

Gait Characterization in Duchenne Muscular Dystrophy (DMD) Using a Single-Sensor Accelerometer: Classical Machine Learning and Deep Learning Approaches

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Abstract

Differences in gait patterns of children with Duchenne muscular dystrophy (DMD) and typically-developing (TD) peers are visible to the eye, but quantifications of those differences outside of the gait laboratory have been elusive. In this work, we measured vertical, mediolateral, and anteroposterior acceleration using a waist-worn iPhone accelerometer during ambulation across a typical range of velocities. Fifteen TD and fifteen DMD children from 3-16 years of age underwent eight walking/running activities. We extracted temporospatial gait clinical features (CFs) and applied multiple machine learning (ML) approaches to differentiate between DMD and TD children using extracted temporospatial gait CFs and raw data. Extracted temporospatial gait CFs showed reduced step length and a greater mediolateral component of total power (TP) consistent with shorter strides and Trendelenberg-like gait commonly observed in DMD. ML approaches using temporospatial gait CFs and raw data varied in effectiveness at differentiating between DMD and TD controls at different speeds, with an accuracy of up to 100%. We demonstrate that by using ML with accelerometer data from a consumer-grade smartphone, we can capture DMD-associated gait characteristics in toddlers to teens.

Methods

Gait and Functional Testing

The children in the study performed eight walking and running activities along a 25 m straightline course. The first five activities were speed-calibration tests (SC) where the child walked along a 25 m long corridor at incrementally increasing gait velocities every 25 m from slowest speed, speed-calibration-L1 (SC-L1), to a slow walk (SC-L2), a comfortable self-selected walk pace (SC-L3), a fast walk (SC-L4), and a run or fastest possible gait (SC-L5). Participants then performed a 6-min walk test (6MWT), followed by a 100 m fast walk/jog/run (100MRW). The evaluator recorded the 6MWT distance and the number of steps in the first 50 m, and the time to complete the 100MRW. Participants also completed the NSAA.

Extraction and Evaluation of Temporospatial Gait Clinical Features

We extracted the following eight temporospatial gait CFs from the raw accelerometer data:

- **Speed (SP):** It is measured in meters per second and normalized by the height of the child in meters.
- **Step Length (SL):** It is measured in meters and normalized by the height of the child in meters.
- **Step Frequency (SF):** It is measured in steps per second.
- **Total Power (TP):** It is measured in W/kg.
- **Mediolateral Power (MP):** It is measured in % of TP.
- **Anteroposterior Power (AP):** It is measured in % of TP.
- **Vertical Power (VP):** It is measured in % of TP.
- **Force Index (FI):** It is measured in N/kg.

* Details regarding calculation methods can be found in the link to our published manuscript below.

Preprocessing of Raw Accelerometer Signals for CML and DL Analysis

We used two different ML approaches to classify accelerometer data collected at a range of gait speeds as belonging to a child with DMD or a TD. For the CML-CF approach, 6 different classifiers were implemented: Random Forest (RF), Decision-Tree (DT), Support-Vector Machine (SVM), K-Nearest Neighbors (KNN), Gaussian Naive Bayes (GNB), and Logistic Regression (LR). In this approach, we used the 8 extracted temporospatial gait CFs as input into CML classifiers with and without dimensionality reduction. The 8 extracted temporospatial gait CFs for each child were used to train the CML model for all 8 activities. Data from each activity for each participant represents an individual input to the model. We employed a low-pass filter to enhance the signal quality by smoothing it and eliminating short-term fluctuations while preserving the underlying longer-term trend. This filter was applied to the raw accelerometer signals capturing anteroposterior movement (z-axis) of individual participants across various speeds, ranging from a slow walk to a jog/run. For the DL-RAW approach, we used a Convolutional Neural Network (CNN) model with the time-windowed raw accelerometer signal as an input in the DL classifier. We used raw acceleration values in each of the three axes as input to the DL model. We used the window-slicing method to segment the raw data from each activity into multiple fixed time-windows (TWs) in order to augment the data input and to facilitate DL model convergence. For each activity, the model predicted whether an individual TW was labeled as DMD or TD. We then used those predictions to calculate the overall percentage of the TWs predicted as DMD or TD. At inference time, we examined the percentage of typical/atypical decisions for each TW, and used majority voting to determine whether the participants were correctly labeled as having DMD.

