

Reconstructing Running Ground Reaction Force Waveforms from a Single Smartwatch IMU

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Abstract

The vertical ground reaction force (vGRF) waveform underpins running gait analysis and informs injury prevention, rehabilitation, and performance monitoring. It is traditionally captured with lab-bound force plates or instrumented treadmills, and recent wearables sit on the shank, sacrum, foot, or ear, locations rarely worn in daily life. The wrist dominates the consumer market and is worn by most runners, yet it is far from the foot, corrupted by arm motion, and no prior work has reconstructed vGRF from it. We present, to our knowledge, the first reconstruction of the running vGRF waveform from a single wrist-worn IMU. Across 30 participants under Leave-One-Subject-Out evaluation, a transformer reconstructs the waveform at a normalised RMSE of $7.6\% \pm 2.2\%$ and Pearson correlation 0.986 ± 0.009 , comparable to sensors mounted much closer to the ground. Temporal gait parameters derived from the waveform are accurate (stride-time MAPE 1.2%, swing-time 4.1%, stance-time 6.4%), while peak force is harder (14.6%). A compact CNN matches the transformer at $36\times$ fewer parameters, and self-supervised pre-training and a peak-weighted loss give no statistically significant gains, suggesting wrist-based vGRF reconstruction is feasible without added model complexity.

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CCS Concepts

• **Human-centered computing** → *Ubiquitous and mobile computing design and evaluation methods.*

Keywords

Wearables; Smartwatch; Wrist IMU; Running; Gait analysis; Ground reaction force; Deep learning

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1 Introduction

Running is among the most popular fitness activities worldwide [19], but it carries a high injury burden: running-related musculoskeletal injuries (RRMIs) affect around 44.6% of runners [22]. Running gait analysis is a key tool for mitigating this risk: gait retraining informed by gait analysis can reduce injury risk by approximately 62% [8], and it is also used to improve performance and guide rehabilitation [5].

Gait can be quantified through spatio-temporal parameters, kinematics, and kinetics [3]. A central kinetic quantity is the ground reaction force (GRF), the force the ground exerts on the body during stance. Its vertical and largest component is known as the vertical ground reaction force (vGRF) [34]. The vGRF waveform is valuable for detecting injury and gait deviation [21]: reconstructing the full curve, rather than isolated parameters, captures loading information that discrete metrics miss [12], and temporal gait parameters can be derived directly from it without training a separate model per parameter.

Traditionally, vGRF is measured with force plates or instrumented treadmills that are expensive and confined to the laboratory [30], motivating wearable alternatives that enable convenient, real-world measurement [32]. However,

most wearable gait studies place inertial measurement units (IMUs) on the lower body, shank, foot, sacrum, or lower back, because these locations experience the most gait-related motion [30], and recent work has also used the ear [39]. These locations are rarely worn in everyday life. The consumer wearable market is instead dominated by wrist-worn devices, which account for roughly 80% of commercial wearables [13], and sports watches are used by 59.5% of runners (rising to 67.1% among devoted runners) [20].

Despite this adoption, wrist wearables remain largely unexplored for gait analysis: prior wrist work has estimated walking speed, cadence, and some temporal parameters [14, 15, 50], but no prior work has reconstructed the vGRF waveform from the wrist. This is a hard setting: the wrist is far from where the GRF is applied, and arm swing introduces motion unrelated to ground contact [25]. If it can be done, gait analysis becomes accessible to the large population already wearing a smartwatch, without specialised equipment.

Contributions. This paper focuses on a single question: *can a single wrist-worn IMU alone reconstruct the vGRF waveform of running gait?* We answer it affirmatively. (1) We present, to our knowledge, the first reconstruction of the running vGRF waveform from a single wrist IMU, achieving a normalised RMSE of $7.6\% \pm 2.2\%$ and Pearson correlation of 0.986 ± 0.009 under Leave-One-Subject-Out (LOSO) cross-validation on 30 participants, comparable to prior work using sensors mounted far closer to the ground. (2) We derive temporal and kinetic gait parameters directly from the reconstructed waveform and quantify their accuracy. (3) As supporting analysis, we show that a compact CNN matches a pre-trained transformer despite being $\sim 36\times$ smaller, and that two-stage self-supervised pre-training and a peak-weighted (gated-MSE) loss provide no statistically significant benefit, indicating that wrist-based vGRF reconstruction does not require added model complexity.

