

DEVELOPMENT OF A COMPREHENSIVE CLINICAL
DECISION SUPPORT SYSTEM FOR GAIT ASSESSMENT IN
CHILDREN WITH SPASTIC CEREBRAL PALSY

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by

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THESIS CERTIFICATE

This is to certify that the thesis titled "**DEVELOPMENT OF A COMPREHENSIVE CLINICAL DECISION SUPPORT SYSTEM FOR GAIT ASSESSMENT IN CHILDREN WITH SPASTIC CEREBRAL PALSY**", submitted by **Rishabh Bajpai**, to the Indian Institute of Technology, Delhi, for the award of the degree of **Doctor of Philosophy in Biomedical Engineering**, is a bonafide record of the research work done by him under my supervision.

The thesis work, in my opinion, has reached the requisite standard. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

KEYWORDS: Reference Profile Generation ; Gait Assessment; Foot Kinematics; Neural Networks, Cerebral Palsy, Foot and Heel Clearance, Automation.

Cerebral Palsy (CP) is the most common pediatric neurodevelopmental disorder that affects motor skills, muscle tones, balance and movements. The overall global prevalence of CP is estimated to be 2 per 1000 live births. According to the Centers for Disease Control and Prevention (CDC), CP is the most common cause of physical disability in children, with an estimated prevalence of 2.1 per 1,000 live births in the United States. In India, there were about 2.5 million children diagnosed with CP in 2010. It is non-progressive damage of the brain, occurring before the growth of the nervous system is complete, most often occurring before or during birth. Some common problems that individuals with CP experience include motor impairment, cognitive impairment, speech and language difficulties, sensory impairments, epilepsy, musculoskeletal problems, psychological and social challenges. The severity of gait abnormalities in individuals with cerebral palsy (CP) can vary widely, and the absence of standardized diagnostic protocols makes it difficult to calculate specific statistics on the prevalence of gait abnormalities in this population. However, it is estimated that about 40% of individuals with CP have some degree of gait abnormality. Since CP is a non-progressive disorder, accurate and timely gait management may significantly recover the movements and improve walking. Assessment of abnormal walking patterns is considered one of the most crucial steps of gait management in CP. Accurate gait assessment helps the doctor select appropriate interventions and, finally, reduces treatment time. Comprehensive gait assessment needs the use of costly laboratory apparatus. Unfortunately, significantly fewer gait assessment laboratories are available in most developing countries. This unavailability of infrastructure leads to misdiagnosis, delayed assessment and treatment, and improper tracking during rehabilitation. Hence, the thesis proposes a cost-effective, precise, and clinical decision support system (CDSS) to aid doctors in the accurate, traceable, and prompt diagnosis of lower limb abnormalities in patients with cerebral palsy (CP). In order to achieve the objectives, the thesis utilizes development of wearable and immense application of Artificial Intelligence (AI) algorithms.

Three wearables, namely, instrumented outsole (IO), instrumented sock (IS), and modified OpenSenseRT, were developed and validated to measure full lower limb kinematics. An IO and an IS were developed for measuring foot kinematics. An open-source inertial measurement unit (IMU) motion capture system (OpenSenseRT) was also modified to make

it compatible with the developed instrumentation. The modified OpenSenseRT measures the pelvic, hip, knee, and ankle joint kinematics in three-dimensional planes. The IO was validated against a standard system (camera-based-motion capture system) at six walking conditions, namely, slow walking speed, medium walking speed, fast walking speed, rearfoot landing (with heel strike), midfoot landing (with flat foot strike), and the forefoot landing (with toe strike). It was found that more than or equal to 96.48% values of the differences in both the systems is between the limit of agreement, values of Pearson’s correlation coefficient (PCC) were more than or equal to 0.76, and values of root mean square error (RMSE) were less than or equal to 3.45° .

By using a similar working principle as IO, an IS was developed for measuring foot kinematics. The IS overcomes various limitations of the IO, such as it can be used for bare-foot analysis, it can be used with a deformed foot, it is 100% replicable, and it is light weighted. Ten CP subjects and ten TD subjects were recruited to validate the accuracy of the IS in measuring the foot’s angular kinematics by comparing it with OpenSenseRT (a verified motion-capture system). The data of IS was compared with the values of OpenSenseRT for pitch and roll angles of foot. IS obtained RMSE of $3.8^\circ \pm 0.8^\circ$ and $2.7^\circ \pm 0.6^\circ$ for pitch and roll angles, respectively. Further, the IS and IO were compared at a self-selected (preferred) walking speed i.e 2.8 km/h for IO and 1 km/h for IS. The results suggested that the performance of IS was comparable to IO (that was extensively verified), and the errors lied in the acceptable range. Therefore, IS can be used for clinical applications. The IS overcomes the limitations of the IO and shows its clinical applicability. However, as the number of foot-to-ground distances and angular degree of freedom are more in IO than IS, and the error of measurement is less in IO than IS, it can be a preference when used with subjects with fewer foot deformities.

