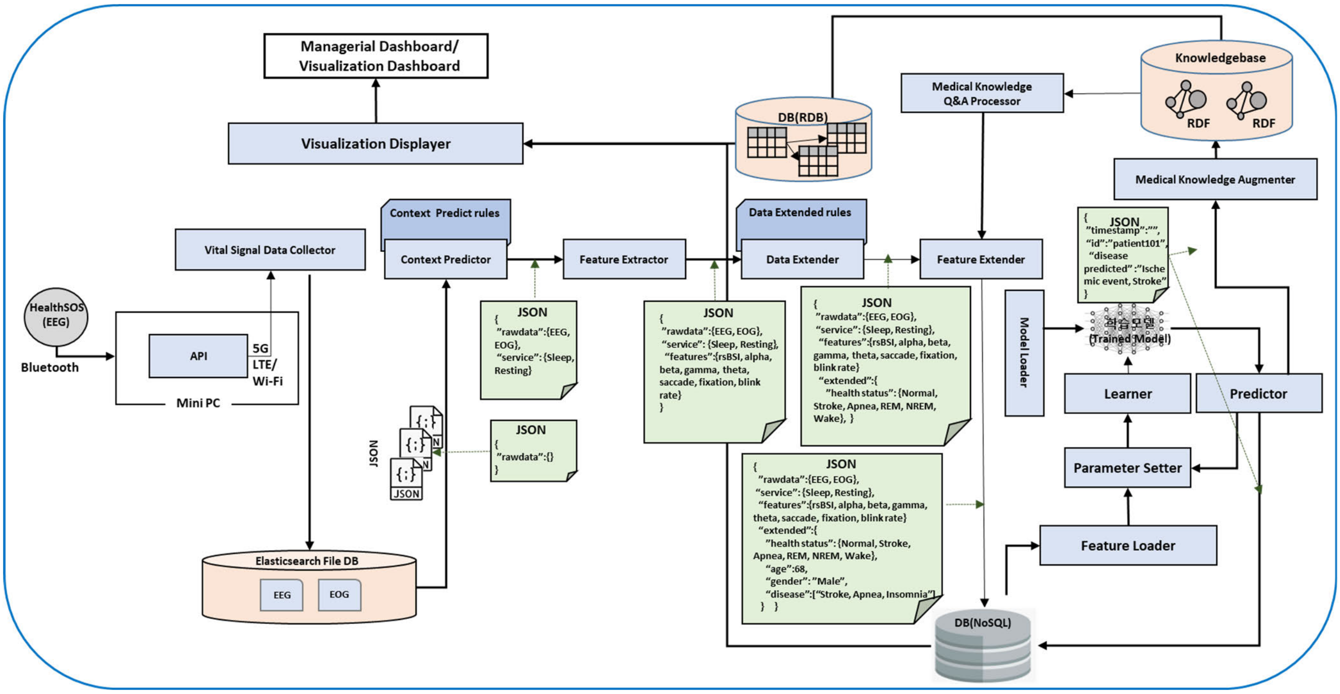

FIGURE 2. System architecture and dataflow of the HealthSOS system. Data acquisition device sends the raw data to nearby MiniPC application through Bluetooth communication. The API send EEG, EOG data in JSON format to web DB using ActiveMQ protocol. The feature extraction package is employed to extract physiological features sensitive to illnesses (both acute and chronic) and rule-based feature extender find out possible health or neural abnormality using feature thresholds and level the data with health status. Machine learning model learns and predicts the health status. Medical Knowledgebase and ontology finds out possible reason of illness, generate health advice and recommendations. Recommendations are forwarded to user, subscribed healthcare centers and the emergency departments to take necessary action. Healthcare centers and subscriber can visualize the signals and recommendations through their dedicated dashboards.

in the following frequency bands: delta (δ) band is specified ranging 0.5–4.0 Hz, theta (θ) band exists in a range of 4.0–8.0 Hz, alpha (α) wave runs on 8.0–13.0 Hz, and beta (β) band maintained in 13.0–30 Hz, Gamma (γ) band exists in a range of 30.0–44 Hz. As there are plenty of features of EEG in time-domain and frequency-domain, it is necessary to screen and reduce features, which fit the model best. Feature selection minimizes computational time and memory requirements so that more focus can be done on only the necessary predictors. Three steps are involved here; screening, ranking, and selection. Feature variables with missing values and constant values are screened out in the initial step. In the second step, the importance of the predictor has been calculated based on how well each variable alone predicts the target variable. The importance value of the feature variables is calculated as (1-p), where p is the p-value of a Pearson's chi-square test of association between the predictor and the target variable.

E. CLASSIFICATION

Several machine-learning algorithms are employed to classify the resting neural features of the patients of ischemic stroke and the control group. Discriminant analysis, Support vector machine (SVM), Neural network, QUEST, and C&R tree algorithms have been used to classify brainwave features of stroke patients and normal persons. 80% of processed feature data has been utilized for training purposes, 20% data for testing of classification models. QUEST (Quick, Unbiased, Efficient) is a binary Statistical tree-growing algorithm [17]. Support Vector Machines (SVM) maps data to a high-dimensional feature space so that features can be categorized by generating the marginal line. Neural networks predict a target based on finding unknown and possibly complex patterns of predictors. The multilayer perceptron (MLP) neural network model is a feed-forward, supervised learning network [18]. Classification and Regression Trees (C&RT) partitions the data more homogeneously than the previous subset.

F. MEDICAL ONTOLOGY AND HEALTH ADVISOR

An ontology is a data model that represents a set of concepts within a domain and the relationships among those concepts [19]. A medical ontology framework is developed to describe a health monitoring network including personal information, wearable sensors, health records, hospital resources, disease ontology, and processes, which serve as a knowledge base for our entire health monitoring system. The disease ontology provides a clear definition for each disease and the relation of the diseases with physiological parameters. The integration of real-time physiological analysis and medical ontology can lead to automate the health advisor framework. The health advisor consists of a recommendation system based on disease prediction and disease ontology. The Health advisor also includes messaging the acute patient

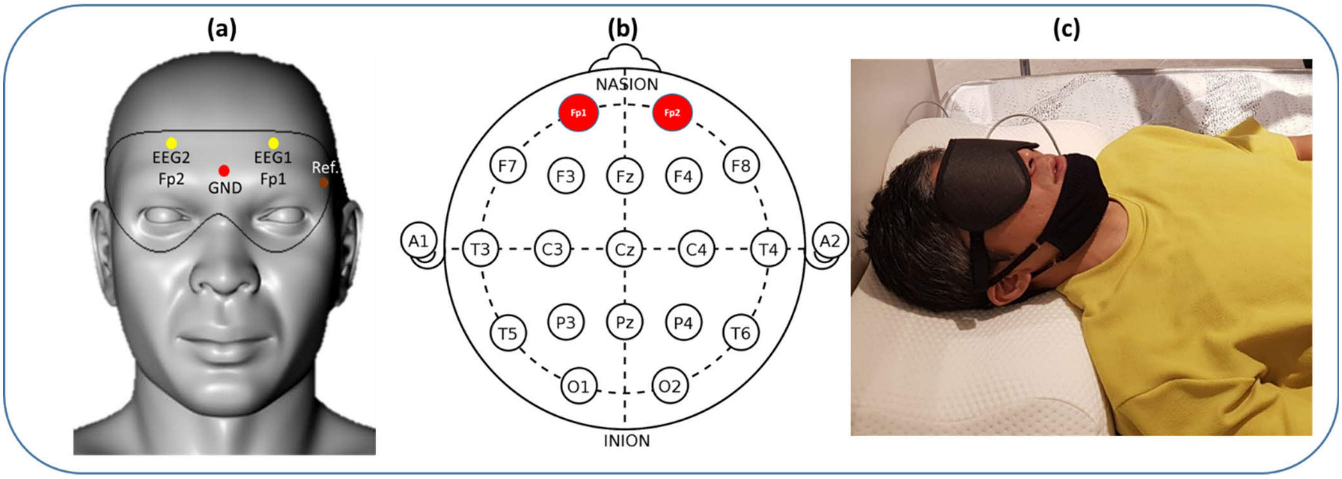

FIGURE 3. Description of device electrodes layout used in experiment (a) positions of EEG electrodes along with reference and ground electrodes in frontal cortex, (b) EEG electrodes (Fp1, Fp2) according to the standard EEG 10-20 system, (c) sample scenario of the experiment.

condition to the emergency control room or relatives to rescue and assist the patient to move to the hospital for diagnostics and treatment.

III. EXPERIMENTAL PROTOCOL

A. PARTICIPANTS OF THE EXPERIMENT

The investigation group (Stroke Patients) included 37 patients (mean age 71.6 years, 61% male) who were diagnosed with ischemic stroke. The control group included 36 healthy elderly volunteers (mean age 76 years, 28% male). Both target and control group is selected within a similar age range to reduce age-related neural activity variation. The study population consists of patients referred to Chungnam National University Hospital Rehabilitation Center, Daejeon, South Korea. Patients' ischemic stroke events were verified clinically using MRI scans or CT. The control group is composed of healthy elderly volunteers with no previous record of ischemic events or underlying known neurologic diseases. The study was approved by the institutional Ethics Committee of Korea Research Institute of Standards and Science, Daejeon, South Korea.

B. EEG DATA ACQUISITION

In this study, the EEG was acquired using the eye-mask system. Two Channels EEG were acquired. In this study, we only focus on EEG data taken on the frontal cortex. EEG electrode layout is shown in Figure 3(a). Frontal Fp1, Fp2 were chosen for brainwave acquisition as per EEG 10-20 system (Figure 3(b)). Fp1 is a representative electrode of the left hemisphere and Fp2 is a representative electrode of the right hemisphere. In the case of the stroke population, EEG data acquisition was done no later than 120 hours after admission to the emergency unit of the hospital. For this study, participants are advised not to take any drink like, Coffee or alcohol before the experiment. During EEG data acquisition, the patients were instructed to be awake, eye-closed, and in a resting (lay-down in bed) position. Only EEG data is considered in this study and EOG data was not used in this study. Room temperature was maintained at 24° and relative humidity 40%. Participants are suggested to moisturize the forehead skin to reduce the impedance of dry electrodes. After wearing the eye-mask, data recording was delayed for five minutes to settle down participants' mental condition to resting state, and then EEG data was recorded for at least 15 minutes in the awake resting state. An example of the experimental scenario is presented in Figure 3(c).

C. PRE-PROCESSING

At first, the EEG signal is filtered out of 60 Hz AC noise (Local 60 Hz power grid). The built-in notch filter cut-off the 60 Hz noise in the OpenBCI Cyton. EOG artifacts are filtered from the EEG signal.

D. FEATURE EXTRACTION

EEG delta (δ) wave, theta (θ) wave, alpha (α) wave, and beta (β) wave, Gamma (γ) wave are extracted from the artifact-free EEG signal. Various EEG features are measured over an epoch length of 10 seconds to understand the power in the EEG bands. Signal transformations, such as Lyapunov exponent, central moment, time-delayed mutual information, skewness, spectral slope, capacity dimension and correlation dimension, correlation coefficient, and so on; have been applied to evaluate the unique EEG features.

1) REVISED BRAIN SYMMETRY INDEX

The Revised Brain Symmetry Index is an efficient marker for continuous EEG monitoring for hemispheric stroke and computed according to the methods suggested by Van putten [6]. As hemispheric stroke causes a lack of neuro-electrical balance between the right and left hemispheres, rsBSI may allow early prediction of stroke [3], [7]. The rsBSI is a numerical value ranging between zero (absolute symmetry) and one (complete asymmetry).

2) THE RATIO OF DELTA-ALPHA AND DELTA-THETA POWER

The ratio of delta power and alpha band power was computed to measure the DAR (delta-alpha ratio). The ratio of delta power and theta band power was defined as the delta-theta ratio (DTR). EEG spectral band power ratios (DAR and DTR) are important markers of cognitive change due to stroke [11].

3) BAND POWER ASYMMETRY INDEX

Spectral Band power asymmetry Index is the relative difference of each band power between two brain hemispheres, such as frontal alpha asymmetry, frontal beta asymmetry, and so on. EEG spectral band asymmetries are found to be related to depression, epilepsy, apnea, and so on [20], [21].

4) LYAPUNOV EXPONENT

Lyapunov exponent gives a measure of the chaotic nature, the divergence or convergence of EEG signal. It is also used to estimate the production of entropy in the EEG waveform. Analysis of the Lyapunov exponent of EEG was studied to classify the Schizophrenia, neurological disorder patients, and the control population [22].

5) KURTOSIS

Kurtosis gives information on whether EEG data is light-tailed or heavy-tailed compared with a normal distribution, also the size of the "tails".

6) CENTRAL MOMENT

Central Moment computes deviations from the mean instead of from zero within the selected EEG signal. The central moment feature of EEG frequency bands can be implemented to detect epileptic seizures [23].

7) TIME-DELAYED MUTUAL INFORMATION

Mutual Information determines the relevance and redundancy of the neuro-electric signal given a time delay. Study shows that time-delayed mutual information of EEG and EMG (Electromyography) of active movement is significantly different from passive movement [24].

8) SKEWNESS AND PEAK-PEAK

Skew is a measure of the degree of asymmetry in an epoch of an EEG waveform [25]. Peak-Peak (P-P) measures the distance between the maximum and minimum peak value in an epoch.

9) SPECTRAL SLOPE

The spectral slope or gradient measures the non-standard regression coefficient and gives information about the direction and steepness of the waveform. The spectral slope of EEG gives a reliable estimate of neurological disorders, such as neonatal seizures [26].

10) CAPACITY DIMENSION & CORRELATION DIMENSION

Capacity Dimension and Correlation Dimension are the fractal dimensions that indicate the extent of changes in the detail of a waveform with the change in scale. Fractal dimension is found effective to detect the EEG changes in an epileptic seizure, a bipolar disorder, behavioral micro-sleep, and so on.

11) CORRELATION COEFFICIENT

Correlate provides the linear correlation between the two variables and has a value ranging from 1 to -1. EEG linear correlation-coefficient is considered as an effective measure of the activity of the neural network of the cortical region [27].

E. DATA ANALYSIS

EEG frequency bands (alpha, beta, theta, delta, gamma) are extracted using fast Fourier transforms. Several frequency bands' features, such as relative power, mean power, mean frequency, median frequency, peak frequency, spectral edge, and so on, are calculated. Descriptive statistics and independent-samples t-test are carried out. Statistical analyses were performed using SPSS 24 software (IBM, Armonk, New York). Feature selection is executed to rank EEG features based on the measurement levels of the target. Pearson's chi-square test computed the feature importance calculated as (1-p), where p is the p-value of the statistical test of association between the feature and the target group (stroke group or control group). Then selected best feature sets from the training dataset is feed to the supervised machine learning models to obtain the classification models, which are later used for testing the datasets. Machine learning analyses were performed using IBM SPSS Modeler 18 software (IBM, Armonk, New York).