2 Related Work

2.1 vGRF reconstruction from wearables

Methods for estimating vGRF from wearable IMUs fall into physics-based and machine-learning approaches [2]. Physics-based models derive force from body kinematics, (e.g., using full-body IMU suits with Newton–Euler dynamics [23] or a single trunk sensor approximating centre-of-mass acceleration [36]). Machine-learning methods range from classical models (e.g., random forests [21], k -NN and regression trees [37], and boosted regression on ear-IMU data [40]) to deep neural networks [6]). Classical approaches typically depend on per-stance segmentation or on a matching stride existing in the training set, which limits subject generalisation [37]; the sequence-to-sequence deep models we adopt avoid both. Recent deep-learning work includes

feed-forward and wavelet networks on shank IMUs [27], CNNs [47], LSTMs [24], and attention-based models [49]. All of these place sensors on the lower body, trunk, sacrum, or ear. Running vGRF is also harder to reconstruct than walking [37]; reported running nRMSE values include 3.2% with pressure insoles [6], ~ 6.4 – 6.7% with a sacrum accelerometer [1], ~ 5.7 – 7.3% with shank IMUs [27], and 13.1% with an ear device [39]. We compare against these in Section 4.

2.2 Wrist wearables for gait

Wrist-based gait research is comparatively sparse and has targeted discrete quantities: walking speed [50], speed and cadence [15], walking detection [25], and a range of temporal/spatial parameters from smartwatches [14]. None reconstruct the continuous vGRF waveform, which is the gap we address. Known challenges are that arm motion degrades wrist-based estimates relative to other locations [25] and that the wrist is distant from the point of force application.

2.3 Pre-training for data-scarce regimes

Self-supervised pre-training improves generalisation when labelled data are scarce [48] and has been applied across NLP [11], vision [9], and medical tasks [44]. For vGRF, Tan *et al.* [43] pre-trained a transformer on unlabelled IMU data via masked reconstruction and matched supervised performance with 1–10% of labels. Chaining two self-supervised stages can help further when no single dataset suffices: Ma *et al.* [29] report an 8–18% gain from two-phase over single-phase pre-training. As no single large dataset contains both wrist accelerometer and gyroscope signals, we adopt a two-stage pre-training scheme (Section 3) and evaluate whether it helps in our setting.

2.4 Evaluation

Subject-independent evaluation is markedly harder than subject-dependent evaluation due to inter-subject variability [35], and k -fold cross-validation can inflate results via data leakage in activity recognition [10]. We therefore use Leave-One-Subject-Out (LOSO) cross-validation [26], and report normalised root mean square error (nRMSE), mean absolute percentage error (MAPE), and Pearson correlation (r), following standard GRF evaluation practice [31].

3 Method

3.1 Dataset and data collection

As no public dataset provides wrist IMU with synchronised vGRF ground truth, we collected a dataset of 30 participants (11 female; mean age 28.2 y, range 18–53; mean height 176.9 cm; mean weight 73.8 kg). All participants signed informed consent forms and the experiment was approved

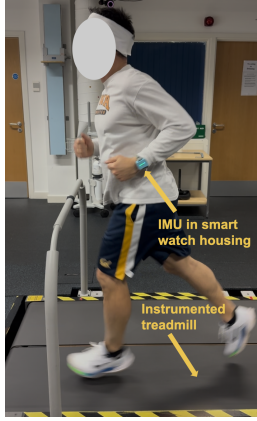


Figure 1: Data-collection setup: a participant with a smartwatch (Trigno Avanti sensor in a 3D-printed housing with an Apple Watch strap) worn on the wrist while running on an instrumented treadmill.

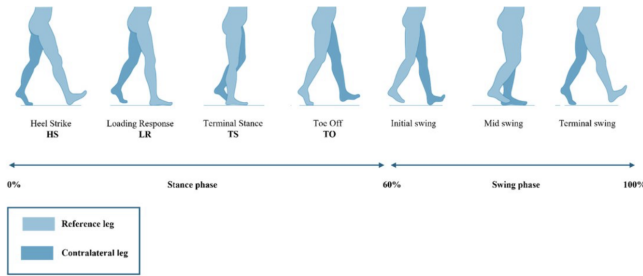


Figure 2: The running gait cycle, composed of stance and swing phases delimited by heel-strike and toe-off. Adapted from [38] (CC BY).

by the University of Cambridge Department of Computer Science and Technology Ethics Committee. Each participant ran on a Bertec instrumented treadmill (no incline) at fixed speeds between 8 and 12 kph for five minutes per session, completing 2–4 sessions, while wearing a smartwatch on the left wrist (Fig. 1). The watch housed a Trigno Avanti sensor recording tri-axial accelerometer and gyroscope data at ~ 1259 Hz; the treadmill recorded ground-truth GRF at 1000 Hz, separated into left- and right-foot vGRF. Time-stamps from both devices were used for temporal synchronisation. A gait cycle and the target vGRF waveform are illustrated in Fig. 2.