Conclusion

Use of ubiquitous and widely available mobile devices with single accelerometers to remotely measure differences in common clinical gait parameters represents an opportunity to expand the study of temporospatial gait characteristics into the community setting. Extension of measurement of ambulatory capacity into the community setting will provide clinicians and researchers with tools that assess changes in patient mobility in real-world conditions against a background of habitual daily activities, seasonal variations, and the built environment. Our initial laboratory-based studies demonstrate an ability to measure selected gait parameters across a range of typical ambulatory velocities in DMD and TD children to detect significant differences in temporospatial gait CFs that are consistent with previous studies, as well as to detect differences in proportional power of accelerations in vertical, mediolateral, and anteroposterior axes. By using these clinical gait parameters and raw data and employing both CML and DL models, we are able to correctly predict whether sensor data is derived from children with DMD up to 100% of the time at a self-selected walking pace (SC-L3). By combining these approaches, we anticipate that through ongoing studies, we will be able to improve predictive accuracy and identify additional clinically useful parameters indicating typical growth and development, gait impairment, and disease progression across a wide range of individuals with neuromuscular disease.

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Publications and More Information



* Gait Characterization in Duchenne Muscular Dystrophy (DMD) Using a Single-Sensor Accelerometer: Classical Machine Learning and Deep Learning Approaches. [Sensors 2024, 24(4), 1123; <https://doi.org/10.3390/s24041123>]
* Gait Event Detection and Travel Distance Using Waist-Worn Accelerometers across a Range of Speeds: Automated Approach. [Sensors 2024, 24(4), 1155; <https://doi.org/10.3390/s24041155>]

Tables and Figures

Table 1. Characteristic of the children included in the study					
Case (Status)	Value	Age (Years)	Weight (kg)	Height (cm)	NSAA (/34)
DMD (N = 15)	Mean	9.5	37.7	127.1	20.5
	(SD)	(3.9)	(16.0)	(16.2)	(8.2)
	Min	3	17.2	101.6	8.0
	Max	16	67.7	153.3	34.0
TD (N = 15)	Mean	7.7	34.2	130.8	33.8
	(SD)	(3.0)	(21.6)	(15.8)	(0.8)
	Min	4	18.6	108.5	31.0
	Max	15	101.0	165.5	34.0
p-value		0.1664	0.6229	0.5331	<0.0001

Figure 1. The position and orientation of the accelerometer. (A) The smartphone with its built-in accelerometer is positioned near the body's center of mass, fastened by a belt around the waist. (B) The accelerometer records acceleration in three axes. The x-axis is vertical, the y-axis is mediolateral, and the z-axis is anteroposterior