IV. RESULTS

A. STATISTICAL ANALYSIS

Independent-samples t-test was performed to compare the means of EEG features for two groups, which provides Levene's test for equality of variances along with both equal- and unequal-variance t values for the difference in means. A p-value of less than 0.05 was considered statistically significant. In the following subsections, the results of significantly important features will be explored only.

1) RESULTS OF THE REVISED BRAIN SYMMETRY INDEX

The Revised Brain Symmetry Index of the stroke and healthy control groups was evaluated based on EEG in the brain frontal lobe at Fp1, Fp2 positions. Figure 4(a) shows the statistical distribution of rsBSI of the stroke and control group. The mean and standard deviation of rsBSI for the stroke group 0.263 and 0.088 respectively. On the other hand, the mean and standard deviation of rsBSI for the control group 0.143, and 0.053 respectively. In Levene's statistical test of the equality of variances between the two groups, the significance value is $p < 0.0001$, which implies that the two groups don't

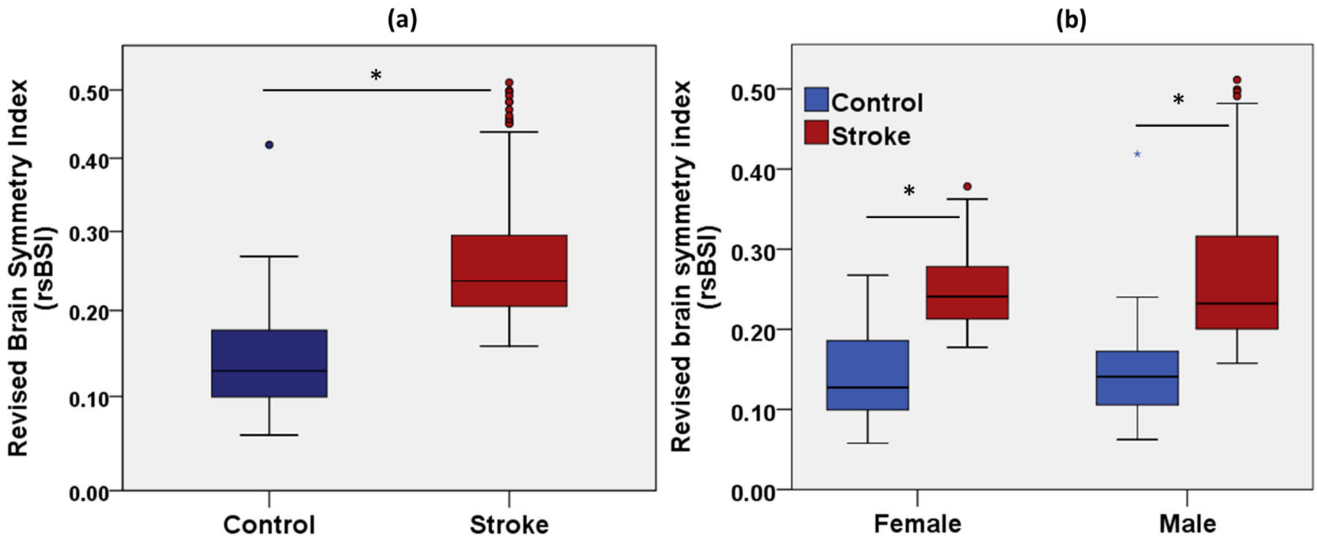

FIGURE 4. Median and interquartile range of rsBSI computed in the frontal scalp among (a) the stroke patient population and the control population, and (b) the male group and female group of the stroke patient population and the control population. $*p < 0.0001$. $*(p < 0.0001)$ indicates significant difference.

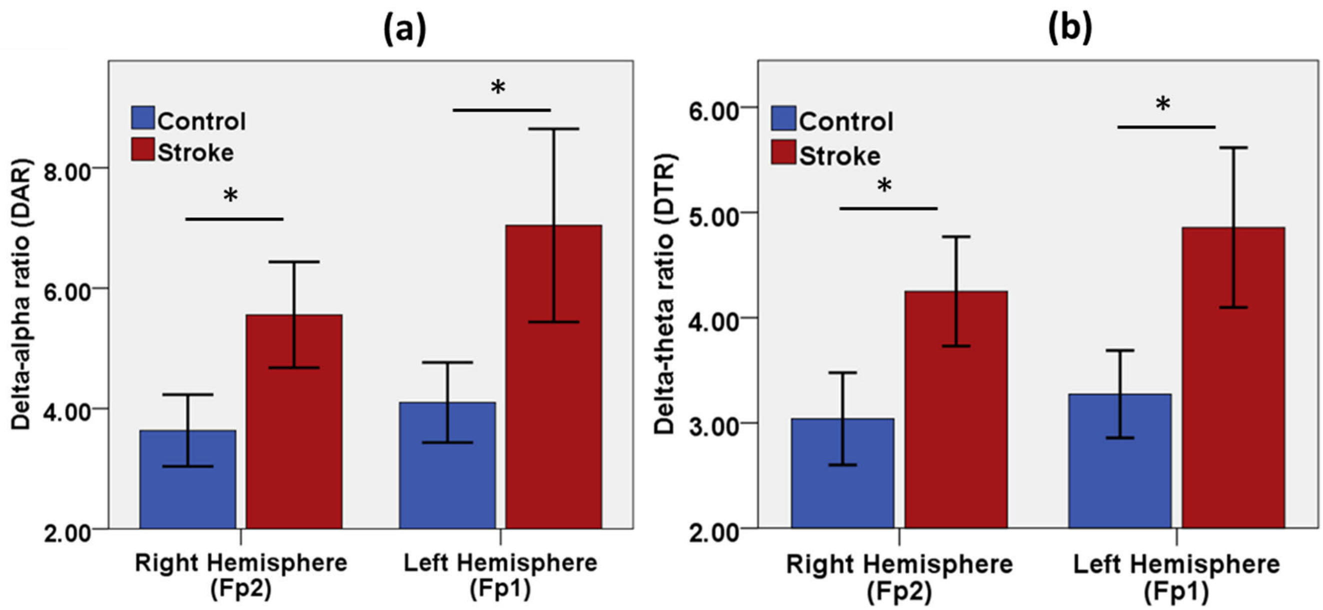

FIGURE 5. Mean and error bar of (a) DAR, $*p < 0.0001$ in Fp1, $*\ p < 0.0005$ in Fp2 (b) DTR, $*p < 0.005$ computed in the frontal electrodes Fp1, Fp2 among the stroke patient population and the control population. Error bar shows 95% confidence interval. $*$ indicates significant difference.

have equal variances. In the t-test for equality of means, the t-statistic is 17.656 with 446 degrees of freedom. The corresponding two-tailed p-value is $p < 0.0001$. As a result, it can be concluded that the difference of means of rsBSI between the stroke group and the control group is different between each other. A higher revised brain symmetry index indicates the neural impairment in one-side of the hemisphere. A similar finding is observed in other EEG electrode positions of the stroke population using a short EEG recording [3], [28]. Van putten used prolonged 12-24 hours EEG monitoring of the stroke patients to understand the correlation between rsBSI and the stroke events [7], [12]. Blood flow to brain tissue is hampered due to ischemic hemorrhage. Brain cell damage impairs the electrical activity of the corresponding brain hemisphere. Eventually, a stroke onset alters the normal symmetric characteristic of left and right hemispheric EEG. As Fp1 and Fp2 are the representative positions of the left and right hemispheres respectively, larger rsBSI variation between Fp1 and Fp2 can be used as an effective indicator of detection of ischemic events, such as stroke. Figure 4(b) shows the rsBSI score of the stroke and control group for the male and female populations. rsBSI of the male stroke group has a wider interquartile range compared with that of the female stroke group. On the other hand, the median rsBSI

(0.23) of the male stroke population is slightly lower than that (0.24) of the female stroke population.

2) RESULTS OF DELTA-ALPHA AND DELTA-THETA RATIO

Figures 5(a) and 5(b) show the statistical means of frontal EEG DAR and DTR for the stroke and control group. The mean of DAR and DTR for stroke group 5.556 and 4.250 respectively in Fp1 and 7.043 and 4.856 respectively in Fp2. On the other hand, the mean of DAR and DTR for the control group 3.634 and 3.040 respectively in Fp1 and 4.10 and 3.273 respectively in Fp2. The independent group t-test is performed to compare the means and variances of DAR and DTR between the two groups. In Levene's statistical test of the equality of variances of DAR between the two groups, the significance value is $p < 0.0001$ in Fp1, $p < 0.0005$ in Fp2 which implies that the two groups don't have equal variances of DAR. In Levene's statistical test of the equality of variances of DTR between the two groups, the significance value is $p < 0.005$ in Fp1, Fp2 which implies that the two groups don't have equal variances of DTR. In the t-test for equality of means of DAR, the t-statistic is 3.59 with 446 degrees of freedom in Fp1 and 3.39 with 446 degrees of freedom in Fp2. Besides, in the t-test for equality of means of DTR, the t-statistic is 3.52 with 446 degrees of freedom in Fp1 and 3.65 with 446 degrees of freedom in Fp2. The corresponding two-tailed p-value is $p < 0.0005$ for DAR in Fp1 and Fp2 respectively, 0.0005 for DTR in both Fp1 and Fp2. As a result, it can be concluded that the difference of means and variances of DAR, DTR of the stroke group and the control group are different from each other.

3) RESULTS OF THE CORRELATION COEFFICIENT, KURTOSIS, SKEWNESS, SPECTRAL SLOPE

Figure 6(a) shows the statistical means of the correlation coefficient of EEG frequency bands (alpha, beta, theta, delta, gamma) for the stroke and control groups. In the results of the correlation coefficient, a significant difference ($p < 0.05$) was observed in the means of correlation coefficients of all bands in Fp1, but no significant difference was observed in the variances of correlation coefficients.

Figure 6(b) shows the statistical means of the kurtosis of EEG frequency bands for the stroke and control groups. In the results of the kurtosis analysis, a significant difference ($p < 0.05$) was observed in the variances of kurtosis of alpha, beta, and gamma bands in Fp2, but no significant difference was observed in the means of kurtosis.

Figure 6(c) shows the statistical means of the spectral slope of EEG frequency bands for the stroke and control groups. In the results of the slope, a significant difference ($p < 0.05$) was observed in the means of the slope of alpha, beta, and gamma bands in Fp1, but no significant difference was observed in the variances of the slope.

Figure 6(d) shows the statistical means of the skewness of EEG frequency bands for the stroke and control group. In the results of the skewness, a significant difference ($p < 0.05$) was observed in the means of skewness of theta and gamma bands in Fp1, but no significant difference was observed in the variances of skewness.

B. MACHINE LEARNING ANALYSIS

All EEG features with feature importance of a p-value greater than 0.95 have been chosen for the classification analysis. A total of 48 features are selected out of 274 initial extracted brainwave features based on feature importance ($p > 0.95$). To evaluate classification accuracy, ROC (Receiver operating characteristic) curve is the most effective tool. AUC (Area under the curve) is a classification performance predictor and defined as the area under the ROC curve. The nearer the AUC is to 1.0, the better the performance of the model. Besides, the Gini coefficient is an alternative measure to the AUC and is defined as the Gini Coefficient, which is two times (AUC-1), ranging between 0 and 1. The confusion matrix or error matrix provides a clear picture of classification performance. From the confusion matrix, several other performance parameters, such as accuracy (ACC), sensitivity (true positive rate), specificity (true negative rate), precision (positive predictive rate), negative predictive value, AUC, and Gini coefficient are calculated. The accuracy was calculated as the ratio of correct prediction to the total observations and considered as the most intuitive performance measure to identify the best model. Precision is the ratio of correct positive prediction to the total predicted positive observations. Sensitivity is the ratio of correct positive prediction to all the actual observations. Specificity is the ratio of correct negative prediction to all the actual observations. The performance evaluation parameters are computed using the following standard formulas:

$$\begin{aligned}
\text{Sensitivity} &= \frac{TP}{TP+FN}\\
\text{Specificity} &= \frac{TN}{TN+FP}\\
\text{Precision} &= \frac{TP}{TP+FP}\\
\text{Negative predictive value (NPV)} &= \frac{TN}{TN+FN}\\
\text{Accuracy(ACC)} &= \frac{TN+TP}{TN+TP+FN+FP}
\end{aligned}$$

where TP stands for the true positive, TN means the true negative, FP stands for the false positive, and FN means the false negative. All the performance measures for the training datasets and the testing datasets are listed in Table 1 and Table 2 respectively.

As listed in Table 1, SVM classified the training dataset with the highest AUC (98%), highest accuracy (ACC: 93%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of SVM are 98%, 88%, 89%, 98%, 98%, and 95%, respectively. Discriminant analysis classified the training dataset with the lowest accuracy (ACC: 88%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of Discriminant analysis are 91%, 86%, 86%, 90%, 96%, and

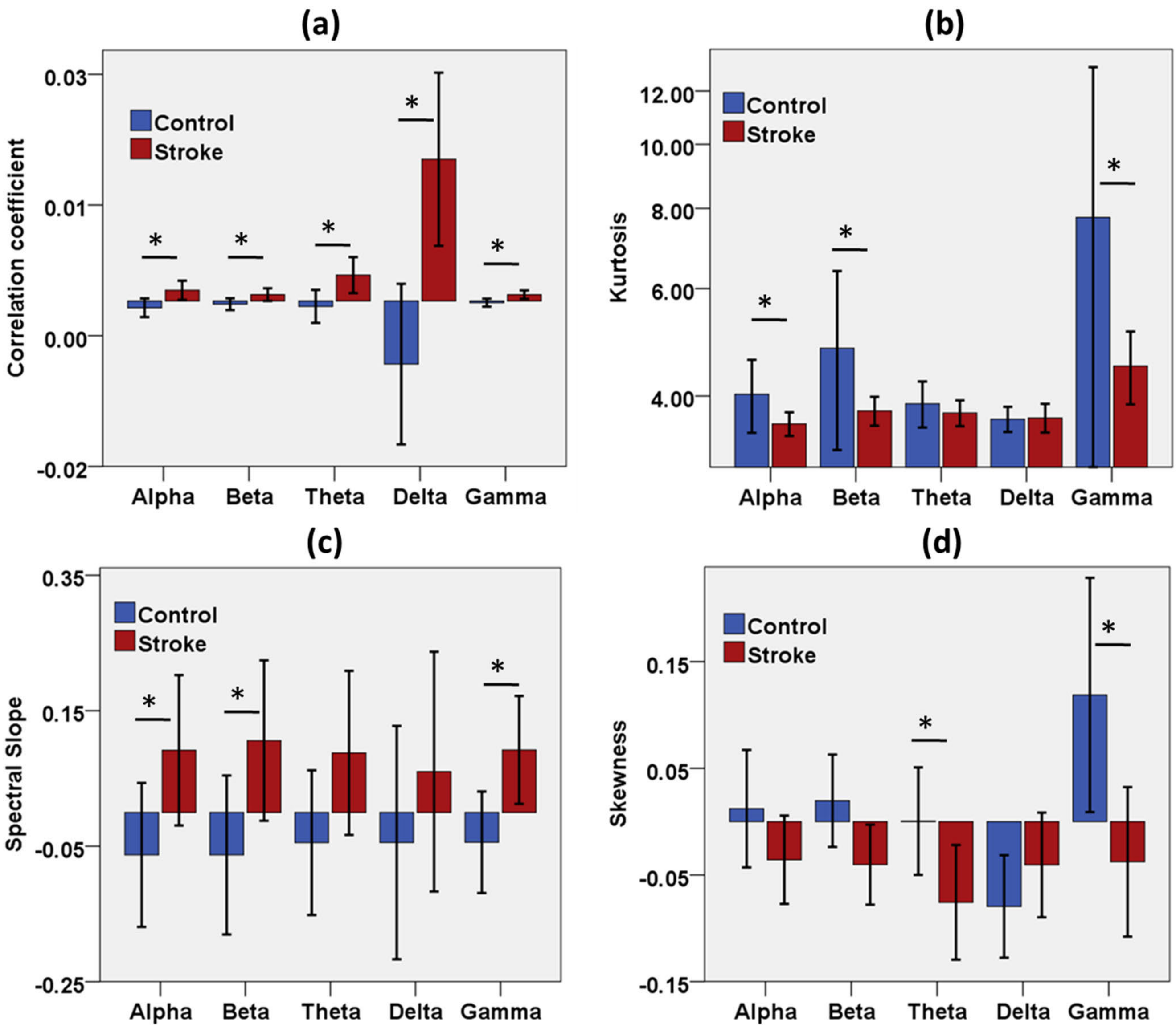

FIGURE 6. Mean and error bar of (a) the correlation coefficient in Fp1, $*p < 0.05$ (b) kurtosis analysis in Fp2, $*p < 0.05$, (c) spectral slope in Fp1, (d) skewness in Fp1 computed among the stroke patient population and the control population. Error bar shows 95% confidence interval. $*(p < 0.05)$ indicates significant difference.