OpenSenseRT was modified to synchronize the clock of OpenSenseRT and the clock of the data acquisition system of IS/IO automatically during booting and transferring data to a local server after data collection. The kinematics data from the devices was stored in a local electronic health record (EHR) for further processing.

The software component of the system consists of two modules: one for improving affordability and reducing data collection time and the other for generating an extended-automated-gait assessment report (extended-A-GAS).

“Foot2hipCP” was developed to estimate lower limb kinematics with robust and fast computation (41 ms). Foot2hipCP predicts ankle, knee, and hip joint angle profiles in the sagittal plane using foot kinematics recorded from IO/IS during walking. When tested using 5-fold cross-validation, (CP: $n = 10$ and TD: $n = 10$), foot2hipCP obtained a mean RMSE of $2.46^\circ \pm 0.17^\circ$ and a correlation coefficient of 0.95 ± 0.01 for all joints (averaged across all folds). “MoveNetCP” was developed to reduce the data collection time by generating lower limb kinematics at any given slope of the walking surface from the zero-degree slope. The

results showed that MoveNetCP could be used to predict joint angle profiles at -10 and 10-degree slopes from ground-level profiles recorded with a MAE of $3.03^\circ \pm 1.37^\circ$.

Extended-A-GAS consists of three diagnostic decision support systems (DDSS), namely, non-knowledge based (KB)DDSS, KBDDSS and A-GAS. In Non-KBDDSS, nine neural network-based models were developed to classify walking patterns into 49 known lower limb abnormalities for people with CP. The networks obtained a classification accuracy of 98%, precision of 0.93, recall of 0.95 and f1-score of 0.95. In KBDDSS, Bayes probability and elementary concepts of reasoning were used to quantify gait abnormality-related features. KBDDSS obtained a mean f1-score of 0.88 for all joints. Automated-Gait Assessment Score (A-GAS) was the first objective, comprehensive gait assessment methodology developed for CP children. For the computation of A-GAS, instance abnormality index (AII) and abnormality index (AI) were calculated. AII quantifies the gait abnormality of a gait cycle instance, while AI quantifies the gait abnormality of a joint angle profile during walking. AII is calculated for all gait cycle instances by performing probabilistic and statistical analyses. The abnormality index (AI) is a weighted sum of AII, computed for each joint angle profile. A-GAS is a weighted sum of AI, calculated for a lower limb. Moreover, a graphical representation of the gait assessment report, including AII, AI, and A-GAS is generated to provide a better depiction of the assessment score. When compared with the current gold standard of gait assessment (human expert's ratings), A-GAS was found to be more accurate and reliable. The EBDDSS and A-GAS were combined to generate a feature (abnormality) specific report (feature-specific A-GAS) to give doctors an idea of the contributions of features in modifying gait. The feature-specific A-GAS was developed to assist the doctor in the better and more detailed diagnosis of the known abnormalities.

The proposed CDSS was validated using qualitative and quantitative analysis. A methodology for replicating a musculoskeletal deformation (contracture) in healthy individuals for objectively evaluating the performance of gait assessment scores with variable severity of musculoskeletal deformations was developed. A-GAS was found to be sensitive and accurate in detecting the change in the degree of contracture and has the potential to track rehabilitation progress during gait rehabilitation. Also, the proposed CDSS was found to be better than the state-of-the-art (human expert's ratings) method in detecting gait abnormalities. Further, Extended-A-GAS was compared with the conventional method where clinical expert raters from AIIMS Delhi for generating gait assessment reports. Results showed that Extended-A-GAS was consistent with ratings of raters for known abnormalities. Also, Extended-GAS was found to be more capable of capturing gait abnormalities than conventional methods. In conclusion, a CDSS was developed and validated using a novel gait assessment evaluation methodology and conventional methods. The proposed CDSS shows clinical and personal applicability and has potential to solve many problems of current methods of gait assessment.