3.2 Pre-processing

IMU and vGRF signals were low-pass filtered with a 6th-order Butterworth filter at a 20 Hz cut-off, chosen because cut-offs ≤ 25 Hz preserve running vGRF correlations [33]. vGRF was normalised by body weight. Both streams were downsampled

Table 1: Sliding windows per dataset.

Dataset	#Participants	#Channels	#Usable windows
Capture24 [7]	50	3	656,000
RealWorld (HAR) [41]	15	6	71,386
Our dataset	30	6	33,929

to 50 Hz (after filtering, to limit ripple), matching our pre-training data and satisfying Nyquist. We segmented signals into 1-second sliding windows (50 samples) with 50% overlap; one second is sufficient to capture more than one stance while keeping the model small. Windows were normalised using statistics computed on the training subjects only and applied to held-out subjects, reflecting deployment where target-subject statistics are unavailable.

3.3 Models

All models take a 6-channel (tri-axial accelerometer + gyroscope) 1-second window and output a 2-channel (left/right foot) vGRF window. We study three architectures.

CNN. A 1-D convolutional encoder-decoder (3 layers each) with ReLU, max-pooling, and dropout; 57.9k parameters.

BiLSTM. Two bidirectional LSTM layers (hidden size 64, dropout 0.2) followed by a fully connected projection; 136.5k parameters. Bidirectionality provides context on both sides of each time step [17].

Transformer. A patch-based transformer encoder (192-dim embeddings, 6 layers, 8 heads, feed-forward 512) with a task-specific head, adapted from Tan *et al.* [42, 43]; 2.08M parameters. We pre-train it with masked-reconstruction self-supervised learning (SSL): patches spanning 10% of the window are masked and reconstructed [43]. Because no single large dataset offers both wrist accelerometer and gyroscope, we use *two-stage* pre-training before fine-tuning on the vGRF task: stage 1 on Capture24 (large-scale wrist accelerometer; accelerometer copied into the gyroscope channels) [7], then stage 2 on the RealWorld (HAR) dataset (wrist accelerometer + gyroscope) [41]. Window counts are given in Table 1.

3.4 Training and evaluation

Models were trained with Adam (learning rate 0.002, weight decay 0.0001), batch size 16, and early stopping (patience 5). The first SSL stage ran on an NVIDIA A100; all other training ran on a MacBook M4 Pro. We evaluate with **Leave-One-Subject-Out (LOSO)** cross-validation over the 30 subjects, reporting metrics averaged across folds to avoid subject leakage [26].

Reconstruction and post-processing. Per-window predictions are stitched into a full sequence with a Kaiser window (order 15), which down-weights the less reliable window boundaries. The sequence is then denormalised and low-pass filtered again at 20 Hz, and values below 0.01 are zeroed to suppress filtering ripple. Heel-strike and toe-off are detected where the curve crosses 0.05 (upward and downward, respectively). A candidate stance is kept only if it spans more than 10 samples (the shortest ground-truth stance is 11) and reaches 33% of the session's peak force. This amplitude threshold is deliberately conservative: the smallest within-session ratio of minimum to maximum peak force we observed was 57%. Swing-phase samples between an accepted toe-off and the next heel-strike are then zeroed, and residual in-stance peaks whose stride time falls below two-thirds of the session mean are removed. The first and last windows, which lack neighbours for overlap, are discarded.

Metrics. We report RMSE normalised by the waveform range $y_{\max} - y_{\min}$ (nRMSE), Pearson correlation r , and mean absolute percentage error (MAPE) for gait parameters derived from the reconstructed waveform: peak force, stride time ($t_{\text{HS},n+1} - t_{\text{HS},n}$), stance time ($t_{\text{TO},n} - t_{\text{HS},n}$), and swing time ($t_{\text{HS},n+1} - t_{\text{TO},n}$). We also report an *error ratio*, the fraction of ground-truth stances the model fails to reconstruct. Statistical comparisons use the two-sided Wilcoxon signed-rank test on per-subject nRMSE ($\alpha = 0.05$).