TABLE 1. Results of the classification performance of different models using the training dataset.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	AUC (%)	Gini (%)
SVM	93	98	88	89	98	98	95
Discriminant	88	91	86	86	90	96	92
Neural Network	90	86	94	94	87	96	93
QUEST	93	94	93	93	94	95	91
C&R Tree	92	98	86	87	98	92	84

92%, accordingly. QUEST classified the training dataset with moderate accuracy (ACC: 93%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of QUEST are 94%, 93%, 93%, 94%, 95%,

TABLE 2. Results of the classification performance of different models using the testing dataset.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	AUC (%)	Gini (%)
SVM	89	94	84	84	94	97	95
Discriminant	87	87	86	85	88	94	88
Neural Network	88	88	88	87	89	92	84
QUEST	91	90	93	92	91	94	88
C&R Tree	89	94	84	84	94	89	78

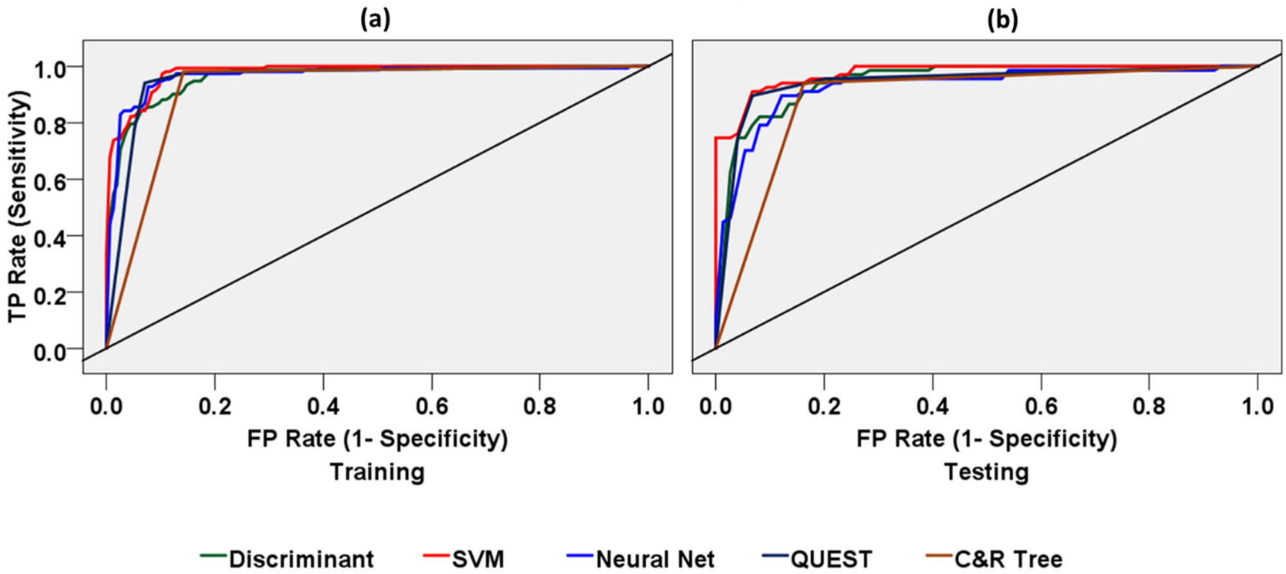

FIGURE 7. Receiver Operating Characteristic (ROC) curves for five different machine-learning models (Discriminant analysis, Support Vector Machine, Neural Network, QUEST, C&R Tree). Area under ROC curve (AUC) is an indicator of prediction accuracy. (a) ROC curve of the training dataset. SVM classified the training dataset with the highest AUC (98%) and highest accuracy (ACC: 93%); (b) ROC curve of the testing dataset. SVM classified the testing dataset with the highest AUC (97%) and moderate accuracy (ACC: 89%). Diagonal black line is the reference line.

and 91%, sequentially. C&R Tree classified the training dataset with moderate accuracy (ACC: 92%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of C&R Tree are 98%, 86%, 87%, 98%, 92%, and 84%, successively. The neural network classified the training dataset with moderate accuracy (ACC: 90%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient are 86%, 94%, 94%, 87%, 96%, and 93%, consecutively. ROC (Receiver operating characteristic) curves of the ML models using the training dataset are shown in Figure 7(a).

According to Table 2, SVM classified the testing dataset with the highest AUC (97%) and moderate accuracy (ACC: 89%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of SVM are 94%, 84%, 84%, 94%, 97%, and 95%, respectively. Discriminant analysis classified the testing dataset with the lowest accuracy (ACC: 87%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of Discriminant analysis are 87%, 86%, 85%, 88%, 94%, and 88%, consecutively. QUEST classified the testing dataset with the highest accuracy (ACC: 91%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of QUEST are 90%, 93%, 92%, 91%, 94%, and 88%, sequentially. C&R Tree classified the testing dataset with moderate accuracy (ACC: 89%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient of C&R Tree are 94%, 84%, 84%, 94%, 89%, and 78%, accordingly. The neural network classified the testing dataset with moderate accuracy (ACC: 88%). The sensitivity, specificity, precision, negative predictive value, AUC, Gini coefficient are 88%, 88%, 87%, 89%, 92%, and 84%, in succession. ROC (Receiver operating characteristic) curves of the ML models using the testing dataset are shown in Figure 7(b). Overall, SVM shows the highest accuracy (ACC: 92%), the highest AUC (98%), and the highest Gini coefficient (95%). Statistical agreement between stroke predictions by the above five models is 84%.

V. DISCUSSION

In our study, we aimed to characterize the electrical activity of the frontal lobes through ambulatory EEG data acquisition of newly diagnosed stroke patients and healthy adults to find out the features showing the effective indication of the brain injury due to stroke events. The frontal lobes are critical for cognitive processes and are easily accessed by the wearable EEG device. Specific EEG band power is associated with the specific functional outcome of the brain and in the case of ischemic stroke, is linked to the degree of neural damage in the lesion area of the brain. The outcome of this study also adds to our understanding of abnormal hemispheric asymmetry in homologous channel pairs (Fp1 and Fp2), which represent the most prominent marker of the human awake resting-state EEG in the stroke impaired brain.

The result of rsBSI showed a statistically significant difference between the stroke patient group and the control group. Our findings match with previous studies revealing that the stroke patients group possesses a higher rsBSI value compared with the healthy control group [6], [7], [12], [29]. Stroke hampers the blood flow to brain tissue, which leads to damage to brain cells and creates a lesion. A higher rsBSI value indicates the lack of interhemispheric neuro-electrical balance due to the presence of the lesion caused by the ischemic stroke. Lower rsBSI correlates with a healthy brain for the absence of lesions [3].

According to this study, resting DAR and DTR, resulting from the relative-band power of the delta, theta, and alpha, are significantly important markers to classify the stroke group and the healthy control group. Higher delta power is observed in the electrodes of the pre-frontal positions after stroke [11], [30]. The alpha activity is significantly lower in the stroke population than in the healthy adult population. Relative alpha power is a less informative predictor for the monitoring and assessment of the ischemic stroke [11], [13]. Some studies from combined EEG, MFI, CT observations suggest that alpha attenuation and slowing reflect brain injury while delta activity rise is indicative of sub-cortical injury [5]. Beta activity is observed to be similar in the stroke group and the control group. Relative Beta power is considered as a less effective predictor and no reported statistically significant difference is found between the beta activity of the stroke patients and the healthy adults [5], [13]. Theta activity was also observed to have the potential to discriminant between the stroke population and the healthy control population [31]. DAR is considered the most reliable EEG feature for the prognostics of the ischemic stroke [11], [12], [14]. The DTABR, defined as the ratio of the sum of delta and theta to the sum of alpha and beta, similar to DAR is another informative predictor of Ischemic stroke. In the current study, DAR is calculated individually in two frontal electrodes. In both electrodes, DAR showed a significant difference between the stroke group and the healthy control group. Besides, as most of the stroke patients have left-side lesions, delta activity is lower on the lesion side and higher on the healthy side of the brain. So, DAR is higher in the Fp1 electrode than the Fp2 electrode. Few studies identified DTR as a potential marker of cognitive outcome after stroke [11]. Higher resting theta activity is associated with the healthy cognitive performance [32]. Lower resting theta power or higher DTR is a predictor indicator of impaired post-stroke cognitive outcome. A similar trend is observed in the DTR of the frontal electrodes in this study. DTR showed a significant difference between the stroke population and the healthy adult population. A rise in delta power, DAR, DTR is associated with the impaired neural functional outcome resulting from stroke. Resting DAR and DTR were also shown to correlate with cognitive outcome following stroke [11], [33].

EEG correlation-coefficient is an informative indicator of interhemispheric connectivity patterns. Ischemic stroke patients' clinical outcome is associated with the change of delta power [33]. In our study, a significant correlation is observed between stroke patients and all EEG bands' power. The kurtosis and spectral slope of alpha, beta, and gamma were observed as a statistically significant indicator of ischemic stroke. Other parameters did not show significant important differences.

In this study, Discriminant analysis, SVM, Neural network, QUEST, and C&R tree have been used to classify stroke patients and healthy control subjects. Good statistical agreement (84%) is observed between stroke predictions by the above five models. Overall, SVM shows the highest accuracy, the highest AUC, and the highest Gini coefficient. SVM is a benchmark machine learning technique as well as proven to show good results in multi-class classification to discriminate stroke patients and healthy control subjects using EEG signal [34], [35]. Though the computational period of the SVM model is longer, the SVM model seems to be the most accurate model to predict stroke prognostics.

To the best of our knowledge, our developed HealthSOS is the first to utilize wearable EEG fabricated on an eye-mask for stroke prognostics purposes. Past several studies used a standard 10-20 EEG system with around 16-32 channels. For real-time health monitoring in daily life activities, such as, resting, sleeping, EEG along with multiple wires and conductive gel can't be a practical solution. So, our portable can be a good alternative for traditional EEG. HealthSOS may be used as an alternative to the traditional sleep study. It is worth noting that our system can also be used as a measure for the prediction of wake-up stroke in an overnight sleep setup. Another potential application of the proposed portable system is the sleep monitoring system.

In this study, we focused on only the frontal lobe for understanding changes of EEG for neural impairment due to the ischemic stroke, not the entire cortex. Although the frontal lobe has a high resemblance to other lobes, there still exist specific cognitive and functional outcomes on each cortical lobe. For this reason, the model developed here generalizes to only the frontal lobe with current parameterization. Although EEG and EOG data can be acquired using the HealthSOS device, we only considered EEG for analysis for the study of the stroke population. Eye movement is significantly important for sleep quality and REM (Rapid Eye movement) sleep. In the future, EEG and EOG both can be utilized in an automated sleep performance and stroke prognostics study.

VI. CONCLUSION

HealthSOS, a portable low-cost eye-mask based EEG system was developed here, which could be used for prognostics of ischemic stroke and change of functional outcome due to stroke. Details of the hardware, API dataflow, description of the extracted features, the stroke prediction based on machine learning are presented. Our system has been successfully validated with 37 stroke patients and 36 healthy volunteers. rsBSI, the delta-alpha ratio, the delta-theta ratio were found as statistically significant markers for the prediction of ischemic stroke. HealthSOS system is expected to be a potential health-care assistance system for prognostics of ischemic stroke outside the clinical environment.

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IQRAM HUSSAIN received the B.Sc. degree in mechanical engineering from the Khulna University of Engineering & Technology, Bangladesh, in 2007. He is currently pursuing the Ph.D. degree in medical physics with the University of Science and Technology (UST), South Korea. He is also working as a Research Associate with the Korea Research Institute of Standards and Science (KRISS), Daejeon, South Korea. Besides, he also works in Knowledgebase Super Brain (KSB) project at the Electronics and Telecommunication Research Institute (ETRI), Daejeon. He has ten years of work experience in power plant operation and maintenance and power plant project management. His research interests include wearable sleep monitoring, neuroscience, medical physics, human factors, and ergonomics.

SE JIN PARK received the Ph.D. degree in industrial engineering from Korea University, in 1994. He is currently the Director of the Data Center for Korean Body Measurement, Korea Research Institute of Standards and Science (KRISS), supported by the Ministry of Trade, Industry and Energy, South Korea. Since joining KRISS in 1988, he has served in various positions, including the Director of Convergence Technology, the Head of Ergonomics Research, and the Head of Medical Metrology. He also served as the President of the Korean Society of Emotion and Sensibility (KOSES), and the Ergonomics Society of Korea. He is also working as a Researcher with the Electronics and Telecommunications Research Institute (ETRI), South Korea. Besides, he is a Professor with the Department of Medical Physics, University of Science and Technology (UST), South Korea. His research interests include human factors and ergonomics, biomechanics, emotion and sensibility, human vibration and seating comfort, human–computer interaction (HCI), the Internet of Everything (IoE), and gerontechnology. He is also a public speaker and provides speech in electronic media on a wide range of issues.