सार

सेरेब्रल पाल्सी (सीपी) सबसे आम बाल चिकित्सा न्यूरोडेवलपमेंटल विकार है जो मोटर कौशल, मांसपेशियों की टोन, संतुलन और गतिविधियों को प्रभावित करता है। सीपी का समग्र वैश्विक प्रसार प्रति 1000 जीवित जन्मों पर 2 होने का अनुमान है। रोग नियंत्रण और रोकथाम केंद्र (सीडीसी) के अनुसार, सीपी बच्चों में शारीरिक विकलांगता का सबसे आम कारण है, संयुक्त राज्य अमेरिका में प्रति 1,000 जीवित जन्मों पर इसका अनुमानित प्रसार 2.1 है। भारत में, 2010 में लगभग 2.5 मिलियन बच्चों में सीपी का निदान किया गया था। यह मस्तिष्क की गैर-प्रगतिशील क्षति है, जो तंत्रिका तंत्र के विकास के पूरा होने से पहले होती है, जो अक्सर जन्म से पहले या उसके दौरान होती है। सीपी अनुभव वाले व्यक्तियों की कुछ सामान्य समस्याओं में मोटर हानि, संज्ञानात्मक हानि, भाषण और भाषा कठिनाइयाँ, संवेदी हानि, मिर्गी, मस्कुलोस्केलेटल समस्याएं, मनोवैज्ञानिक और सामाजिक चुनौतियाँ शामिल हैं। सेरेब्रल पाल्सी (सीपी) वाले व्यक्तियों में चाल असामान्यताओं की गंभीरता व्यापक रूप से भिन्न हो सकती है, और मानकीकृत निदान मूल लिपि की अनुपस्थिति इस आबादी में चाल असामान्यताओं की व्यापकता पर विशिष्ट आंकड़ों की गणना करना मुश्किल बना देती है। हालाँकि, यह अनुमान लगाया गया है कि सीपी वाले लगभग 40% व्यक्तियों में कुछ हद तक चाल में असामान्यता है। चूंकि सीपी एक गैर-प्रगतिशील विकार है, इसलिए सटीक और समय पर चाल प्रबंधन से गतिविधियों और चलने में काफी सुधार हो सकता है। असामान्य चलने के पैटर्न का आकलन सीपी में चाल प्रबंधन के सबसे महत्वपूर्ण चरणों में से एक माना जाता है। सटीक चाल मूल्यांकन से डॉक्टर को उचित हस्तक्षेप चुनने में मदद मिलती है और अंत में, उपचार का समय कम हो जाता है। व्यापक चाल मूल्यांकन के लिए महंगे प्रयोगशाला उपकरण के उपयोग की आवश्यकता होती है। दुर्भाग्य से, अधिकांश विकासशील देशों में काफी कम चाल मूल्यांकन प्रयोगशालाएँ उपलब्ध हैं।

बुनियादी ढांचे की इस अनुपलब्धता के कारण गलत निदान, मूल्यांकन और उपचार में देरी और पुनर्वास के दौरान नज़र रखना मुश्किल होता है। इसलिए, थीसिस सेरेब्रल पाल्सी (सीपी) के रोगियों में निचले अंगों की असामान्यताओं के सटीक, पता लगाने योग्य और त्वरित निदान में डॉक्टरों की सहायता के लिए एक लागत प्रभावी, सटीक और नैदानिक निर्णय समर्थन प्रणाली (सीडीएसएस) का प्रस्ताव करती है। निर्धारित उद्देश्यों को पूरा करने के लिए, थीसिस स्व-विकसित पहनने योग्य उपकरणों और आर्टिफिशियल इंटेलिजेंस (आई) एल्गोरिदम के व्यापक उपयोग का लाभ उठाती है।