4 Results

4.1 vGRF waveform reconstruction from a single wrist IMU

Our central result is that a wrist IMU alone can reconstruct the running vGRF waveform. Using the two-stage pre-trained transformer with an MSE loss, LOSO cross-validation over 30 subjects yields a nRMSE of $7.6\% \pm 2.2\%$ and Pearson correlation $r = 0.986 \pm 0.009$ (Table 2). Reconstruction rarely fails: only 8 stances across all 92 sessions were missed, an error ratio of 0.016%. Temporal gait parameters derived from the reconstructed waveform are accurate: stride-time MAPE 1.2%, swing-time 4.1%, stance-time 6.4%. Peak force is harder at 14.6%, reflecting the known difficulty of recovering force *magnitude* from a sensor far from the foot and corrupted by arm motion. Fig. 3 shows a representative reconstruction: stance timing aligns closely with ground truth.

Comparison to prior wearable locations. Table 3 places our wrist result against published running vGRF reconstructions, all of which use sensors much closer to the point of force application. Pressure insoles achieve the lowest nRMSE (3.2%) [6], as expected from measuring directly under the foot. Shank [27] and sacrum [1] sensors reach $\sim 6\%$, marginally better than our 7.6%. Our wrist-based result *outperforms* the ear-based approach (13.1% nRMSE, $r = 0.953$) [39]. That a

Table 2: Performance of the two-stage pre-trained transformer (LOSO, 30 subjects). MAPE reported for derived gait parameters.

nRMSE	r	error ratio	#missed stance	MAPE			
				peak force	stride time	stance time	swing time
0.076	0.986	0.00016	8	0.146	0.012	0.064	0.041

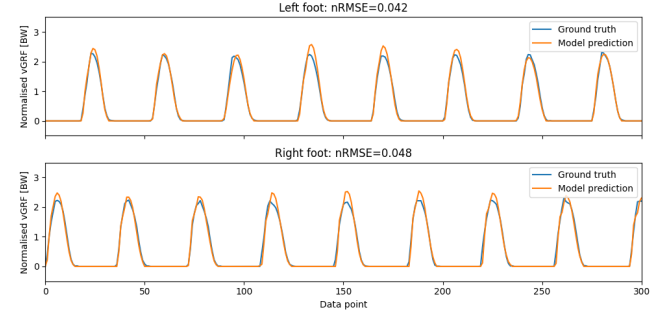


Figure 3: Reconstructed vGRF waveform (subject 0, 9 kph) from the wrist IMU versus ground truth. Both feet are shown; stance timing is well aligned.

Table 3: Running vGRF reconstruction across wearable locations. Our wrist result is comparable to sensors mounted near the foot/ground.

Work	Wearable	Model	nRMSE	r
Carter <i>et al.</i> [6]	insole	BiLSTM	0.032	–
Alcantara <i>et al.</i> [1]	sacrum	BiLSTM	0.067	–
Li <i>et al.</i> [27]	shank	WNN	0.057	–
Li <i>et al.</i> [27]	shank	FFNN	0.073	–
Stuchbury-Wass <i>et al.</i> [39]	ear	Boosted reg.	0.131	0.953
Ours	wrist	Pre-tr. transf.	0.076	0.986

wrist sensor lands within this range shows that wrist IMU signals carry sufficient information to reconstruct vGRF, and that gait analysis need not be tied to lower-body instrumentation.

Per-subject breakdown. Fig. 4 shows per-subject nRMSE. Performance is consistent across subjects; the few outliers correspond to participants with atypical peak force (e.g., subject 26 has unusually low peak force, absent from the training folds under LOSO), which inflates peak-force MAPE while temporal alignment remains good. This points to dataset size rather than the sensing modality as the main limitation on magnitude estimation.

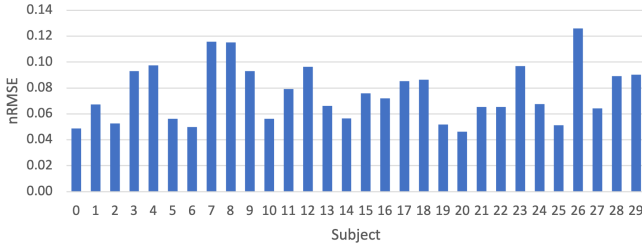


Figure 4: Per-subject nRMSE under LOSO cross-validation for the pre-trained transformer.