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Upper Limb Rehabilitation System for Stroke Survivors Based on Multi-Modal Sensors and Machine Learning

SHENG MIAO[1], CHEN SHEN[1], XIAOCHEN FENG[2], QIXIU ZHU[2], MOHAMMAD SHORFUZZAMAN[3], (Member, IEEE), AND ZHIHAN LV[1], (Senior Member, IEEE)

[1]School of Data Science and Software Engineering, Qingdao University, Qingdao 266071, China
[2]Department of Rehabilitation, Affiliated Hospital of Qingdao University, Qingdao 266000, China
[3]Department of Computer Science, College of Computers and Information Technology, Taif University, Taif 21944, Saudi Arabia

Corresponding author: Sheng Miao (smiao@qdu.edu.cn)

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ABSTRACT Nowadays, rehabilitation training for stroke survivors is mainly completed under the guidance of the physician. There are various treatment ways, however, most of them are affected by various factors such as experience of physician and training intensity. The treatment effect cannot be fed back in time, and objective evaluation data is lacking. In addition, the treatment method is complicated, costly, and highly dependent on physicians. Moreover, stroke survivors' compliance is poor, which leads to various limitations. This paper combines the Internet-of-Things, machine learning, and intelligence system technologies to design a smartphone-based intelligence system to help stroke survivors to improve upper limb rehabilitation. With the built-in multi-modal sensors of the smart phone, training action data of users can be obtained, and then transfer to the server through the Internet. This research presents a DTW-KNN joint algorithm to recognize accuracy of rehabilitation actions and classify to multiple training completion levels. The experimental results show that the DTW-KNN algorithm can evaluate the rehabilitation actions, the accuracy rates of the classification in excellent, good, and normal are 85.7%, 66.7%, and 80% respectively. The intelligence system presented in this paper can help stroke survivors to proceed rehabilitation training independently and remotely, which reduces medical costs and psychological burden.

INDEX TERMS Machine learning, multi-modal sensor, Internet-of-Things, upper limb rehabilitation, intelligent system.

I. INTRODUCTION

Stroke, which has the characteristics of high incidence and disability, is a serious, common, and disabling global health-care problem in current years [1]. It is usually caused by a blood clot that blocks the blood vessels in the brain. In addition, stroke can also be caused by a blood vessel rupture, causing blood to leak into the surrounding area [2]. Stroke is a common neurological disease and a leading cause of chronic disability worldwide [3]. The main symptom after stroke is hemiplegia, which is accompanied by a variety of complications, including movement, perception and cognition, paresthesias, language and visual disorders [4]. Stroke seriously affects stroke survivors' quality of daily life [5]. According to the World Health Organization report, 80% of stroke survivors have varying degrees of limb dysfunction, and more than 60% of them still have upper limb dysfunction after entering the chronic phase [6]. Rehabilitation of the lower limbs of stroke survivors is mainly carried out in the hospital, while after discharging from the hospital, stroke survivors usually need long-term rehabilitation training to restore and maintain upper limb movement ability. Studies have shown that regular high-intensity repetitive rehabilitation training is essential for stroke recovery. However, only a small number of stroke survivors actually follow the physician's recommendations for the recommended training [7].

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Rehabilitation treatment is an effective way to reduce the disability rate of stroke. Therefore, the rehabilitation of upper limb function is particularly important for stroke survivors.

Modern rehabilitation therapy techniques and methods are effective in restoring and improving the physical abilities of the physically disabled community [8]. Mudied *et al.* have proposed a bilateral upper limb training therapy [9]. Giovanni *et al.* have attempted to use the properties of mirror neurons to train stroke survivors with upper limb paralysis to restore neurological control and coordination of their movements [10], as well as myoelectric biofeedback [11] and neuromuscular electrical stimulation [12]. Floriana *et al.* have studied the use of motor imagination exercises during the recovery period of stroke survivors based on the brain-computer interface [13]. In recent years, virtual reality technology is often used in upper limb rehabilitation after stroke. But Laver K E *et al.* have found evidence that using virtual reality and interactive video games is not more beneficial than traditional therapies in improving upper limb function [14].

The above methods all rely on medical venues and equipment, and can't meet the long-term rehabilitation needs of stroke survivors. Traditional rehabilitation training is inefficient, and the quality of the rehabilitation training program completed by stroke survivors who discharged from the hospital is not satisfactory. There is also a lack of a comprehensive rehabilitation training evaluation system, and it is difficult for physicians to optimize training to obtain the best treatment plan for stroke survivors [15]. In addition, a large number of stroke survivors and a limited number of physicians lead to a heavy workload for physicians and lack of comprehensive rehabilitation guidance for stroke survivors.

Through the analysis of the above research status, it can be seen that there are still the following problems in the upper limb rehabilitation research for the stroke group: The existing stroke rehabilitation treatment technology is expensive and not conducive to use at home. The number of stroke survivors is large, the medical resources are limited, and the traditional rehabilitation training is difficult to guarantee training intensity and efficiency. There is a lack of objective data to evaluate the training parameters and rehabilitation effects. Stroke survivors still need to undergo long-term rehabilitation training after discharging from the hospital. Due to the lack of subjective enthusiasm, only a few stroke survivors may complete the rehabilitation plan, and the rehabilitation data could not be fed back to the rehabilitation physicians in time, resulting in the physicians being unable to track the health status of those discharged stroke survivors. Furthermore, the COVID-19 aggravates the difficulties of rehabilitation tracking and increase the medical risks during the training sessions in rehabilitation facilities. Some researchers have focused on developing COVID-19 related intelligent systems to improve healthcare services [16], [17].

Considering these issues, an IoT and machine learning based intelligent system for stroke survivors to improve upper limb rehabilitation is designed and presented in this paper, which applies the built-in sensors of the mobile device to collect data on stroke survivors' rehabilitation actions, transfers the data to the remote server, and uses Dynamic Time Warping (DTW) and K-Nearest Neighbor (K-Nearest Neighbor, KNN) to complete the classification and evaluation of action accuracy, so as to realize an end-to-end upper limb functional rehabilitation system.

II. RELATED WORKS

With the development of technologies such as the Internet-of-Things and artificial intelligence, a large number of new methodologies have been widely used in the field of healthcare, disease diagnosis, and rehabilitation [18]. Some researchers have utilized sensor technology to acquire and aggregate health information for multiple applications [19]– [21]. Moreover, data mining, multiple data fusion, and human-machine collaboration have been utilized to analyze and evaluate the rehabilitation of stroke survivors, which will effectively improve the quality of health service, assist stroke survivors in rehabilitation and improve the quality of life. The number of people who need to recover after a stroke is increasing rapidly, and the cost and pressure of medical budgets are also increasing [22].

Research in traditional therapy and motor learning theory demonstrates that the intensity of practice and feedback on tasks is important [23]–[26]. And there are studies showing that multiple repetitions of intensive exercise training can improve the acute and long-term treatment effects after a stroke [27], [28]. This recognition has promoted the development of new therapies, such as robotic therapy, which provides opportunities for repetitive exercise training [29]. Due to the high cost of such high-intensity training and the need for a lot of effort, a robotic rehabilitation system has been proposed to help physicians provide consistent and repeatable training [30]– [32]. Stanford University has developed a robotic upper limb rehabilitation system based on the PUMA 500 and 600 industrial robots, which can assist stroke survivors in performing mirror movements of the affected and healthy sides of the upper limb [33], [34]. Some universities in Europe have also designed and developed various upper limb rehabilitation robot systems [35]– [38]. However, studies have shown that some upper limb robots are not capable of performing wrist flexion and extension training, and these robots are expensive [39].

The key to upper limb rehabilitation training for stroke survivors is to efficiently and accurately identify and acquire stroke survivors' movements data. Zhang X *et al.* have proposed a gesture recognition framework based on the information fusion of a three-axis accelerometer and a multi-channel EMG sensor [40]. Kinect is a somatosensory peripheral of the home video game console XBOX360 developed by Microsoft [41]. It has functions of dynamic capture and image recognition. Aşkın A *et al.* have studied that the use of Kinect-based VR training may help improve the motor function of stroke survivors with chronic stroke [42].However, the Kinect device has high requirements in the field,

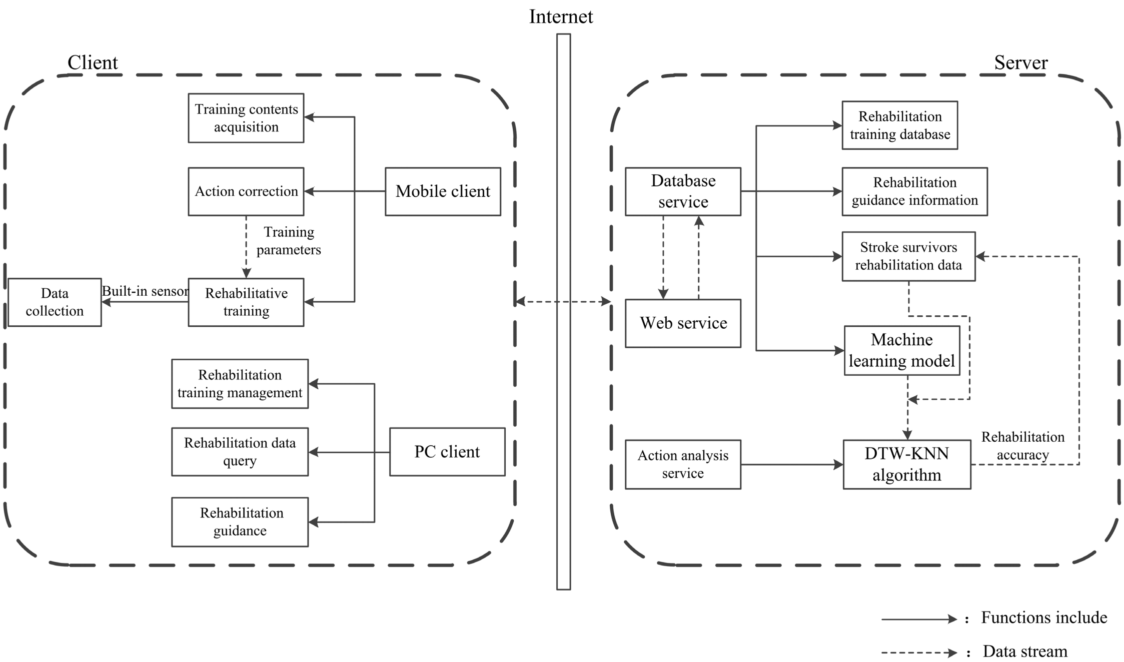

FIGURE 1. **Structure diagram of upper limb functional rehabilitation system.**

there must be no obstacles and there is a distance constraint between stroke survivors and equipment. In contrast, mobile devices can be easily carried anywhere and do not require complicated installation and configuration procedures [43]. Although only 37% of the population over 55 in developed countries had a smartphone in 2013, it is expected to exceed 80% by 2020 [44]. In addition, researchers have applied machine learning in the field of rehabilitation system [45]. At the same time, Some researchers have also used machine learning-based methods to identify the activities of daily living (ADL) dependence of stroke survivors [46]. These references all show that machine learning methods can be effectively applied to the area of human rehabilitation.

III. SYSTEM ARCHITECTURE

With the spread of smartphones, the variety of sensors built into mobile phones has diversified, and smartphones have become portable mobile electronic devices with comprehensive functions. The built-in gyroscope and device orientation sensor of the smartphone can make good measurements of rotation and deflection. With the accelerometer, it can measure and reconstruct a complete three-dimensional movement. Therefore, the combination of above three sensors can accurately analyze and judge the actual situation of the user. The system realizes the acquisition of rehabilitation movement data of stroke survivors through the built-in multi-sensor of the smartphone, and uses the Internet, artificial intelligence and other technologies to make the upper limb functional rehabilitation system intelligent operation. Stroke survivors perform rehabilitation training according to the training contents bound by the physicians through the mobile phone, and then the rehabilitation action data is sent to the server through the Internet for classifying and evaluating action accuracy. Based on this end-to-end upper limb function rehabilitation system, the physicians can remotely know stroke survivors' rehabilitation situation in time, and they can better formulate the next stage of rehabilitation training for stroke survivors and deliver it to stroke survivors remotely.

The upper limb functional rehabilitation system consists of two main parts, the client side and the server side. The structure of the upper limb rehabilitation system is shown in Figure 1. The client includes mobile client and PC client. Mobile client is implemented through an intelligent mobile platform, which aims to help stroke survivors with rehabilitation training. Stroke survivors are able to take the mobile phone for rehabilitation according to the training contents added by the physician, and the rehabilitation movement data is sent to the server through the Internet for accurate classification and evaluation. Physicians can view stroke survivors' rehabilitation through the PC client, and they can manage stroke survivors' rehabilitation training and provide remote rehabilitation guidance. The server includes database service and action analysis service. Database service is used to manage the database and provide data storage function. Action analysis service is designed to process and analyze the rehabilitation data from mobile client and perform accuracy classification judgments. In the following chapters, this article will introduce the four modules of the two parts of the upper limb functional rehabilitation system in detail.

A. MOBILE CLIENT

Mobile client is implemented through a smart mobile platform and supports multiple operating systems, such as Android and iOS. Mobile client and the server use the B/S mode for network communication through the HTTP protocol based on the TCP/IP protocol. Mobile client is mainly used to server stroke survivors, which includes functions such as training contents acquisition, movement correction, and rehabilitation training.

Stroke survivors can obtain training contents from the server through the Internet, since the need for feedback during rehabilitation training varies from different stroke survivors, and the upper limb function is expected to recover gradually with rehabilitation training. Therefore, it's necessary to perform action correction for each stroke survivors, that is, set the training parameters of the action. There is no doubt that uncorrected training movements can't be trained. The phone will provide vibration and audible feedback to stroke survivors when stroke survivors' training reaches the training parameters of the action. When stroke survivors perform a certain training action correction, mobile client will prompt stroke survivors to do the action three times as hard as possible. After calculating and comparing the maximum resultant acceleration of the three actions, multiply it by the proportional coefficient to obtain the training parameters of the action for stroke survivors. The resultant acceleration value is the sum of the square of the three-axis acceleration of the mobile device, and the proportional coefficient is set by the physicians.

The rehabilitation training function utilizes a smartphone's built-in accelerometer, gyroscope and directional sensors. The three-axis direction of the mobile device is shown in Figure 2. As the displacement and angle of the mobile phone varies, the value of its built-in multi-sensor is constantly changing. According to the rehabilitation actions performed by stroke survivors, mobile client performs data sampling of the accelerometer, gyroscope, and device direction. Since the rehabilitation training is an upper limb movement, stroke survivors' overall movement is slower, smoother and there will be no major mutations in a short time. The sensor data will not fluctuate greatly, so the sampling frequency is set to 16Hz, and the collected data meet the data requirements of the system. Mobile client can adapt to a variety of operating systems of mobile devices, and has good compatibility with user devices and high operational efficiency. Figure 3 is a screenshot of mobile client interface. There are two types of rehabilitation training, fast training and custom training respectively. The content of fast training is added by the physicians through the PC client for stroke survivors. The content of custom training includes all the rehabilitation actions in the rehabilitation training action database, and stroke survivors can choose any training action to add for training, as shown in Figure 3(a). When stroke survivors start training, relevant training instructions and action diagrams will be shown to them, and mobile phone built-in sensor data will be displayed in real time, as shown in Figure 3(b). In addition, stroke survivors can view the completion of the day's training in the training history, as show in Figure 3(c).