तीन पहनने योग्य उपकरण, अर्थात्, इंस्ट्रुमेंटेड आउटसोल (आईओ), इंस्ट्रुमेंटेड सॉक (आईएस), और संशोधित OpenSenseRT, पूर्ण निचले अंग कीनेमेटिक्स को मापने के लिए विकसित और मान्य किए गए थे। पैर गतिकी को मापने के लिए एक आईओ और एक आईएस विकसित किया गया था। एक ओपन-सोर्स इनर्शियल मेजरमेंट यूनिट (IMU) मोशन कैप्चर सिस्टम (OpenSenseRT) को भी विकसित इंस्ट्रुमेंटेशन के साथ संगत बनाने के लिए संशोधित किया गया था। संशोधित OpenSenseRT त्रि-आयामी समन्वय में श्रोणि, कूल्हे, घुटने और टखने के जोड़ की गतिकी को मापता है। आईओ को छह चलने की स्थितियों में एक मानक प्रणाली (कैमरा-आधारित-मोशन कैप्चर सिस्टम) के साथ तुलना की गई थी, अर्थात् धीमी गति से चलने की गति, मध्यम चलने की गति, तेज चलने की गति, रियरफुट लैंडिंग (एड़ी प्रहार के साथ), मिडफुट लैंडिंग (समतल पैर के साथ प्रहार), और फोरफुट लैंडिंग (पैर के अंगूठे से प्रहार के साथ)। यह पाया गया कि दोनों प्रणालियों में 96.48% से अधिक या उसके बराबर अंतर समझौते की सीमा के बीच है, पियर्सन के सहसंबंध गुणांक (पीसीसी) के मान 0.76 से अधिक या उसके बराबर थे, और मूल माध्य वर्ग त्रुटि के मान (आरएमएसई) 3.45° से कम या उसके बराबर थे।

आईओ के समान कार्य सिद्धांत का उपयोग करके, पैर की गतिकी को मापने के लिए एक आईएस विकसित किया गया था। आईएस, आईओ की विभिन्न सीमाओं को पार करता है, जैसे इसका उपयोग नंगे पैर विश्लेषण के लिए किया जा सकता है, इसका उपयोग विकृत पैर के साथ किया जा सकता है, यह 100% प्रतिकृति योग्य है, और यह हल्के वजन का है। दस सीपी विषयों और दस टीडी विषयों को ओपनसेंसआरटी (एक सत्यापित मोशन-कैप्चर सिस्टम) के साथ तुलना करके पैर के कोणीय गतिकी को मापने में आईएस की सटीकता को मान्य करने के लिए भर्ती किया गया था। आईएस

के डेटा की तुलना पिच और पैर के रोल कोणों के लिए ओपनसेंसआरटी के मूल्यों से की गई थी। IS ने पिच कोण के लिए $3.8^\circ \pm 0.8^\circ$ का आरएमएसई प्राप्त किया और रोल कोण के लिए $2.7^\circ \pm 0.6^\circ$ आरएमएसई प्राप्त किया। इसके अलावा, आईएस और आईओ की तुलना स्व-चयनित (पसंदीदा) चलने की गति पर की गई, यानी आईओ के लिए 2.8 किमी/घंटा और आईएस के लिए 1 किमी/घंटा। परिणामों ने दर्शाया कि आईएस का प्रदर्शन आईओ के बराबर था (जिसे बड़े पैमाने पर सत्यापित किया गया था), और त्रुटियां स्वीकार्य सीमा में थीं। इसलिए, आईएस का उपयोग नैदानिक अनुप्रयोगों के लिए किया जा सकता है। आईएस आईओ की सीमाओं को पार करता है और अपनी नैदानिक प्रयोज्यता दिखाता है। हालाँकि, चूंकि जमीन से पैर की दूरी की संख्या और स्वतंत्रता की कोणीय डिग्री आईएस की तुलना में आईओ में अधिक है, और माप की त्रुटि आईएस की तुलना में आईओ में कम है, कम पैर विकृति वाले विषयों के साथ उपयोग किए जाने पर इसे प्राथमिकता दी जा सकती है।

डेटा संग्रह के बाद स्थानीय सर्वर पर डेटा को बूट करने और स्थानांतरित करने के दौरान OpenSenseRT की घड़ी और IS/IO की डेटा अधिग्रहण प्रणाली की घड़ी को स्वचालित रूप से सिंक्रनाइज़ करने के लिए OpenSenseRT को संशोधित किया गया था। उपकरणों से किनेमेटिक्स डेटा को आगे की प्रक्रिया के लिए स्थानीय इलेक्ट्रॉनिक स्वास्थ्य रिकॉर्ड (ईएचआर) में संग्रहीत किया गया था।

सिस्टम के सॉफ्टवेयर घटक में दो मॉड्यूल होते हैं: एक सामर्थ्य में सुधार और डेटा संग्रह समय को कम करने के लिए और दूसरा एक विस्तारित-स्वचालित-चाल मूल्यांकन रिपोर्ट (विस्तारित-ए-जीएस) उत्पन्न करने के लिए।