Table 4: Ablations on the transformer (LOSO): input normalisation and loss function. Defaults in bold.

Variant	nRMSE	r	peak-force MAPE
<i>Input normalisation</i>			
None	0.093	0.969	0.151
IMU only	0.077	0.985	0.149
vGRF only	0.091	0.972	0.163
IMU + vGRF	0.076	0.986	0.146
<i>Loss function</i>			
MSE	0.076	0.986	0.146
Huber	0.078	0.985	0.150
Gated-MSE (unweighted)	0.079	0.984	0.148
Gated-MSE (weighted)	0.084	0.983	0.152

Ablations. Table 4 reports two design-choice ablations on the transformer. Input normalisation is the single most important choice: normalising the IMU reduces nRMSE from 9.3% to 7.7% (Wilcoxon $p = 1.4 \times 10^{-5}$), whereas additionally normalising vGRF gives no significant change ($p = 0.60$). The choice of loss function had no significant effect: MSE matched or beat Huber and both weighted and unweighted gated-MSE losses on nRMSE and peak-force MAPE ($p > 0.05$ in all peak-force comparisons), despite gated-MSE being designed to improve peak estimation [28].

4.2 Supporting analyses

Model architecture: a compact CNN suffices. Table 5 compares the three models. The pre-trained transformer gives the best nRMSE (0.076), but the differences are small. There is no significant difference between the transformer and the CNN ($p = 0.114$), while the transformer significantly outperforms the BiLSTM ($p = 0.008$). The CNN attains this near-equal performance with only 57.9k parameters, $\sim 36\times$ fewer than the transformer’s 2.08M. This makes it well suited to on-device inference on a smartwatch or smartphone.

Table 5: Architecture comparison (LOSO). The CNN matches the transformer at a fraction of the size.

Model	#param	nRMSE	r	MAPE	
				peak force	stance time
CNN	57.9k	0.080	0.983	0.157	0.094
BiLSTM	136.5k	0.083	0.981	0.156	0.072
Pre-tr. transformer	2.08M	0.076	0.986	0.146	0.064

Table 6: Effect of self-supervised pre-training on the transformer (nRMSE, LOSO). No strategy differs significantly from no pre-training.

Pre-training	nRMSE	r
None	0.079	0.984
Capture24 only	0.079	0.985
RealWorld only	0.076	0.985
Two-stage (both)	0.076	0.986

Self-supervised pre-training does not help. Table 6 compares pre-training strategies for the transformer. Contrary to expectations from the literature, neither single-stage nor two-stage SSL produces a statistically significant improvement over training from scratch (all $p > 0.05$; nRMSE differs by $<1\%$). We attribute this to the periodic and low-complexity nature of the vGRF target and the modest input dimensionality (6 channels $\times$ 50 samples): pre-training adds compute without payoff in this regime. Together with the architecture comparison above, this suggests wrist-based vGRF reconstruction is achievable with simple, compact models and without pre-training.

Masking ratio has little effect. The default masking ratio hides 10% of each window during pre-training [43]. Table 7 compares this default against a wider 50% mask on SSL2-only pre-training. Widening the mask leaves every metric essentially unchanged: nRMSE rises marginally from 0.076 to 0.079, r is unchanged at 0.986, and the derived-parameter MAPEs shift by at most 0.011 (peak force). The 50%-mask model is not significantly different from the default two-stage model (Wilcoxon $p = 0.07$). The masking ratio thus joins architecture and pre-training data as a design choice that does not materially affect wrist-based vGRF reconstruction.

Dropout is unnecessary. Dropout was expected to curb over-fitting, but it consistently hurt. For the default two-stage model, nRMSE rose monotonically with the dropout rate, from 0.076 at 0 to 0.091 at 0.4, and the same trend held for every pre-training regime (Fig. 5). We attribute this to the periodic, low-complexity target: weight decay and early

Table 7: Effect of the SSL masking ratio (LOSO). The 10% row is the default two-stage model (Table 2); the 50% row uses SSL2-only pre-training. MAPE reported for derived gait parameters; default in bold.