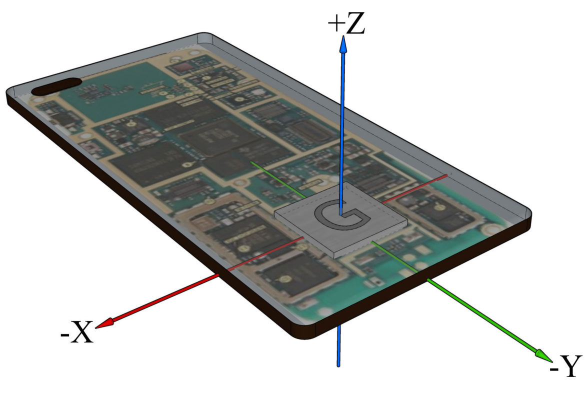

FIGURE 2. Three-axis pointing diagram of mobile equipment.

B. PC CLIENT

PC client can carry out data interaction with mobile client. It includes some functions such as managing rehabilitation training, querying stroke survivors rehabilitation data and providing remote rehabilitation guidance. Physicians can manage the rehabilitation training of stroke survivors, that is, access the rehabilitation training database through PC client, upload the rehabilitation training content and set the proportion coefficient of the training action for stroke survivors on mobile client, and can provide corresponding rehabilitation guidance information. Physicians are able to query all stroke survivors' rehabilitation data and the completion of their rehabilitation training from mobile client, but they can only manage their own stroke survivors. In addition, physicians can provide stroke survivors with remote rehabilitation guidance and adjust rehabilitation training plans through PC client according to stroke survivors' rehabilitation progress, so that stroke survivors can complete rehabilitation training in an efficient and convenient way. Stroke survivors can also use PC client to view their personal information and training status.

C. DATABASE SERVICE

Database service coordinates the requests sent by mobile client and PC client, performs corresponding data storage, and manages the database. This study uses a lightweight MySQL database, HTTP protocol is used for communication between database service and clients. Database service mainly includes rehabilitation training database, rehabilitation guidance information, stroke survivors rehabilitation database and machine learning models, etc. The rehabilitation training database and rehabilitation guidance information store various rehabilitation training content and rehabilitation guidance information of the physician, respectively, and the rehabilitation data and records from mobile client

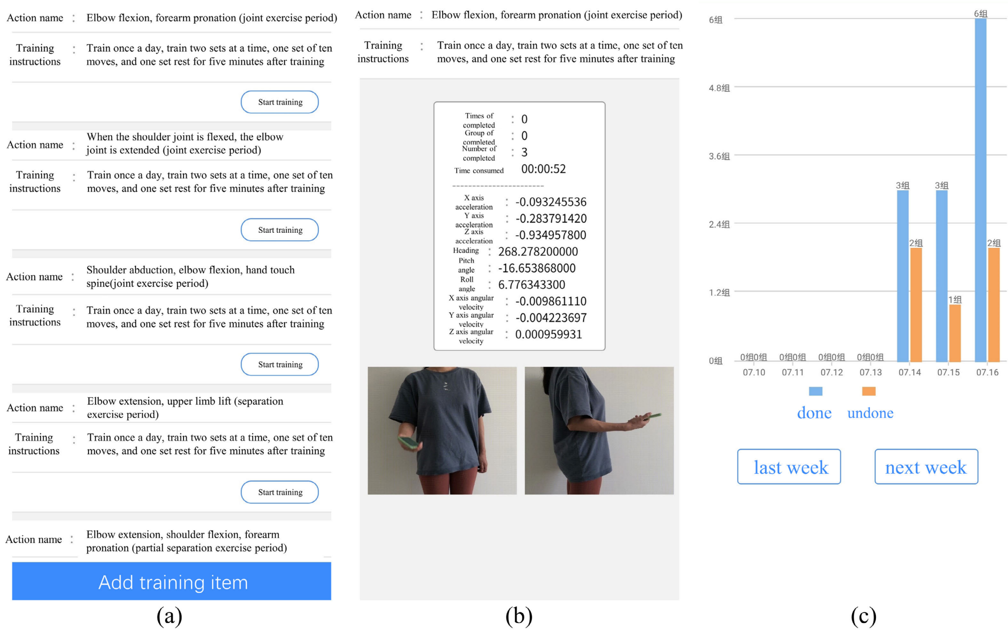

FIGURE 3. Mobile client interface.

are stored in stroke survivors rehabilitation database. The machine learning model is built for stroke survivors rehabilitation data and aims to process stroke survivors rehabilitation data.

D. ACTION ANALYSIS SERVICE

Stroke survivors' rehabilitation movement data acquired through the built-in sensors of the mobile device can be regarded as an movement sequence, including nine attributes: three-axis acceleration values a_x, a_y, a_z measured by the accelerometer, angular velocity value ω_x, ω_y, ω_z of mobile phone rotating around three-axis measured by gyroscope, and the pitch angle β, heading angle α and roll angle γ of the mobile phone measured by the device direction sensor. The action analysis service uses DTW-KNN algorithm to analyze stroke survivors' rehabilitation action data and judge the accuracy of the rehabilitation action.

1) DYNAMIC TIME WARPING ALGORITHM (DTW)

Dynamic Time Warping algorithm(DTW) is a dynamic planning algorithm that calculates the similarity of two time series, especially series of different lengths. It can flexibly realize template matching and solve many discrete time series matching problems. Since the speed and amplitude of rehabilitation actions performed by stroke survivors in different stages of rehabilitation will be quite different, there must be a difference between stroke survivors' rehabilitation actions and standard actions, and DTW algorithm can measure the similarity of two non-equal length sequences, which is suitable for processing sequence data collected in this study. Figure 4 shows a comparison of the x-axis acceleration between two rehabilitation movements.

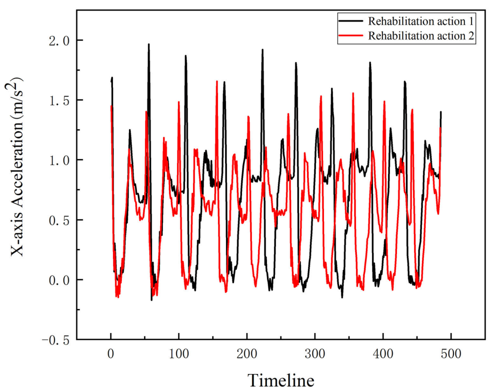

FIGURE 4. Comparison of acceleration in the x-axis direction between two rehabilitation actions.

Suppose there is a sample sequence and a test sequence, and there is a point-to-point distance function in the sequence:

$$d(i, j) = f(x_i, y_j) \geq 0 \tag{1}$$

DTW first obtains a sequence distance matrix M according to the distance between the sequence points, and then generates a loss matrix M_c according to the distance matrix. The core of DTW is to solve the distortion curve, that is the correspondence between points, which can be expressed as:

$$\phi(k) = (\phi_x(k), \phi_y(k)) \tag{2}$$

The possible value of $\phi_x(k)$ is $1, 2, \ldots, N$, and the value of $\phi_y(k)$ may be $1, 2, \ldots, M$, $k = 1, 2, \ldots, T$. That is to find out T correspondences from the midpoint of the X sequence to the midpoint of the Y sequence. In a given situation, the cumulative distance of the two sequences can be solved:

$$d_{\phi}(X, Y) = \sum_{k=1}^{T} d(\phi_x(k), \phi_y(k)) \tag{3}$$

The final output of DTW is to find the most suitable distortion curve to minimize the cumulative distance, that is, the value of the last row and last column of the loss matrix:

$$DTW(X, Y) = \min_{\phi} d_{\phi}(X, Y) \tag{4}$$

This output value is used to measure the similarity between stroke survivors' movements and the standard movements, and the output standardized distance can be further input to the KNN classifier.

2) K-NEAREST NEIGHBOR ALGORITHM (KNN)

K-Nearest Neighbor method is one of the most intuitive and effective methods in data mining classification technology. The core idea is that if most of the K nearest training samples in the feature space of a test sample belong to a certain category, then the samples also fall into this category. KNN finds the K training samples closest to the test sample in the training sample based on a certain distance metric, and the selected training samples have been correctly classified. We consider that this is a voting mechanism. For multi-classification problems, in order to avoid the same number of votes for the two categories, the K value of K-Nearest Neighbors is generally an odd number. In order to ensure the accuracy of the classification algorithm and voting efficiency, the K value in this research is 11.

3) JUDGMENT METHOD OF REHABILITATION ACTIONS BASED ON DTW-KNN MODEL

In this study, we have collected several template actions in advance through mobile client and invited physicians to classify them. DTW is used to calculate the distance for 9 attributes between the test action and each template action, and the cumulative sum of the distances between the 9 attributes is used as the distance between two actions, then the data is normalized for several distances, and the distance data is imported into the KNN algorithm classifier. In this study, the completion of rehabilitation actions of stroke survivors is divided into three categories, namely A (excellent), B (good), and C (general). The KNN classification algorithm votes based on the selected K value to obtain the category to which the test action belongs, that is, the completion status, so as to realize the classification and judgment of the accuracy of stroke survivors' rehabilitation action. The flowchart of the rehabilitation action evaluation method based on the DTW-KNN model is shown in Figure 5.

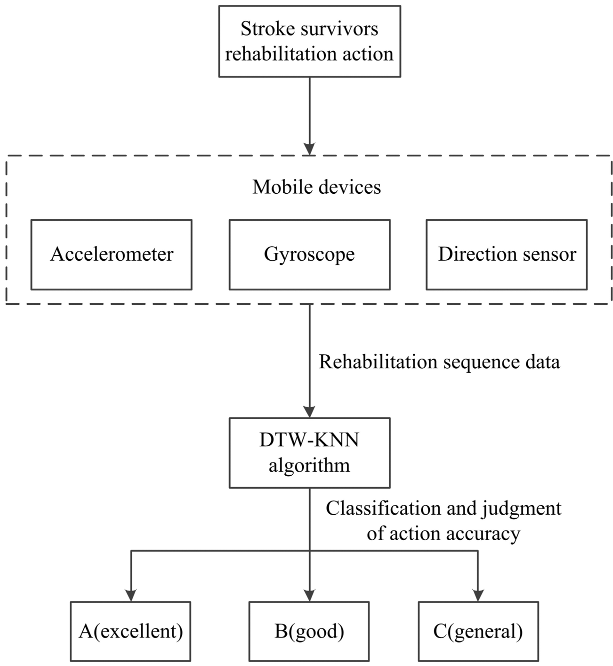

FIGURE 5. Judgment method of rehabilitation actions based on DTW-KNN model.

IV. EXPERIMENTAL RESULTS

This study intends to verify the design experiment of the research results of the upper limb functional rehabilitation system, and use the DTW-KNN model to classify and judge the completion of rehabilitation actions. In this experiment, a number of stroke survivors with Brunnstrom staging as the joint exercise phase(III) are used as examples to verify, and choose elbow flexion as an example of rehabilitation action. This experiment collects stroke survivors training data through mobile client, obtains a total of 150 sets of data as template actions, and invites physicians to classify the accuracy of the actions completed in three categories, A(excellent), B(good), C(general). There are 50 groups of each type of action, and each group contains 10 actions.

In the experiment, a number of joint exercise phase stroke survivors are selected to train for a number of test actions(elbow flexion). The actual situation of the test actions are judged and classified by the physician through observation on the spot, from excellent, good to general, in order of A, B, and C. There are 18 groups of test actions. After the physicians' observation and judgment, there are 6 groups of A,B, and C test actions. Figure 6 is a comparison diagram of some attributes of a test action and a type A action. The solid line is the test action, the dashed line is the type A template action. Figure 6 (a), (b), (c), (d) are the x-axis acceleration comparison, the x-axis angular velocity comparison, the z-axis angular velocity comparison and the heading angle comparison between the two actions in sequence.

The output of the experimental results is Type A 5, Type B 3, Type C 3, that is, the 11 template actions closest to the test action include 5 type A actions, 3 type B actions, and 3 type C actions, so DTW-KNN model judges that the completion of the test action is a type A action, that is, the completion is excellent, and the actual situation of the test

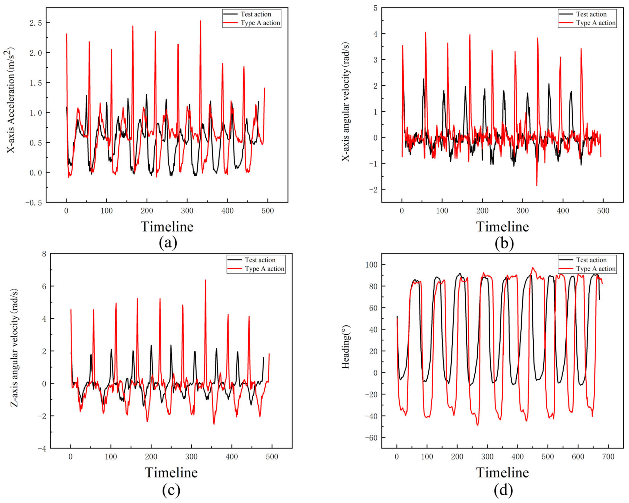

FIGURE 6. Comparison of some attributes between test action and A-type template action.

action observed by the physicians is also A. Subsequently, the remaining 17 sets of test action data were put into the DTW-KNN model for classification and evaluation, and the actual situation and the classification confusion matrix determined by the model were obtained, as shown in Table 1.

TABLE 1. Classification confusion matrix.

Actual situation / *Model decision*	*A*			*B*			*C*		
	A	*B*	*C*	*A*	*B*	*C*	*A*	*B*	*C*
Number of groups	6	0	0	1	4	1	0	2	4

Through the confusion matrix, the following conclusions can be drawn: the accuracy of the classification model is 77.8%, and the relevant indicators of the three types of test actions of A, B, and C are shown in Table 2.

TABLE 2. Detailed indicators of ABC three types of test actions.

Indicators	*A test action*	*B test action*	*C test action*
Accuracy	85.7%	66.7%	80%
Recall	100%	66.7%	66.7%
Specificity	91.7%	83.3%	91.7%

In Table 2, the A,B,C test actions are the completion of the test actions(elbow flexion) performed by the stroke survivors tested in the experiment, A test action represents excellent completion, B test action represents good completion, and C test action represents general completion. It can be seen from Table 2 that the overall classification accuracy of the classification model is good, the accuracy of class A and C test action prediction classification is well, and the accuracy of class B test action prediction classification is good. In the later period, this research will be promoted to expand the data volume of the test samples, and improve by introducing other algorithms combined with DTW-KNN comparison, so as to obtain the optimal algorithm to classify and judge stroke survivors' rehabilitation actions.