"Foot2hipCP" को मजबूत और तेज़ गणना (41 एमएस) के साथ निचले अंग कीनेमेटिक्स का अनुमान लगाने के लिए विकसित किया गया था। Foot2hipCP चलने के दौरान IO/IS से रिकॉर्ड किए गए पैर कीनेमेटिक्स का उपयोग करके धनु तल में टखने, घुटने और कूल्हे के जोड़ के कोण प्रोफाइल की भविष्यवाणी करता है। जब 5-गुना क्रॉस-वैलिडेशन, (सीपी: एन = 10 और टीडी: एन = 10) का उपयोग करके परीक्षण किया गया, तो Foot2hipCP ने $2.46^\circ \pm 0.17^\circ$ का औसत आरएमएसई और सभी जोड़ों के लिए 0.95 ± 0.01 का सहसंबंध गुणांक प्राप्त किया (सभी सिलवटों पर औसत)। शून्य-डिग्री ढलान से चलने वाली सतह के किसी भी ढलान पर निचले अंग कीनेमेटिक्स उत्पन्न करके डेटा संग्रह समय को कम करने के लिए "मूवनेटसीपी" विकसित किया गया था। परिणामों से पता चला कि मूवनेटसीपी का उपयोग $3.03^\circ \pm 1.37^\circ$ के MAE के साथ रिकॉर्ड किए गए जमीनी स्तर के प्रोफाइल से -10 और 10-डिग्री ढलान पर संयुक्त कोण प्रोफाइल की भविष्यवाणी करने के लिए किया जा सकता है।

विस्तारित-ए-जीएस में तीन नैदानिक निर्णय समर्थन प्रणालियाँ (डीडीएसएस) शामिल हैं, अर्थात् गैर-ज्ञान आधारित (केबी)डीडीएसएस, केबीडीडीएसएस और ए-जीएस। गैर-केबीडीडीएसएस में, सीपी वाले लोगों के लिए चलने के पैटर्न को 49 ज्ञात निचले अंगों की असामान्यताओं में वर्गीकृत करने के लिए नौ न्यूरल नेटवर्क-आधारित मॉडल विकसित किए गए थे। नेटवर्क ने 98% की वर्गीकरण सटीकता, 0.93 की सटीकता, 0.95 की रिकॉल और 0.95 का एफ1-स्कोर प्राप्त किया। केबीडीडीएसएस में, बेयस संभाव्यता और तर्क की प्राथमिक अवधारणाओं का उपयोग चाल असामान्यता-संबंधी विशेषताओं को मापने के लिए किया गया था। केबीडीडीएसएस ने सभी जोड़ों के लिए 0.88 का औसत f1-स्कोर प्राप्त किया। स्वचालित-चाल मूल्यांकन स्कोर (ए-जीएस) सीपी बच्चों के लिए विकसित पहला विषयनिष्ठ, व्यापक चाल मूल्यांकन पद्धति थी। ए-जीएस की गणना के लिए, उदाहरण असामान्यता सूचकांक (एआईआई) और असामान्यता सूचकांक (एआई) की गणना की गई। एआईआई चाल चक्र उदाहरण की चाल असामान्यता को मापता है, जबकि एआई चलने के दौरान संयुक्त कोण प्रोफाइल की चाल असामान्यता को मापता है। एआईआई की गणना संभाव्य और सांख्यिकीय विश्लेषण करके सभी चाल चक्र उदाहरणों के लिए की जाती है। असामान्यता सूचकांक (एआई) एआईआई का एक भारित योग है, जिसकी गणना प्रत्येक संयुक्त कोण प्रोफाइल के लिए की जाती है। ए-जीएस एआई का भारित योग है, जिसकी गणना निचले अंग के लिए की जाती है। इसके अलावा, मूल्यांकन स्कोर का बेहतर चित्रण प्रदान करने के लिए एआईआई, एआई और ए-जीएस सहित चाल मूल्यांकन रिपोर्ट का एक ग्राफिकल प्रतिनिधित्व तैयार किया

जाता है। चाल मूल्यांकन के वर्तमान स्वर्ण मानक (मानव विशेषज्ञ की रेटिंग) के साथ तुलना करने पर, ए-जीएस अधिक सटीक और विश्वसनीय पाया गया। ईबीडीडीएसएस और ए-जीएस को एक फीचर (असामान्यता) विशिष्ट रिपोर्ट (फीचर-विशिष्ट ए-जीएस) उत्पन्न करने के लिए संयोजित किया गया था ताकि डॉक्टरों को चाल को संशोधित करने में सुविधाओं के योगदान का अंदाजा मिल सके। ज्ञात असामान्यताओं के बेहतर और अधिक विस्तृत निदान में डॉक्टर की सहायता के लिए फीचर-विशिष्ट ए-जीएस विकसित किया गया था।

