

# Machine Learning Approaches for Automatic Characterization of Incline Treadmill and Walking Speed

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**INTRODUCTION:** Plantar flexor function significantly influences ambulation in diverse populations. Impaired function, evident in the elderly and injured individuals, hampers ambulation, and reduces quality of life. Plantar flexion moments, originating from the triceps surae and conveyed through the Achilles tendon, are susceptible to continuous mechanical stress, resulting in prevalent Achilles tendon ruptures demanding lengthy rehabilitation. Understanding plantar flexor function's importance, especially in real-world scenarios, prompts the need for novel data collection and analysis methods. Conventional reliance on laboratory tools hinders prospective studies and deep mechanistic insights into musculoskeletal pathology. Wearable sensors offer potential solutions for out of the lab musculoskeletal monitoring, overcoming limitations of wearable sensors unable to estimate internal tissue-level loading. To bridge this gap, researchers integrate inverse kinematics and dynamics, exemplified by calculating plantar flexion moments using moment arms and exerted. However, this transition introduces data challenges, exemplified by the copious output of wearable sensors, encompassing complex variables like ground reaction forces (GRF). Machine learning emerges as a solution, automating the analysis of substantial wearable sensors dataset, with Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long-Short Term Memory Networks (LSTMs) excelling in high-throughput data processing and analysis. This case study aims to explore the synergy between wearable sensors and machine learning in studying Achilles Tendon loading. Specifically, we endeavor to 1) Develop an adaptable machine learning framework for GRF data processing from instrumented wearable sensors to quantify tissue-specific loading, and 2) Assess the precision and feasibility of amalgamating wearable sensors with machine learning algorithms.

**METHODS:** Fourteen healthy adults (6 males, 8 females;  $31 \pm 4$  years; BMI  $27.1 \pm 6$  kg/m<sup>2</sup>) participated, performing treadmill exercises at various incline and walking speed conditions. Participants provided written informed consent for the Institutional Review Board-approved protocol at the University of Pennsylvania, adhering to relevant guidelines. The study encompassed inclines of 0% to 25% with 5% increments and walking speeds of 0.8, 1.2, and 1.6 m/s, yielding 18 distinct experimental conditions. A standardized warm-up and cooldown were conducted, followed by treadmill walking for at least 30 seconds at each condition, with 20 seconds of data collection following a 10-second adjustment period. Ground reaction forces (GRFs) were captured using wearable sensors (Loadsol, Novel Electronics, St. Paul, MN, USA) at 100 Hz, normalized by body weight. Plantar flexion moment was determined by adding up the scalar products of the moment arm and the force exerted on each zone, and individual steps were identified using a novel algorithm that combined peaks and intersection detection. Long Short-Term Memory (LSTM) neural networks were employed in three configurations, including 3-class, 6-class, and 18-class models for different combinations of speed and incline. Models were trained on balanced datasets, utilizing layers like LSTM with 64 units and dense layers with ReLU activation. Models were compiled and trained for 200 epochs, evaluated for speed and incline prediction performance.

**RESULTS:** Achilles tendon loading was found to increase as a function of incline and walking speed (Table 1). The highest walking speeds at the highest incline resulted in a plateau in the data, potentially indicating a transition in ambulation method. To evaluate the machine learning models, the data from each subject was split into train and test sets at an 80:20 split. The test set was stratified to include all the labels available in the dataset. Then the remaining training set was further split into an 80:30 train-validation split, accompanied by a model checkpointing technique to enhance training efficiency and mitigate overfitting. Notably, the 3-class classification model designed solely for speed prediction exhibited a test accuracy of 84% (Test Loss = 0.50). Similarly, the 6-class classification model, encompassing all inclines (0%, 5%, 10%, 15%, 20%, 25%) demonstrated predictive capabilities, achieving a test accuracy of 63% (Test Loss = 1.24). However, when addressing the intricate 18-class classification model representing every incline and speed combinations, the test accuracy was found to be 53% (Test Loss = 1.84).

**DISCUSSION:** This study underscores the importance and feasibility of shifting the focus of musculoskeletal research beyond traditional laboratory settings, aligning with the call for collecting data outside these confines. The adoption of wearable sensors emerges as a significant advancement, facilitating real-world musculoskeletal monitoring and analysis while addressing the need for novel approaches to data collection and analysis through the integration of machine learning techniques. Specifically for our model, the 3-class classification accurately forecasts distinct walking speeds, while the 6-class classification showcased commendable competence in distinguishing between distinct levels of incline. Despite the 18-class classification model's reduced accuracy with complexity, it significantly surpasses random classifier accuracy (5.5%), highlighting model robustness. These outcomes resonate with complexity's impact on accuracy while maintaining model competence. The study exemplifies machine learning and wearable sensors' synergy, enabling rapid analysis of wearable sensor data with the goal of Achilles tendon loading predictions in real-world settings.

**SIGNIFICANCE/CLINICAL RELEVANCE:** The integration of wearable sensors and machine learning techniques showcases potential for real-world musculoskeletal analysis, offering insights into gait dynamics that could inform personalized interventions and clinical assessments.

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**IMAGES AND TABLES:**

% grade	0	5	10	15	20	25	0	5	10	15	20	25	0	5	10	15	20	25
walking speed (m/s)	0.8	0.8	0.8	0.8	0.8	0.8	1.2	1.2	1.2	1.2	1.2	1.2	1.6	1.6	1.6	1.6	1.6	1.6
Achilles tendon loading (BW)	3.11 ± 0.52	3.13 ± 0.46	3.28 ± 0.42	3.31 ± 0.45	3.44 ± 0.47	3.51 ± 0.5	3.48 ± 0.41	3.74 ± 0.34	3.8	3.88 ± 0.48	3.95 ± 0.48	3.88 ± 0.56	3.97 ± 0.43	4.2 ± 0.43	4.23 ± 0.53	4.25 ± 0.64	4.24 ± 0.69	4.12 ± 0.68