V. CONCLUSION

This research aims at the upper limb functional rehabilitation stroke survivors group, combined with the Internet and artificial intelligence and other technologies to design a remote rehabilitation intelligent system based on multi-mode sensors. Stroke survivors hold mobile devices for rehabilitation training, and use the built-in multi-sensor of the smartphone to capture stroke survivors' upper limb rehabilitation action. Then the rehabilitation movement data is sent to the remote server through the Internet, and the DTW-KNN algorithm is used on the server to realize the analysis and accuracy classification of stroke survivors' rehabilitation movement, thereby realizing an end-to-end upper limb rehabilitation system. Compared with traditional rehabilitation training, this method is not limited by time and space, and stroke survivors are suitable for self-rehabilitation training at home. Physicians can manage their own stroke survivors through the PC client, and can know stroke survivors' rehabilitation progress in time, so that they can better formulate the next stage of rehabilitation training plan for stroke survivors.

Since the output value of the built-in accelerometer of the mobile device is referenced to the mobile phone coordinate system, it is difficult to truly reflect the actual action state of stroke survivors under the inertial coordinate system, which results in a certain error in the rehabilitation action. In the KNN classification algorithm, since various template actions have to be traversed each time, a larger amount of calculation and a larger storage resource will be generated. In addition, the accuracy of class B actions needs to be improved. Since this research is still in the initial stage, the later stage will be through the introduction of related mathematical methods for spatial coordinate conversion, and the acceleration data will be mapped from the mobile phone coordinate system to the inertial coordinate system, so as to ensure that the data can accurately reflect the actual stroke survivors' actual situation under any position of the mobile phone. In addition, relevant improved algorithms or neural network methods will be introduced to improve the efficiency and accuracy of classification and evaluation of the accuracy of rehabilitation actions.

In addition, this rehabilitation system can be used not only for stroke rehabilitation, but also for physical rehabilitation in other situations, such as limb dysfunction caused by rheumatoid arthritis, cervical spondylosis and lumbar disc herniation etc.

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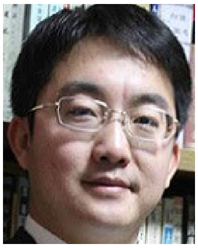
SHENG MIAO received the Ph.D. degree from Towson University, USA, in 2017. He is currently an Assistant Professor with the School of Data Science and Software Engineering, Qingdao University. His research interests include machine learning, data mining, the Internet of Things, smart healthcare, and intelligence systems.

CHEN SHEN was born in Linyi, Shandong, China, in 1996. He is currently pursuing the master's degree with Qingdao University, China. His research interests include artificial intelligence systems and machine learning. He won the Second Prize of the 2020 China Postgraduate Electronic Design Competition National Finals.

XIAOCHEN FENG was born in Linyi, Shandong, China, in 1991. She is currently pursuing the bachelor's degree with the Jining Medical College, China. Her research interest includes neurorehabilitation.

QIXIU ZHU was born in Qingdao, Shandong, China, in 1963. She received the M.S. degree in neurorehabilitation from Qingdao University. She is currently a Professor and a Master's Supervisor with Qingdao University. Her research interest includes neurorehabilitation.

MOHAMMAD SHORFUZZAMAN (Member, IEEE) is currently an Associate Professor with the Department of Computer Science, College of Computers and Information Technology (CCIT), Taif University, Taif, Saudi Arabia. He is also a member of the Big Data Analytics and Applications Research Group (BDAAG), CCIT. His primary research interests include applied artificial intelligence in the areas of computer vision and natural language processing, big data, and cloud computing.



ZHIHAN LV (Senior Member, IEEE) received the Ph.D. degree from the Ocean University of China and the University of Paris 7, in 2012. From 2012 to 2016, he was an Assistant Professor with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. He worked with CNRS, France, as a Research Engineer, Umeå University, Sweden, as a Postdoctoral Research Fellow, the Fundación FIVAN, Spain, as an Experienced Researcher, and University College London, U.K., as a Research Associate. He held a postdoctoral position with the University of Barcelona, Spain. He is currently an Associate Professor of Qingdao University, China. He has contributed more than 200 articles in the related fields on journals, such as IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, IEEE TRANSACTIONS ON FUZZY SYSTEMS, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS: SYSTEMS, IEEE TRANSACTIONS ON EMERGING TOPICS IN COMPUTING, IEEE TRANSACTIONS ON BIG DATA, IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS, IEEE JOURNAL OF SELECTED TOPICS IN SIGNAL PROCESSING, IEEE INTERNET OF THINGS JOURNAL, *ACM Transactions on Multimedia Computing, Communications, and Applications*, *ACM Transactions on Internet Technology*, and *ACM Transactions on Intelligent Systems and Technology*, and conferences, such as ACM MM, ACM CHI, ACM Siggraph Asia, ICCV, and the IEEE Virtual Reality. His main research interests include the Internet of Things, blockchain, multimedia, augmented reality, virtual reality, computer vision, 3D visualization and graphics, serious game, HCI, big data, and GIS. He was a Marie Curie Fellow of the European Union's Seventh Framework Program LANPERCEPT. He is a Program Committee Member of ACM IUI2015, 2016, 2019, and 2020, the IEEE CHASE Workshop on BIGDATA4HEALTH 2016 and 2017, the IEEE/CIC WIN Workshop 2016, IIKI2016 to 2019, WASA2016, 2017, IEEE PDGC2016, the ACM SAC2017-WCN Track, the IEEE CTS2016 Workshop on IoT2016, IEEE DASC2017 and 2020, ISAPE2017, IoTBDS2017, IEEE AIMS2017, IEEE iThings-2017, the IEEE VTC2017-Fall, the IEEE INFOCOM 2020 Workshop, and the ACM MobiCom 2020 Workshop. He has been an Associate Editor of *PLOS one*, since 2016, IEEE ACCESS, since 2016, *Neurocomputing*, from 2016 to 2018, and *IET Image Processing*, since 2017. He is the Leading Guest Editor of IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, *IEEE Network*, IEEE SENSORS, *IEEE Consumer Electronics Magazine*, *Future Generation Computer Systems*, *Neurocomputing*, and *Neural Computing and Applications*.

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Use of Accelerometry for Long Term Monitoring of Stroke Patients

Alfredo Lucas[1*], John Hermiz PhD[2*], Jamie LaBuzetta MD[3], Yevgeniy Arabadzhi[2], Navaz Karanjia MD[3], Vikash Gilja PhD[2]
University of California, San Diego, Department of (1) Bioengineering, (2) Electrical and Computer Engineering, (3) Neurosciences
* Both authors contributed equally to this work.

Abstract

Stroke patients are monitored hourly by physicians and nurses in an attempt to better understand their physical state. To quantify the patients' level of mobility, hourly movement (i.e. motor) assessment scores are performed, which can be taxing and time consuming for nurses and physicians. In this study we attempt to find a correlation between patient motor scores and continuous accelerometer data recorded in subjects who are unilaterally impaired due to stroke. The accelerometers were placed on both upper and lower extremities of 4 severely unilaterally impaired patients and their movements were recorded continuously for 7 to 14 days. Features that incorporate movement smoothness, strength and characteristic movement patterns were extracted from the accelerometers using time-frequency analysis. Support Vector Classifiers were trained with the extracted features to test the ability of the long term accelerometer recordings in predicting dependent and antigravity sides, and significantly above baseline performance was obtained in most instances ($P < 0.05$). Finally a leave-one-subject-out approach was carried out to assess the generalizability of the proposed methodology, and above baseline performance was obtained in two out of the three tested subjects. The methodology presented in this study provides a simple, yet effective approach to perform long term motor assessment in neurocritical care patients.

1. Introduction

Motor impairment monitoring in stroke patients admitted to the Intensive Care Unit (ICU) is crucial for understanding patient prognosis and recovery, as well as for identifying critical times for the application of medications, such as Tissue Plasminogen Activator (tPA), which can significantly improve patient outcomes [1]. It is also relevant for detection of early onset of Intensive Care Unit Acquired Weakness (ICU-AW), which can persist for up to 2 years after patient discharge [2].

The measurement of motor function is usually done through standardized measurement tests. Of particular interest for this study is the Oxford Grading system for hourly neuroassessments [3], performed by a nurse or clinical provider on the patient, whose strength is assessed and scored 0 to 5 on each limb. While such scoring is of clinical utility, it is non-ideal for multiple reasons; firstly, the exams are labor intensive and usually performed not more frequently than every hour, leaving the possibility for major changes in motor ability to remain undetected for long periods of time. Furthermore, interobserver variability still remains a problem, where the accuracy of the assigned score is highly dependent on external factors such as the provider's expertise and time of stroke onset [4]. Finally, frequent neurological exams during a patient's hospital stay disturbs sleep and may increase delirium, which worsens morbidity and mortality [5, 6].

The use of accelerometers to monitor physical activity in critically ill subjects has been explored previously with successful results [7]. In the Neurological Intensive Care Unite (Neurological ICU), the use of accelerometers for patient monitoring has been explored to detect agitation and sedation patterns [8], and to study sedentary behavior [9]. The use of accelerometers, specifically to detect changes in patient motor score in the Neurological ICU, has been explored previously utilizing the NIHSS motor score as a metric [10–12], as well as using different motor score scales [13]. However, these studies only performed the recordings over small time windows, with maximum recording times consisting of 10 minute epochs [10] and 12 second epochs [14] over 24 hours.

Machine learning algorithms have proven successful in characterizing motor activities extracted from accelerometers [15, 16]. Specifically, support vector ma-

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Table 1: Subject Demographics

Subject Number	Age	Gender	Impaired Side	Length of Data Collection (days)	Minimum Limb Scores (RUE-LUE-RLE-LLE)	Maximum Limb Scores (RUE-LUE-RLE-LLE)
Subject 1	46	M	Right	7	0-1-0-1	2-5-1-5
Subject 2	39	F	Left	7	0-0-0-0	4-2-5-2
Subject 3	48	M	Left	14	1-0-1-0	4-3-4-2
Subject 4	74	M	Left	7	5-3-5-4	5-5-5-5

chines (SVMs) have been used for movement characterization and activity recognition in accelerometers and other activity monitoring devices with surprising success rates [17–21]. While studies applying machine learning and big data approaches for assessment in the ICU have been explored before, they have been focused towards determining agitation and sedation patterns, and delirium state, but not motor impairment [22–24]. Additionally, in the studies that do apply machine learning, they do so in controlled settings, where accelerometer recordings are only done in the first days after admission and in certain controlled time windows [10].

In the present study we assess whether long term monitoring of seven days or more, using accelerometers in unilaterally impaired stroke patients in the ICU, is useful in determining motor impairment. An SVM classifier was created and trained using accelerometer derived features to classify dependent and antigravity limbs. The usefulness of the extracted features is also assessed through a recursive feature selection approach. The methods and results of this study serve as a proof of concept for the use of accelerometers as a monitoring mechanism in a challenging clinical environment, and as a way of translating acceleromtery based machine learning models, widely used in other settings, into the Neurological ICU.

2. Methods

2.1. Clinical Data Acquisition

Subject Recruitment

This study was designed to be HIPAA compliant and all study procedures were reviewed and approved by the Institutional Review Board of the University of California, San Diego. Study subjects were recruited from the Neurological Intensive Care Unit at UC San Diego Medical Center - Hillcrest hospital. A total of four unilaterally impaired adult subjects were recruited, subject demographics are presented in Table 1. All subjects had experienced a stroke which led to severe unilateral impairment as determined by the practicing clinician. The subjects were enrolled in the study under their consent and remained enrolled in the study for up to 14 days or until discharged from the Neurological ICU, whichever occurred first.

Motor Assessment

As part of the Physical Function ICU Test (PFIT) [25], muscle movement grading was routinely performed using the Oxford Grading Motor Scale (Table 2) by the medical practitioner, and recorded on an hourly basis on the subjects' medical chart. The clinical motor score data were downloaded from the electronic medical record after removing all identifying information. Subjects 1 through 3 were recorded for the duration of their stay in the hospital without interruptions in the data collection procedure with hourly assessments. Subject 4 had some interruptions in the data collection procedure and motor scores were often obtained every 1 to 4 hours to mitigate the risk of experiencing delirium as determined by the clinical team.

Information from the Oxford Grading Motor Scale was used for this study since it has been shown to be the best estimator of antigravity muscle strength [3]. Furthermore, the Oxford Grading Scale is considered the gold standard for determining ICU acquired weakness (ICU-AW) [26], which early onset detection can aid in successful recovery post-ICU.

Limb Impairment Characterization

During each limb assessment a limb was classified as "dependent" if it had a motor score of 0-2 and "antigravity" if it had a motor score of 3-5. A score of 3 is chosen as a threshold since it separates those movements that can be done against gravity (scores 3, 4, and 5) and those that can not (scores 0, 1, and 2), effectively giving a binary representation of impairment. It also allows each limb classification to contain 3 motor scores. The creation of the two groups of limbs allows the motor impairment assessment from the accelerometer features to be treated as a binary classification problem which can be analyzed with the proposed methodology. Motor score values and impairment information for each subject is shown in Table 1.

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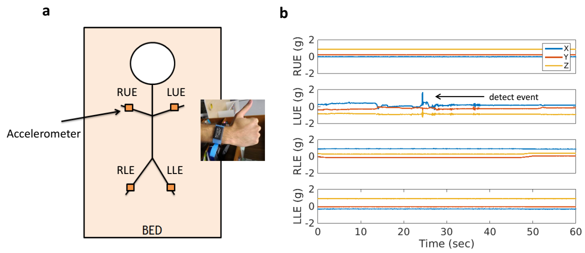

Figure 1: a) Illustration of experimental setup, where 4 accelerometers are mounted onto hospital bands and placed around each of the patients extremity. b) Raw tri-axial accelerometer measurements are performed continuously across all 4 extremities. Changes in accelerometry are detected, interpreted as movements, and counted per hour.

Table 2: Oxford Motor Grading Scale

Motor Score	Description
Score 0	No muscle movement
Score 1	Muscle movement without joint motion
Score 2	Moves with gravity eliminated
Score 3	Moves against gravity but not resistance
Score 4	Moves against gravity and light resistance
Score 5	Normal strength

Accelerometer Data Collection

Upon enrollment, four tri-axial accelerometers (Axtivity AX3 Accelerometers) were placed in the left upper extremity (LUE = left arm), the right upper extremity (RUE = right arm), the left lower extremity (LLE = left leg) and the right lower extremity (RLE = right leg). All accelerometers were attached to hospital bands and placed on the subjects' wrists and ankles as shown in Figure 1. Data were continuously acquired at 100Hz for up to 14 days or until the subject was discharged from the Neurological ICU, whichever occurred first. After the study was completed, the accelerometers were removed from the extremities and the data were downloaded to a computer.

2.2. Data Processing and Analysis

All of the subsequent analyses were performed on a personal laptop computer with 16GB of RAM and an Intel Core i7 CPU with 2.80GHz running Windows 10.