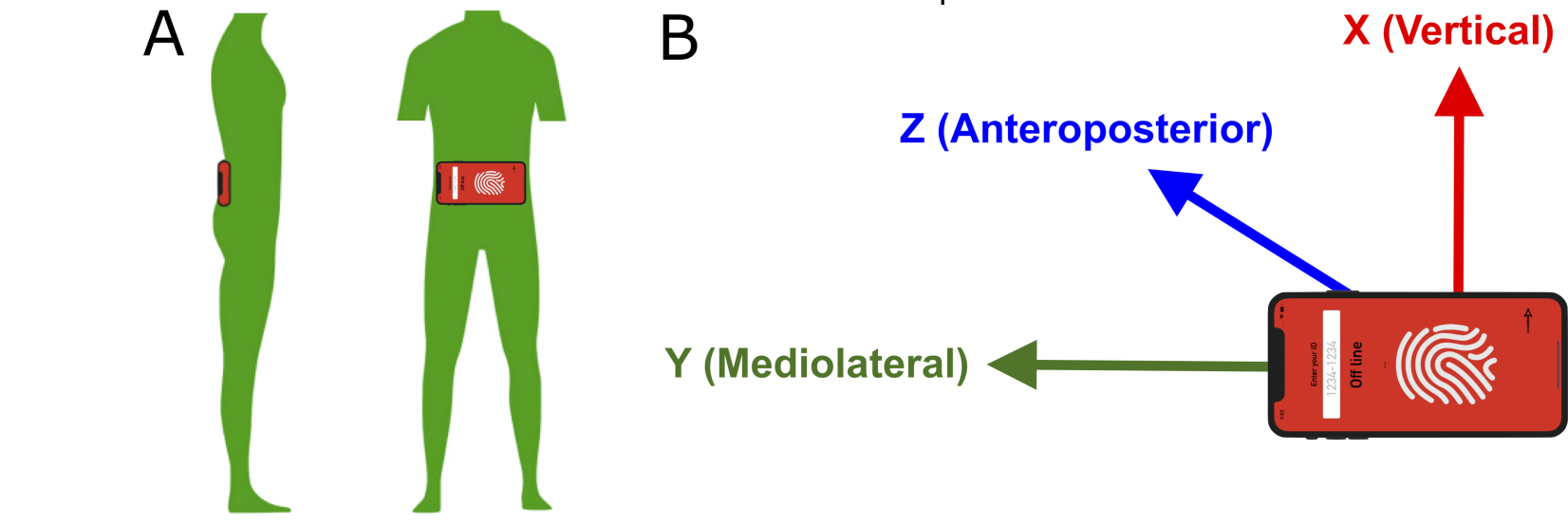


Figure 2. Figures illustrate a comparison between two children, DMD (ID = 11) and TD (ID = 5), in the three-axial accelerations Vertical (x-axis), Mediolateral (y-axis), and Anteroposterior (z-axis) of 6MWT. Figures (A–C) represent a 2 s time-window (TW) acceleration signal captured from a TD child performing 5 steps and a DMD child performing 4 steps. Figures (D–F) represent the acceleration signal of a TD child and a DMD child performing the whole 6MWT. Figures (G–I) represent the power spectrum density (PSD) of a TD child and a DMD child performing the whole 6MWT.