Masking ratio	nRMSE	r	MAPE			
			peak force	stride time	stance time	swing time
10% (default)	0.076	0.986	0.146	0.012	0.064	0.041
50%	0.079	0.986	0.157	0.012	0.071	0.045

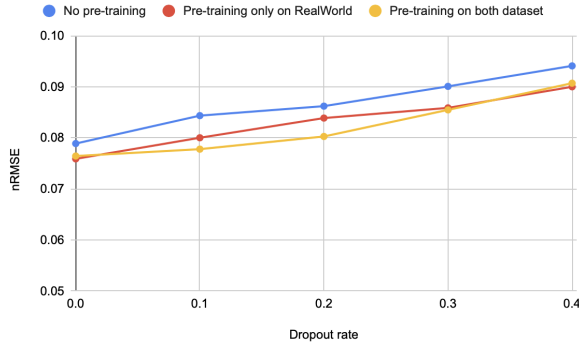


Figure 5: Transformer nRMSE against dropout rate (LOSO) for three pre-training regimes. Lower is better; nRMSE is smallest at a dropout rate of 0 in every regime.

stopping already regularise the model, so dropout only impedes learning. The transformer therefore uses no dropout, in line with the architecture, pre-training, and masking results above.

5 Discussion

Feasibility and accessibility. Our results show that the running vGRF waveform can be reconstructed from a single wrist IMU with accuracy comparable to sensors placed near the foot or trunk. Because wrist devices dominate the consumer market [13] and are already worn by the majority of runners [20], this lowers a barrier to out-of-lab gait analysis: no specialised instrumentation or unusual sensor placement is required. The accurate temporal parameters (stride, stance, swing) recovered directly from the waveform are clinically relevant: altered swing and stance timing are associated with conditions including multiple sclerosis and Parkinson’s disease [16, 46], and a swing- and stance-dominated gait-rhythm factor tracks cognitive decline [45]. The kinetic parameters matter too: elevated peak force is associated with chronic ankle instability [4], and spatiotemporal gait measures inform fall and mortality risk [18].

Magnitude is the hard part. Peak-force MAPE (14.6%) lags the temporal parameters and the ear-based comparison [39]. Two factors plausibly contribute: arm swing injects motion uncorrelated with vertical loading, and with only 30 subjects, LOSO leaves the training folds without peers for subjects at the extremes of the force distribution. The ablations support the latter: error concentrates on atypical subjects rather than being uniform. A larger, more diverse dataset or a dedicated peak-force head would therefore most improve magnitude estimation.

Simplicity suffices. Neither a peak-weighted loss nor self-supervised pre-training yielded significant gains, and a compact CNN matched the transformer. For a periodic, low-dimensional target, added model complexity appears unnecessary. This is encouraging for on-device deployment: the 57.9k-parameter CNN is well within a smartwatch’s budget.

Future Work. Participants were healthy adults running at constant treadmill speeds in a controlled lab for short (~5-minute) sessions. Generalisation to clinical populations, free-living variable-speed running, prolonged (fatigued) running, and other activities such as walking remains future work, as does extending reconstruction to all three GRF axes.

6 Conclusion

We presented, to our knowledge, the first reconstruction of the running vertical ground reaction force waveform from a single wrist-worn IMU. A transformer model achieves a normalised RMSE of $7.6\% \pm 2.2\%$ and Pearson correlation 0.986 ± 0.009 under Leave-One-Subject-Out cross-validation on 30 participants, comparable to prior work using sensors mounted far closer to the ground, and yields accurate temporal gait parameters derived directly from the reconstructed curve. Our supporting analyses show that this is achievable without added complexity: a compact CNN matches the transformer at $\sim 36\times$ fewer parameters, and self-supervised pre-training and a peak-weighted loss provide no significant benefit. These findings indicate that the smartwatch already on a runner’s wrist is a viable tool for accessible, out-of-lab vGRF-based gait analysis. Future work will target force-magnitude accuracy, larger and more diverse cohorts, free-living conditions, and other activities.