Signal Preprocessing and Movement Event Extraction

The raw accelerometer data were down-sampled from 100Hz to 50Hz, because significant signal power

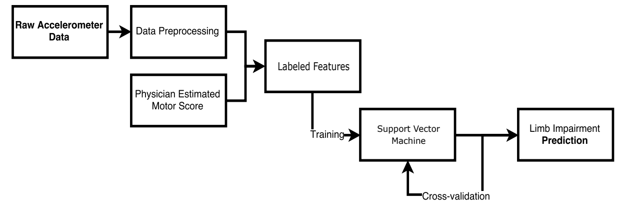

Figure 2: Flowchart presenting the pipeline used to generate the results

was only seen below 25Hz. After down-sampling, the magnitude of each accelerometer was calculated according to equation 1

$$A[t] = \sqrt{x[t]^2 + y[t]^2 + z[t]^2} \tag{1}$$

where $A[t]$ corresponds to the magnitude of the accelerometer signal at time t and $x[t]$, $y[t]$ and $z[t]$ to the acceleration in the x, y and z direction, at time t in the accelerometers' frame of reference. Subsequently, to eliminate the baseline normal force ($9.8m/s^2$), measured in the accelerometer as a constant offset, the difference between subsequent timepoints, $A'[t]$, was taken. Matlab software was used to compute features.

To classify movement events, an empirically chosen threshold was applied to the $A'[t]$ of the signal. The parameters used to detect features were manually chosen and were determined to be sufficient based on their ability to detect events from an example window of data. Instances that lasted longer than 1 sec and had a subsequent silent period of 0.5 sec after the instance were then classified as movement events, and stored with the corresponding timestamp. All extracted movement events consisted of non-overlaping windows and were specific to each limb.

It is important to note that some of the detected movement events are not generated by the subject, but rather by clinicians who need to interact with the patient. The approach to filter these movements out is discussed in the following sections.

Feature Generation

The start and end timestamps for each detected event following the procedure from the previous section, were used to extract the magnitude corresponding to that time window. The time magnitude vector for each event window was subsequently used to create 9 scalar valued features. The features were selected on their ability to characterize movement on the basis of smoothness, intensity and pattern behavior, and all have been successfully used to characterize motor activity in

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wrist and ankle worn accelerometers [17, 27]. Furthermore, feature computation time was also considered in the selection process to ensure translational applicability.

The features extracted for each event are shown in table 3. From the time domain, the first feature consisted of the time average of the magnitude vector as shown in Equation 2,

$$A_{avg} = \frac{1}{t_f - t_i} \int_{t_i}^{t_f} A[t]dt \tag{2}$$

for t_i and t_f corresponding to the initial and final timepoints of the event. The maximum and minimum values of the magnitude vector were also used. To characterize movement smoothness, the jerk of the signal has been previously used to characterize tremors in bradykinesia and Parkinson's disease [28, 29]. To convert the jerk into a scalar quantity the Normalized Average Rectified Jerk (NARJ) was used instead of the time average jerk since the NARJ has been shown to be a consistent metric for movement smoothing independent of signal duration [30]. The NARJ was computed as follows

$$NARJ = \frac{1}{t_f - t_i} \int_{t_i}^{t_f} \left| \frac{dA[t]}{dt} \right| \tag{3}$$

An FFT transform of the magnitude vector was used to obtain frequency based features. The first and second dominant frequencies (excluding DC) and their corresponding FFT power were extracted as features, all of which have been proven successful for accelerometer based movement characterization [27]. The use of multiple combinations of these features have also proven useful, but with minimal improvements in the classification accuracy, therefore they were excluded as a means of minimizing the number of features [17].

After the above scalar features were computed for every extracted event, the average of each feature for events taking place in a single hour was computed, resulting in one feature vector for every limb and for every hour. This allowed us to include a final feature that consisted of the number of events that took place in that given hour. The reason for combining event features in an hourly fashion is twofold. First, since motor assessments are performed every hour, the clinical score between assessments is not accurately known and assuming that every event within the hour has the same score as the hour itself would be an oversimplification. Secondly, some of the registered events will correspond to movements induced by interactions between the practitioner and the subject. Under the assumption that those interactions only happen a small number of times within the hour, taking the hourly average of the features will allow to minimize the effects these confounding movements have on the performance of the system.

Table 3: Accelerometer derived features

Name	Description
Magnitude Average	- Time average of the magnitude vector
Maximum Magnitude	- Maximum value of the magnitude vector
Minimum Magnitude	- Minimum value of the magnitude vector
NARJ	- Normalized average rectified jerk [30]
Power 1	- Power of the first dominant FFT coefficient
Power 2	- Power of the first dominant FFT coefficient
Frequency 1	- Frequency corresponding to the first dominant FFT coefficient
Frequency 2	- Frequency corresponding to the second dominant FFT coefficient
Movement Count	- Number of events recorded in the hour

The features were organized into a matrix where each row corresponds to an hour where events were recorded and columns correspond to the respective features for that hour. A given row of the feature matrix was labeled to be from a dependent limb if the motor score for that limb at that hour was less than 3, and antigravity otherwise, in keeping with the previously defined thresholds. The columns of the feature matrix (feature vectors) were scaled to have zero mean and unit variance, which is necessary to prevent uneven feature scaling to affect the results. This normalization was done per subject, per day. That is, the feature vectors corresponding to the same subject for a given day were normalized under the same distribution to zero mean and unit variance.

Support Vector Machine Classifier

The use of Support Vector Machines for the characterization of movements using accelerometers has been successfully explored before [17–21]. Furthermore, SVM's suitability for binary classification problems with small numbers of features makes it an ideal choice of algorithm for this study [31].

The open source Python library *scikit-learn* [32] was used, together with Python 3.6 to apply the classification analysis to the data. Support Vector Classifiers (SVCs) were trained to classify between dependent and antigravity limbs. In its essence SVCs project the input feature space into a higher dimensional features space in which a hyperplane described by "support vectors" is

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used to classify the data [33]. A linear kernel was chosen for all the trained SVCs. The choice of a simple linear kernel prevents overfitting of the training set in the presence of small datasets. The two hyperparameters of the classifier, C and γ were determined using a coarse parameter grid search with values $C = 2^{-5}, 2^{-3}, ..., 2^{15}$ and $C = 2^{-15}, 2^{-13}, ..., 2^{3}$, according to the procedure described in [34]. The optimal parameters obtained from the grid search were $C = 2$ and $\gamma = 0.5$.

SVCs were trained for each subject and separately for upper and lower extremities within each subject. The data were divided using an 80/20 approach, where 80% of the data is used for training and validation and 20% is used for testing. Testing and training sets were ensured to have similar ratios of dependent and antigravity instances. This process was repeated for every patient and type of extremity (upper and lower). In order to evaluate the ability of cross-limb information in helping to classify dependent limbs, a third combined classifier was created for each subject, in which training and prediction occurred in combined upper and lower limbs. The feature selection process and cross-validation was identical.

To determine the validity of a classification, the probability output from the classifier was used. In general, if the posterior probability of an instance belonging to the dependent class is over 50%, the SVC will assign that class to the tested instance. However, since the classifier is not perfect, there will be a certain degree of uncertainty with each prediction, which can be estimated by the closeness of a given prediction to the decision boundary. As a means of increasing the certainty of the predictions, those that had probabilities within a region close to the decision boundary were labeled as uncertain. To determine this region, the probability of an instance belonging to the dependent class was used. Since the clinical risk of a false negative (incorrectly predicting a dependent limb as antigravity) is larger than the risk of a false positive (incorrectly predicting an antigravity limb as dependent), the lower bound of the probability region was set to 42% while the upper bound was set to 54%. That is, for an instance to be classified as antigravity, the probability of it belonging to the dependent class must be smaller than 42%, while for it to be classified as dependent, the probability of it belonging to the dependent class must be larger than 54%. Instances with probabilities between 42% and 54% are otherwise labeled as uncertain. These bounds were chosen such that the number of instances labeled as uncertain was less than 20% of the tested instances.

Maintaining the dependent and antigravity labels of the feature matrix as a template, the entries of the matrix were populated with normalized random data between 0 and 1 to train a baseline classifier. The random feature matrix was subject to the same scaling as the actual feature matrix and used to train a SVC. Cross-validation scores were computed for the baseline classifier and used as the baseline accuracy for its corresponding actual classifier. Given that the number of cross validation accuracy scores is only 10 for every actual classifier, the normality of this data can not be accurately determined. For this reason a nonparametric Wilcoxon rank-sum test was used to compare the cross-validation scores of the actual classifier with the accuracy of the baseline classifier. The statistical significance of the accuracy values for each trained classifier was calculated by subtracting the cross-validation accuracy scores from their corresponding baseline accuracy and performing a one sided Wilcoxon rank-sum test in the resulting datapoints.

Only subjects 1 through 3 were used for creating the individual classifiers since subject 4's minimum motor score on the dependent side was 3, therefore all of its features were labeled as antigravity.

Feature Relevance Assessment

In order to validate the choice of features, a recursive feature selection approach was taken. Given the complete set of features described previously, an SVC was trained using all possible combinations of features in sets ranging from 1 feature to 9 features. Each individual classifier previously described (upper, lower and combined extremity classifiers), for subjects 1 through 3 was used. With the same specifications described in the previous section, a 10-fold cross-validation was applied to each classifier and the average cross-validation accuracy for all folds and all classifiers was used as a metric for the performance of each feature set. The test set did not enter the feature selection process in any way.

Leave-One-Subject-Out Approach

In order to assess the generalizability of the proposed methodology, a leave-one-subject-out approach was used. For this approach, all the data from a single subject were excluded from the training set and then the model was tested on that excluded data. The SVCs used in this approach had the same hyperparameters and linear kernel type as in the previously described classifiers. To assess which features were generalizable across subjects, a leave-one-subject-out approach leaving subject 3 out, and training on subjects 1, 2, and 4, was performed. Using a similar approach as that shown in the previous section, the performance in the left out test set after training with different feature sets was assessed for a classifier using only information from the upper

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extremities, the lower extremities, and combined upper and lower extremities. After the features with the best performance were identified in subject 3, a final leave-one-subject-out approach training on subjects 2, 3 and 4, and testing on subject 1 was carried out. For comparison, a baseline classifier was also trained following the same approach described previously, and tested on the data of subject 1. Subject 4 was not assessed for the leave-one-subject-out approach due to the absence of any impaired limbs according to the specified criteria. Subject 2 was assessed for the leave-one-subject-out approach by training on subjects 1, 3, and 4, however, it seemed that none of the features generalized well as performance was no better than baseline.

3. Results

The results from the recursive feature selection are shown in Figure 3. It can be seen that every feature used yields above baseline mean cross validation accuracy. The largest accuracy is achieved with classifiers trained using all available features as shown by the blue triangle, and with a classifier using all features except the *average magnitude*, which is represented by highest red circle. A general downwards trend is observed as less features are used for training the model, and there seems to be a clear separation between certain sets of features, as represented by a large vertical gap in the figure. The single features with the largest accuracy were the *average magnitude*, *movement count* and *power 2*. Furthermore, feature sets ranging between 2 and 7 features containing either of these three features always appeared above the vertical gap suggesting the relative importance of these three features. The individual classifiers were trained using all features as the difference in cross-validation performance between the highest performing 8 feature set and the complete feature set was negligible.

The results from the trained SVCs are shown in Figure 4. The combined classifiers, across all trained subjects, had on average a cross-validation accuracy of 0.72 ± 0.05 and a test set accuracy of 0.73 ± 0.05, the upper classifiers an average cross-validation accuracy of 0.76 ± 0.08 and a test set accuracy of 0.81 ± 0.02, and the lower classifiers an average a cross-validation accuracy of 0.78 ± 0.13 and a test set accuracy of 0.80 ± 0.06. Most instances had cross-validation performance statistically significant ($P < 0.05$) above that of the baseline classifier, with the exception of the combined ($P = 0.25$) and lower ($P = 0.39$) extremity classifiers for subject 2. Furthermore, all test set accuracies were within the cross-validation scores range and above baseline, with the exception of the combined classifier

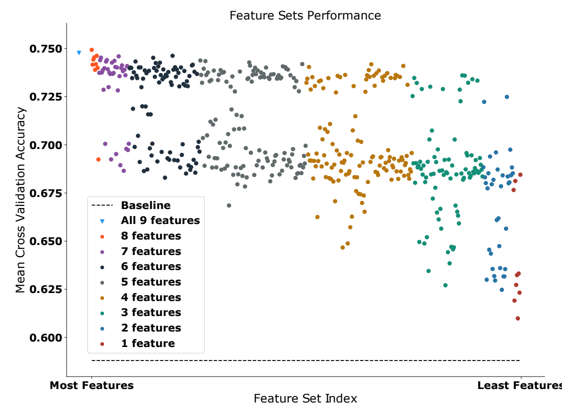

Figure 3: Scatterplot showing the recursive feature sets mean cross-validation accuracy across all individual classifiers. Each data point is color coded to the number of features in the feature set it represents. The number of features in each set decreases as the points go to the right. Mean baseline classifier is shown with a dashed line.

in subject 2.

The feature selection process showed that the features that performed the best in the leave-one-subject-out approach were the *maximum magnitude*, *power 2* and the *movement count*. The leave-one-subject-out approach on subject 3, which was used for feature selection, yielded test set accuracies of 0.66, 0.77 and 0.73, with baseline accuracies of 0.51, 0.51 and 0.49, for combined, upper and lower extremity classifiers respectively. The leave-one-subject-out approach on subject 1, had accuracies of 0.74, 0.82 and 0.72, and baseline accuracies of 0.61, 0.56 and 0.65 for combined, upper and lower extremity classifiers respectively. Finally the leave-one-subject-out approach on subject 2, had accuracies of 0.50, 0.51 and 0.47, and baseline accuracies of 0.35, 0.61 and 0.74 for combined, upper and lower extremity classifiers respectively. These results are summarized in Table 4 The confusion matrices and ROC curves for the leave-one-subject-out approach on subject 1 are shown in Figure 5. The confusion matrices shown in Figure 5A-C have the largest values in their diagonals, with a large number of true negatives (antigravity instances classified as antigravity), followed by a smaller number of true positives (dependent instances classified as dependent). In the off-diagonals, there was a larger number of false negatives (dependent instances classified as antigravity), than false positives (antigravity limbs classified as dependent), and this is consistent across all matrices. The receiver operator characteristics (ROC) curves for combined, upper and lower ex-

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Table 4: Leave-one-subject-out accuracy for subjects 1 through 3, and all corresponding classifiers. Baseline accuracy is shown in parenthesis.

	Combined	**Upper**	**Lower**
Subject 1	0.74 (0.61)	0.82 (0.56)	0.72 (0.65)
Subject 2	0.50 (0.35)	0.51 (0.61)	0.47 (0.74)
Subject 3	0.66 (0.51)	0.77 (0.51)	0.73 (0.49)

tremity classifiers are also shown in Figure 5D-F. The area under the ROC curves was largest for the upper extremity trained classifier with a value of 0.87, followed by the combined classifier with a value of 0.76 and the lower extremity classifier with a value of 0.74. For the leave-one-subject-out approach of subject 1, 67% of the incorrect classifications took place in the second half of the dataset, that is, in the latter days in which the subject was monitored. For the leave-one-subject-out approach of subject 3, the errors were distributed equally amongst the two halves of the dataset.