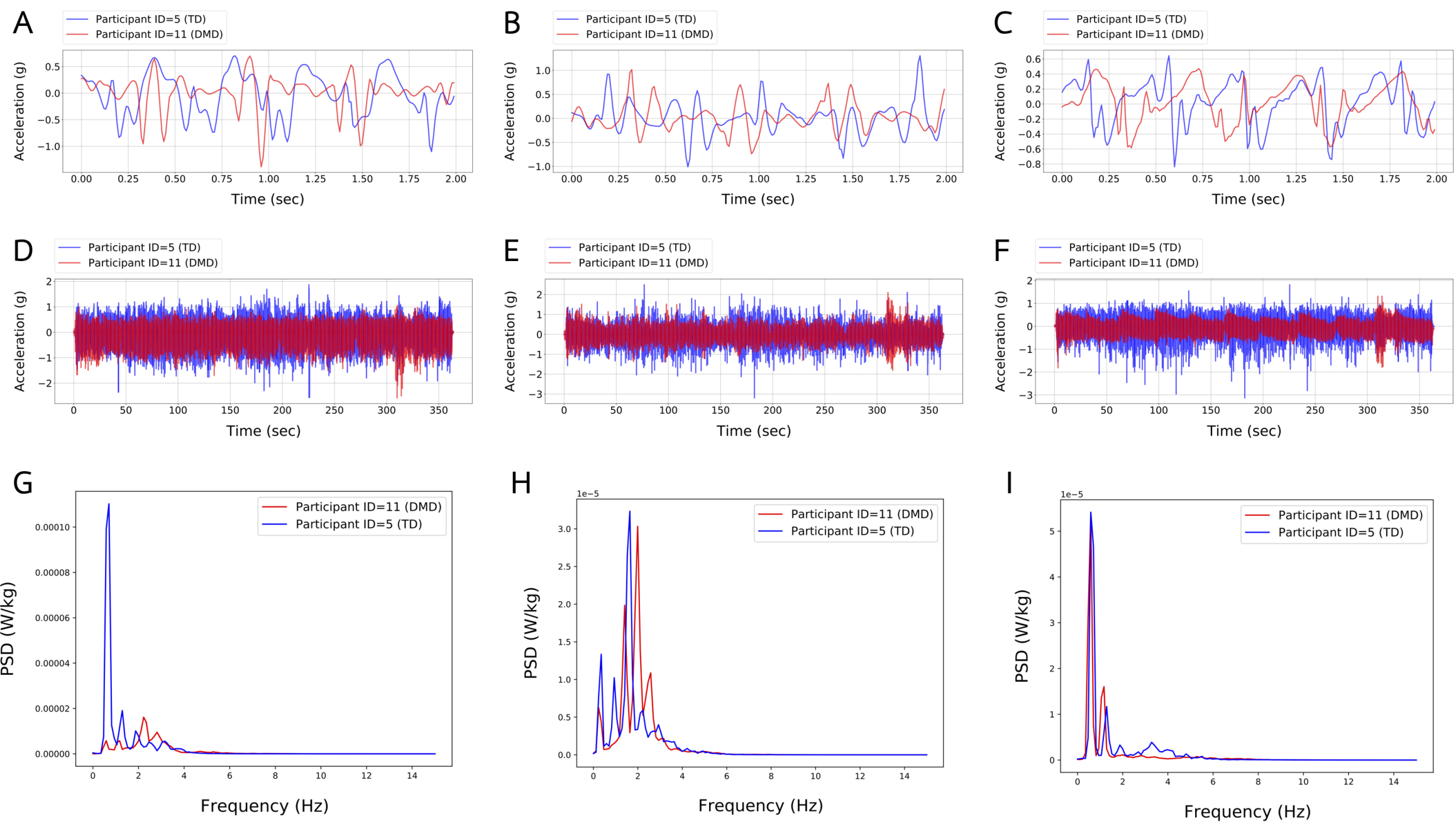


Figure 3. The process diagram of (1) the DL-RAW approach and (2) the CML-CF approach.

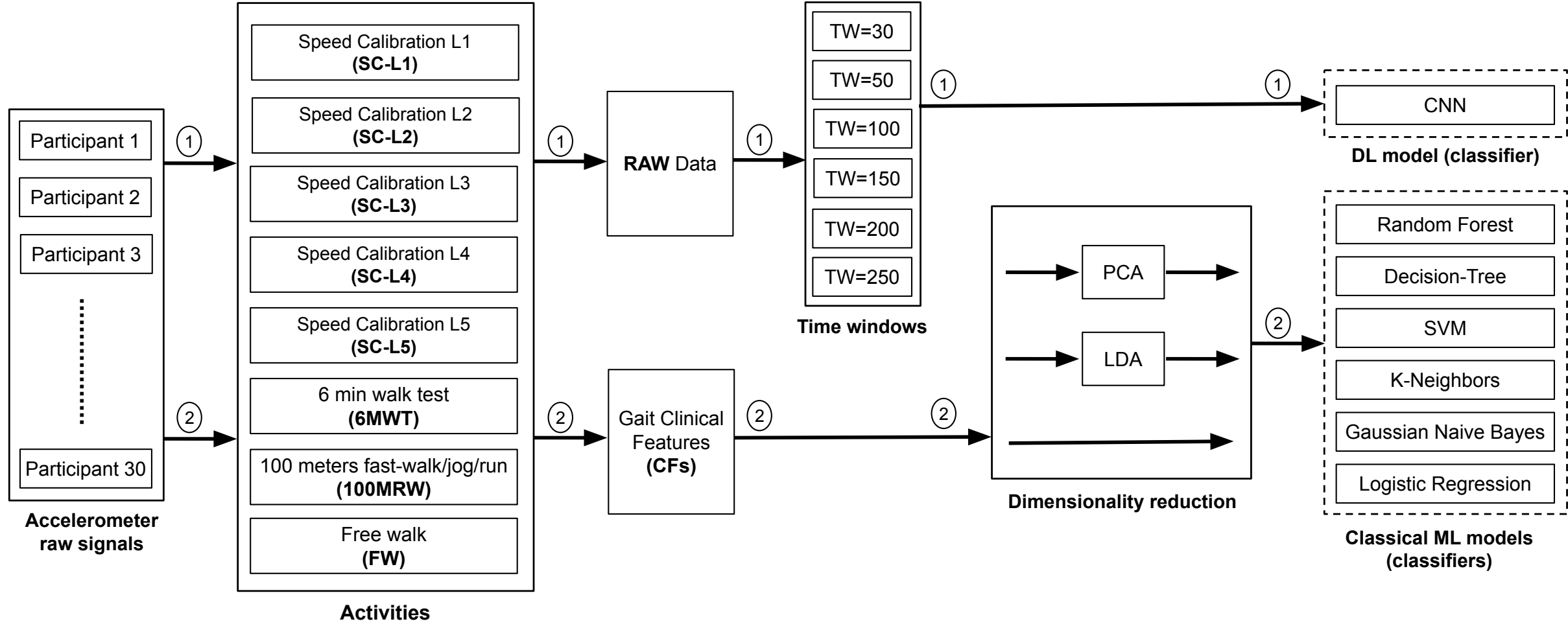


Figure 4. Accuracy of the optimal classifier of CML-CF and DL-RAW. The y-axis represents the classifier accuracies, while the x-axis represents different activities.