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References

- [1] Ryan S Alcantara, W Brent Edwards, Guillaume Y Millet, and Alena M Grabowski. 2022. Predicting continuous ground reaction forces from accelerometers during uphill and downhill running: a recurrent neural network solution. *PeerJ* 10 (Jan. 2022), e12752.
- [2] Andrea Ancillao, Salvatore Tedesco, John Barton, and Brendan O'Flynn. 2018. Indirect Measurement of Ground Reaction Forces and Moments by Means of Wearable Inertial Sensors: A Systematic Review. *Sensors* 18, 8 (2018). doi:10.3390/s18082564
- [3] Tarlochan Singh Bhambra, Abdal Qadir Zafar, and Adelle Fishlock. 2024. Understanding gait assessment and analysis. *Orthopaedics and Trauma* 38, 6 (2024), 371–377. doi:10.1016/j.mporth.2024.10.003
- [4] John Bigouette, Janet Simon, Kathy Liu, and Carrie L Docherty. 2016. Altered Vertical Ground Reaction Forces in Participants With Chronic Ankle Instability While Running. *J Athl Train* 51, 9 (Nov. 2016), 682–687.
- [5] M. M. Bruneau, L. W. Gaudette, B. C. Heiderscheit, C. Napier, J. Posilkin, M. J. Rauh, F. Oldenburg, L. Wasserman, A. S. Tenforde, and K. Holmlander. 2025. Gait Retraining in Injured Distance Runners: A Clinical Review. *German Journal of Sports Medicine* 76, 1 (01 Mar 2025), 22–28. <https://www.germanjournalsportsmedicine.com/archive/archive-2025/issue-1/gait-retraining-in-injured-distance-runners-a-clinical-review/>
- [6] Joshua Carter, Xi Chen, Dario Cazzola, Grant Trewartha, and Ezio Preatoni. 2024. Consumer-priced wearable sensors combined with deep learning can be used to accurately predict ground reaction forces during various treadmill running conditions. *PeerJ* 12, 8 (29 Aug. 2024). doi:10.7717/peerj.17896
- [7] Shing Chan, Yuan Hang, Catherine Tong, Aidan Acquah, Abram Schonfeldt, Jonathan Gershuny, and Aiden Doherty. 2024. CAPTURE-24: A large dataset of wrist-worn activity tracker data collected in the wild for human activity recognition. *Scientific Data* 11, 1 (16 Oct 2024), 1135. doi:10.1038/s41597-024-03960-3
- [8] Zoe Y S Chan, Janet H Zhang, Ivan P H Au, Winko W An, Gary L K Shum, Gabriel Y F Ng, and Roy T H Cheung. 2017. Gait Retraining for the Reduction of Injury Occurrence in Novice Distance Runners: 1-Year Follow-up of a Randomized Controlled Trial. *Am J Sports Med* 46, 2 (Oct. 2017), 388–395.
- [9] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. 2020. A simple framework for contrastive learning of visual representations. In *Proceedings of the 37th International Conference on Machine Learning (ICML'20)*. JMLR.org, Article 149, 11 pages.
- [10] Akbar Dehghani, Tristan Glatard, and Emad Shihab. 2019. Subject Cross Validation in Human Activity Recognition. *CoRR* abs/1904.02666 (2019). arXiv:1904.02666 <http://arxiv.org/abs/1904.02666>
- [11] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *North American Chapter of the Association for Computational Linguistics*. <https://aclanthology.org/N19-1423.pdf>
- [12] Thomas Ertelt. 2025. Physiologically-constrained decomposition of vertical ground reaction forces using gaussian basis functions: A full-curve approach to gait characterization. *Journal of Biomechanics* 193 (2025), 112990. doi:10.1016/j.jbiomech.2025.112990
- [13] Elena Escobar-Linero, Luis Muñoz-Saavedra, Francisco Luna-Perejón, José Luis Sevillano, and Manuel Domínguez-Morales. 2023. Wearable Health Devices for Diagnosis Support: Evolution and Future Tendencies. *Sensors* 23, 3 (2023). doi:10.3390/s23031678
- [14] Amir B. Farjadian, Shun Liao, Alicia Y. Kokoszka, Kyle DeHolton, Jonathan Hsu, Jonathan Wang, Lawrence Cai, Mark Malhotra, Shwetak Patel, Anupam Pathak, and Ming-Zher Poh. 2025. Smartwatch-Based Walking Metrics Estimation. In *Proceedings of the 2025 ACM International Symposium on Wearable Computers (ISWC '25)*. Association for Computing Machinery, 156–162. doi:10.1145/3715071.3750401