4. Discussion

The results presented in this study successfully demonstrate the ability of features extracted from continuous accelerometer recordings in the NeuroICU to determine gravity and antigravity limbs. Of primary importance is that this is the first study, to our knowledge, that has attempted to assess motor impairment in the ICU for 7 days or more in individual subjects. We have also demonstrated that the proposed methodology is capable of generalizing to new subjects with minimal modifications, allowing for a simple, yet effective, way of performing motor assessment in the NeuroICU. While the sample size is limited, the results should serve as a lower bound for the performance that future studies should aim to achieve.

The iterative feature assessment shown in Figure 3 demonstrates that all the features extracted from the accelerometer are informative. The general downward trend as the number of features is decreased suggests that while certain features might dominate in importance, such as the *average magnitude* and the *movement count*, the contribution of the other features is sufficient to yield larger accuracies when they are included in the model. Simply using the movement count, as traditionally done in approaches involving actigraphy [35], has been shown to be ineffective in an ICU setting [36]. The incorporation of these new features attempts to account for other characteristics of the subject's movement such as smoothness and idiosyncratic movement patterns, which might explain the additional accuracy obtained by including these features. Additionally, their computation is fast and straightforward. After extraction of all the movement events with the proposed approach, the computation of the entire feature matrix for a given subject takes on average 3 seconds, resulting in about 0.5 milliseconds to compute all the features for a single event. The relative simplicity in terms of their computation makes them ideal for mobile or portable applications. Since they are purely derived from accelerometer information, they can be easily incorporated into digital actigraphs to improve their effectiveness in ICU settings [36]. Furthermore, all of the proposed methodology involved easily accessible resources such as off-the-shelf accelerometers and open source software, which significantly increases the accessibility of the proposed approach.

The results of the support vector classifiers (Figure 4) also proved to be promising. Despite certain instances where the test set performance was sub-optimal, such as in the combined limb classifier of subject 2, the results from the cross validations seem to generalize well into the testing sets. Furthermore, most cross-validation accuracy measurements were statistically above those of the baseline classifiers, with differences in accuracy of up to 0.35 in some cases. Additionally, the training of each classifier, after the feature matrix had been constructed and filtered, ranged between 20 to 100 milliseconds, once again proving to be sufficiently fast for portable applications.

In general, the results shown in Figure 4 suggest that the performance of the combined classifier is equivalent or better than that of the lower classifiers, and equivalent or slightly inferior to the upper classifier. These cross-limb combinations have not been explored in the literature for ICU monitoring, likely due to the expected differences between movements in the upper and lower limbs, which are likely to be exacerbated in bed ridden individuals. However, since these individuals are unilaterally impaired, the degree of mobility between ipsilateral limbs might be sufficiently similar to successfully train a model using information from all limbs. These results show that models trained on information from both upper and lower limbs in unilaterally impaired patients in the Neurological ICU can be successfully used for long term hourly limb classification.

The leave-one-subject-out approach results are also promising. With a maximum test set accuracy of 0.82 in the upper limb classifier, and an average accuracy of 0.76 across all classifiers, it can be seen that the performance of this approach is similar to the individually trained classifiers. Furthermore, the features that performed well in this approach encompass the strength, the smoothness and the frequency (as in movement

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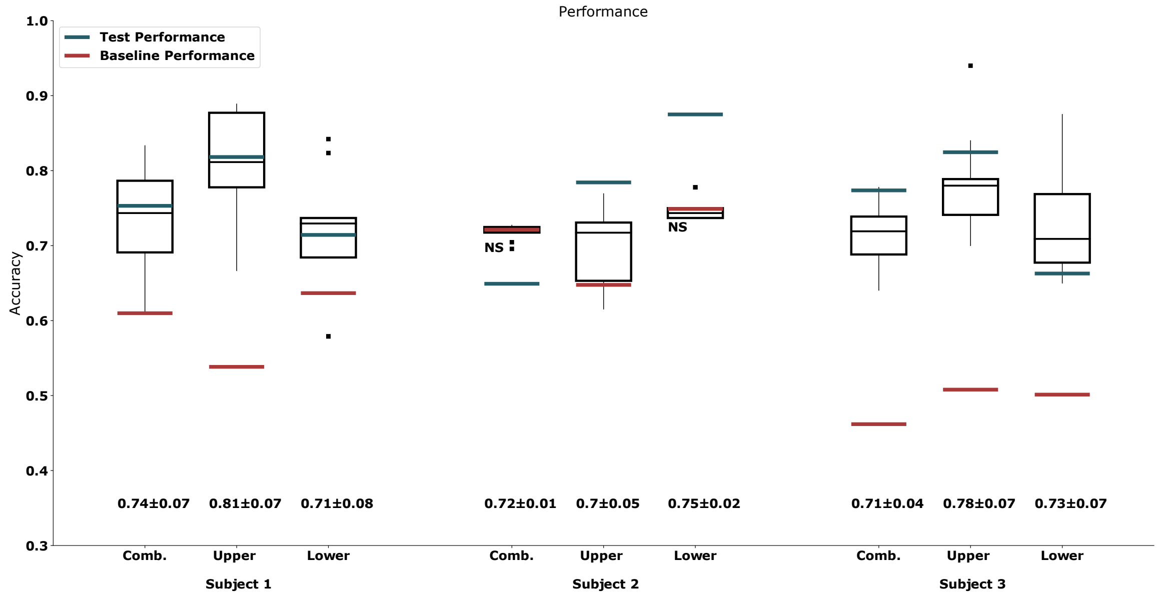

Figure 4: Boxplot representing the accuracy obtained after a 10-fold cross-validation for each limb classifier and the combined classifier for each subject. Baseline obtained values are shown as a red line and test set accuracy is shown as a blue line. Outliers are shown as black squares. Mean± standard deviation for all boxplots shown underneath. Not statistically significant differences between the cross-validation results and the baseline classifier are denoted by **NS**.

counts) of the movements in each subject. The *maximum magnitude* directly relates to the acceleration of the movement, as it determines the upper limit of that acceleration, and therefore it is expected to directly relate to the strength of the subject. The *power 2* relates to the smoothness of the movements, as it describes the relevance of the second dominant frequency. These two features, combined with the *movement count*, roughly provide the same information as all the other features used for the individual classifiers. As shown in the recursive feature selection for the individual classifiers the movement count, power 2 and the average magnitude contributed positively to the performance of the classifiers. Therefore, it is not surprising that two of these three features, the movement count and the power 2, are able to generalize well across subjects. The third feature, the maximum magnitude, is closely related to the average magnitude, therefore it is also consistent with the previous discussion. The fact that the entire feature set does not perform as well as the reduced feature set in the leave-one-subject-out approach might be evidence that the entire feature set might be causing the model to over-fit to individual subjects. This can be useful in cases when individualized models are desired, such as in the individual classifiers that were studied. In the case of a generalized model, however, a small subset of features capable of encompassing the diverse movement dynamics of multiple subjects, such as the ones chosen here, seems to prove more useful.

The confusion matrices shown in Figure 5A-C also show that in general, the model is highly capable of determining when a limb belongs to the antigravity class, while it struggles more in distinguishing dependent limbs. This behavior is consistent across classifiers, and might be due to the decreased number of dependent training examples due to the nature of the hemiparesis. Nevertheless, the results still suggest that the model has the capacity to classify dependent limbs with a performance above random guessing. The distribution of the errors seems to be slightly skewed towards the latter part of the dataset in subject 1, and equally distributed in subject 3. This is promising, as it suggests that the model performs very similar, at least in subject 3 and to a lesser extent in subject 1, at the beginning and end of the subject's stay in the ICU. This can serve as potential evidence of the ability of the proposed methodology to generalize well in long term Neurological ICU monitoring. While still below the 90% multiclass accuracy presented in [10], these results are tested in more than 130 instances, while previous studies only do so in 5 or less. While the generalization of the model only worked in two the three subjects tested in the leave-one-subject-out approach, the results are still promising since both subjects were very different in terms of the

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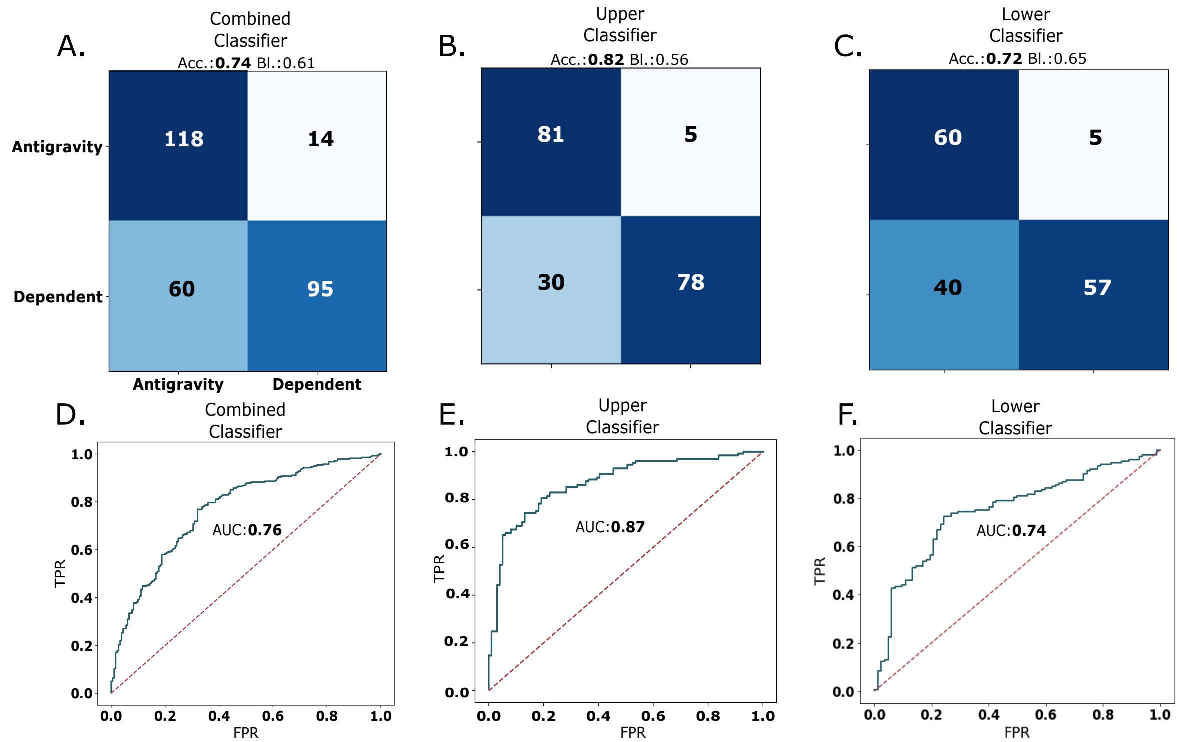

Figure 5: Confusion matrices for the A. combined, B. upper and C. lower extremity classifiers for the final leave-one-subject-out approach tested in subject 1. The classifier accuracy (Acc.) and baseline classifier accuracy (Bl.) are shown at the top of the confusion matrix. The corresponding ROC curves for the D. combined, E. upper and C. lower extremity classifiers are shown in blue. The dashed line represents the ideal ROC for a completely random classifier. The area under the ROC curve (AUC) is also shown.

study. Subject 1 was right side impaired and subject 3 was left side impaired, and both had very different distribution of motor scores and lengths of stay. Despite not testing subject 4 in the leave one out approach, training with data from subject 4 seemed to have contributed to the performance, as ignoring it from the training set caused decreased accuracy when testing on subjects 1 and 3. Similarly, despite the poor performance when testing on subject 2, training with data from subject 2 in the leave-one-subject-out approach of subjects 1 and 3 proved useful in terms of performance. This is indicative that the model is indeed learning from these subjects, and might suggest that there is potential for improvement if more data is provided.

The results of the SVCs are also important in the context of long term monitoring of individuals admitted to the ICU. Similar studies [7, 10, 11, 37] have only performed accelerometry recordings in small time windows and up to 3 days of interrupted monitoring, and to our knowledge, this is the only study that has obtained this performance using long term recordings. Since every SVC is trained and tested using information from the entirety of the subject's stay in the ICU, the significantly above baseline performance of these classifiers suggests that they are flexible enough to make accurate predictions in situations where a limb might transition from dependent to antigravity, as it was the case in initially dependent limbs of subjects 1, 2 and 3 (Table 1).

A clear limitation of this study is the sample size, and despite our results using a leave-one-subject-out approach might suggest a potential for generalizability, a larger sample size is needed for a definite conclusion. However, given the absence of a study with longer than 24 hour continuous accelerometry based monitoring in ICU settings, the results from this study serve as a lower bound for the performance, and as a proof of concept of a potential course of action . Another important limitation is the presence of confounding movements induced by clinical practitioner-patient interactions. While efforts were made to mitigate the effects of these movements, more effective filtering approaches such as video monitoring could prove more

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useful and improve upon the results. An alternative strategy is to use video alone to monitor activity. Previous work has demonstrated the ability to track upper body joints in the Epilepsy Monitoring Unit from RGB-video [38]. This approach is advantageous because sensors do not touch the body, which removes the risk of skin irritation and other compilations such as neglecting to remove non-MRI compatible sensors prior to MRI. There are many approaches and opportunities to capture patient movement information that may useful for determining neurological state. Future studies should also aim at performing a finer motor assessment that is not only hourly, but includes assessments in smaller time windows in order to achieve a finer temporal resolution. This can aid in detecting important changes earlier, such that the proper intervention can take place. A final limitation is the susceptibility of the ground truth labels, namely the clinician assigned motor scores, to individual bias. Despite efforts to standardize the way hourly clinical assessments are performed, inter and intra-observer variability still serve as confounding factors that limit the accuracy of a given score, specially in overcrowded hospitals, where the time per patient needs to be minimized and mistakes are more likely. This study should serve as one of many starting points to develop consistent and objective ways to monitor motor impairment in the Neurological ICU.

5. Conclusion

The present work served to explore the use accelerometry for long term monitoring of severe motor impairment in unilaterally impaired subjects in the Neurological ICU.We have shown that the movement information obtained from the accelerometers can be used to create informative features that can potentially be used in new monitoring approaches. We have also shown that Support Vector Classifiers are capable of classifying dependent and antigravity limbs with above baseline performance using solely movement information extracted from the accelerometers. The incorporation of a leave-one-subject-out approach shows that accelerometer information acquired from different subjects can be useful in training classifiers that generalize to new subjects for long term ICU monitoring. The proposed approaches serve as an initial proof of concept for the use of accelerometers as a long term monitoring mechanism in a challenging clinical environment such as the Neurological Intensive Care Unit.

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