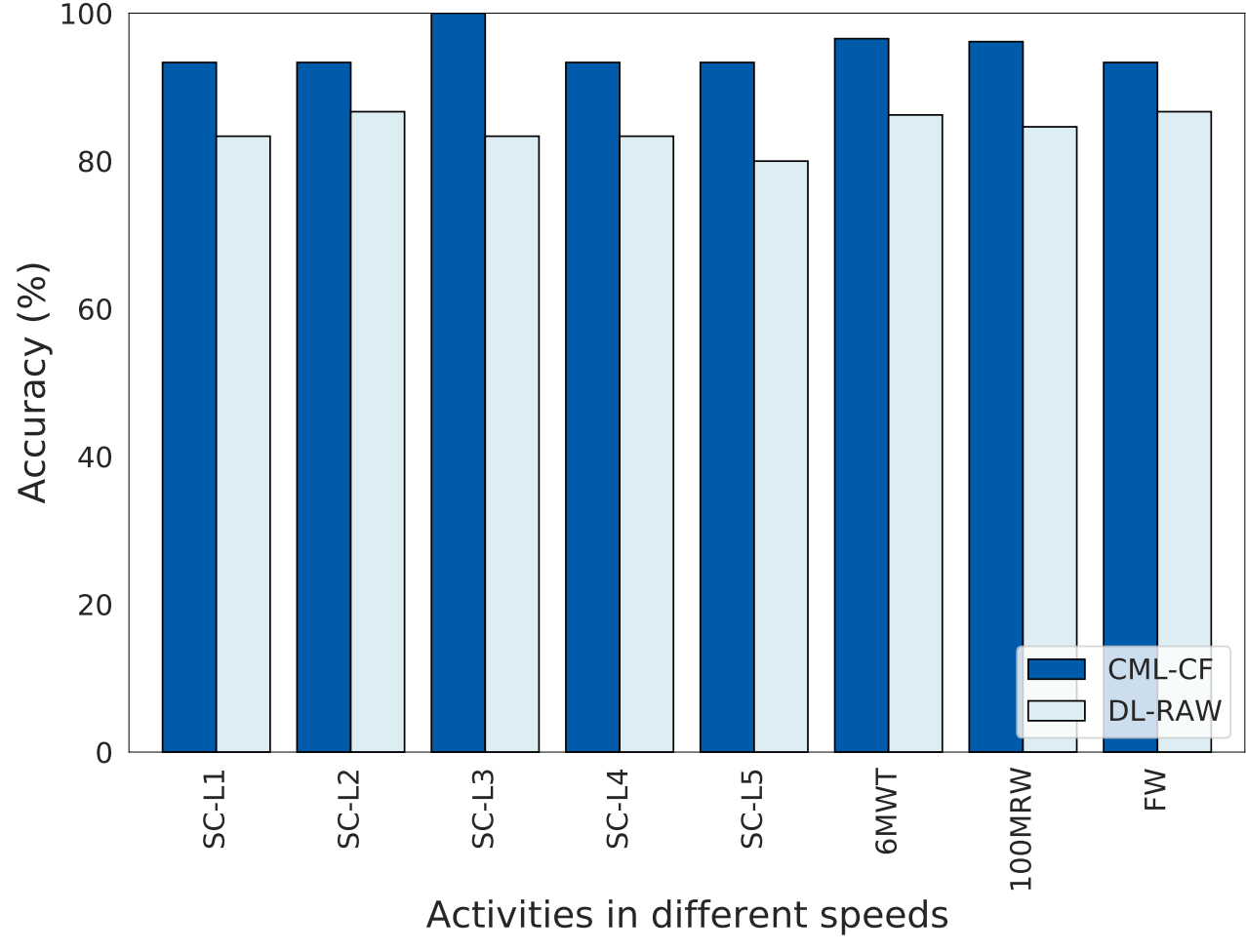


Figure 5. Step Length by Different Gait Speeds. NSAA severity group in ambulatory DMD children.