प्रस्तावित सीडीएसएस को गुणात्मक और मात्रात्मक विश्लेषण का उपयोग करके मान्य किया गया था। मस्कुलोस्केलेटल विकृति की परिवर्तनीय गंभीरता के साथ चाल मूल्यांकन स्कोर के प्रदर्शन का निष्पक्ष मूल्यांकन करने के लिए स्वस्थ व्यक्तियों में मस्कुलोस्केलेटल विकृति (संकुचन) की नकल करने की एक पद्धति विकसित की गई थी। ए-जीएस संकुचन की डिग्री में परिवर्तन का पता लगाने में संवेदनशील और सटीक पाया गया और चाल पुनर्वास के दौरान पुनर्वास प्रगति को ट्रैक करने की क्षमता रखता है। साथ ही, प्रस्तावित सीडीएसएस को चाल संबंधी असामान्यताओं का पता लगाने में अत्याधुनिक (मानव विशेषज्ञ की रेटिंग) पद्धति से बेहतर पाया गया। इसके अलावा, एक्सटेंडेड-ए-जीएस की तुलना पारंपरिक पद्धति से की गई, जहां चाल मूल्यांकन रिपोर्ट तैयार करने के लिए एम्स दिल्ली के नैदानिक विशेषज्ञ मूल्यांकनकर्ता थे। परिणामों से पता चला कि एक्सटेंडेड-ए-जीएस ज्ञात असामान्यताओं के लिए मूल्यांकनकर्ताओं की रेटिंग के अनुरूप था। इसके अलावा, एक्सटेंडेड-जीएस पारंपरिक तरीकों की तुलना में चाल असामान्यताओं को पकड़ने में अधिक सक्षम पाया गया। अंत में, एक सीडीएसएस को एक नवीन चाल मूल्यांकन मूल्यांकन पद्धति और पारंपरिक तरीकों का उपयोग करके विकसित और मान्य किया गया था। प्रस्तावित सीडीएसएस नैदानिक और व्यक्तिगत प्रयोज्यता को दर्शाता है और इसमें चाल मूल्यांकन के मौजूदा तरीकों की कई समस्याओं को हल करने की क्षमता है।

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ABBREVIATIONS

A-GAS	Automated-Gait Assessment Score
AI	abnormality index
AII	instance abnormality index
AIIMS	All India Institute of Medical Sciences
ANOVA	One-way Analysis of Variance
AOI	angle of inclination
CDC	Centers for Disease Control and Prevention
CDSS	clinical decision support system
CNN	convolutional neural network
COG	center of gravity
CoP	center of pressure
CoPFF	CoP at the foot
CP	Cerebral Palsy
DAQ	data acquisition
DAS	data acquisition system
DDSS	diagnostic decision support systems
DLoA	differences lie between the limit of agreement
DNN	deep neural network
EHR	electronic health record
EMG	Electromyography
Extended-A-GAS	extended-automated-gait assessment report
FGA	foot to ground angle
GMFCS	Gross Motor Function Classification System
HC	heel clearance
HTTP	Hypertext Transfer Protocol
II	Instrumented insole
IK	inverse kinematics
IMU	inertial measurement unit
IO	instrumented outsole
IOT	internet of things
IR	Infrared
IS	instrumented sock
KB	knowledge based
KBDDSS	knowledge based diagnostic decision support systems

LSTM	long short-term memory networks
MAE	Mean Absolute Error
MRI	magnetic resonance imaging
mTC	minimum toe clearance
NN	neural network
non-KBDDSS	non-knowledge based diagnostic decision support systems
NTP	Network Time Protocol
OS	operating system
PCC	Pearson's correlation coefficient
PDF	probability density function
PID	patient identification number
RMS	root mean square
RMSE	root mean square error
ROM	range of motion
SD	Standard Deviation
SUS	System Usability Scale
TC	toe clearance
TD	typically developing
US	ultrasound
VCS	video capturing system
VCSEL	Vertical Cavity Surface-Emitting Laser
vGRF	vertical ground reaction force
SSP	Subject-specific parameters