- [15] Benedikt Fasel, Cyntia Duc, Farzin Dadashi, Flavien Bardyn, Martin Savary, Pierre-André Farine, and Kamiar Aminian. 2017. A wrist sensor and algorithm to determine instantaneous walking cadence and speed in daily life walking. *Med Biol Eng Comput* 55, 10 (2017), 1773–1785.
- [16] Uri Givon, Gabriel Zeilig, and Anat Achiron. 2009. Gait analysis in multiple sclerosis: Characterization of temporal-spatial parameters using GAITRite functional ambulation system. *Gait & Posture* 29, 1 (2009), 138–142. doi:10.1016/j.gaitpost.2008.07.011
- [17] A. Graves and J. Schmidhuber. 2005. Framewise phoneme classification with bidirectional LSTM networks. In *Proceedings. 2005 IEEE International Joint Conference on Neural Networks, 2005.*, Vol. 4. 2047–2052 vol. 4. doi:10.1109/IJCNN.2005.1556215
- [18] John H Hollman, Eric M McDade, and Ronald C Petersen. 2011. Normative spatiotemporal gait parameters in older adults. *Gait Posture* 34, 1 (April 2011), 111–118.
- [19] Ryan M. Hulteen, Jordan J. Smith, Philip J. Morgan, Lisa M. Barnett, Pedro C. Hallal, Kim Colyvas, and David R. Lubans. 2017. Global participation in sport and leisure-time physical activities: A systematic review and meta-analysis. *Prev. Med.* 95 (2017), 14–25. doi:10.1016/j.ypmed.2016.11.027
- [20] Mark Janssen, Ruben Walravens, Erik Thibaut, Jeroen Scheerder, Aarnout Brombacher, and Steven Vos. 2020. Understanding Different Types of Recreational Runners and How They Use Running-Related Technology. *International Journal of Environmental Research and Public Health* 17, 7 (2020). doi:10.3390/ijerph17072276
- [21] Xianta Jiang, Christopher Napier, Brett Hannigan, Janice J. Eng, and Carlo Menon. 2020. Estimating Vertical Ground Reaction Force during Walking Using a Single Inertial Sensor. *Sensors* 20, 15 (2020). doi:10.3390/s20154345
- [22] Nicolas Kakouris, Numan Yener, and Daniel T.P. Fong. 2021. A systematic review of running-related musculoskeletal injuries in runners. *Journal of Sport and Health Science* 10, 5 (2021), 513–522. doi:10.1016/j.jshs.2021.04.001
- [23] Angelos Karatsidis, Giovanni Bellusci, H Martin Schepers, Mark de Zee, Michael S Andersen, and Peter H Veltink. 2016. Estimation of Ground Reaction Forces and Moments During Gait Using Only Inertial Motion Capture. *Sensors (Basel)* 17, 1 (Dec. 2016).
- [24] Junggil Kim, Hyeon Kang, Seulgi Lee, Jinseung Choi, and Gyerae Tack. 2023. A Deep Learning Model for 3D Ground Reaction Force Estimation Using Shoes with Three Uniaxial Load Cells. *Sensors* 23, 7 (2023). doi:10.3390/s23073428
- [25] Felix Kluge, Yonatan E Brand, M Encarna Micó-Amigo, Stefano Bertuletti, Ilaria D'Ascanio, Eran Gazit, Tecla Bonci, Cameron Kirk, Arne Küderle, Luca Palmerini, Anisoara Paraschiv-Ionescu, Francesca Salis, Abolfazl Soltani, Martin Ullrich, Lisa Alcock, Kamiar Aminian, Clemens Becker, Philip Brown, Joren Buekers, Anne-Elie Carsin, Marco Caruso, Brian Caulfield, Andrea Cereatti, Lorenzo Chiari, Carlos Echevarria, Bjoern Eskofier, Jordi Evers, Judith Garcia-Aymerich, Tilo Hache, Clint Hansen, Jeffrey M Hausdorff, Hugo Hiden, Emily Hume, Alison Keogh, Sarah Koch, Walter Maetzler, Dimitrios Megaritis, Martijn Niessen, Or Perlman, Lars Schwickert, Kirsty Scott, Basil Sharrack, David Singleton, Beatrix Vereijken, Ioannis Vogiatzis, Alison Yarnall, Lynn Rochester, Claudia Mazzà, Silvia Del Din, and Arne Mueller. 2024. Real-World Gait Detection Using a Wrist-Worn Inertial Sensor: Validation Study. *JMIR Form Res* 8 (May 2024), e50035.
- [26] Sajeev Kunjan, T. S. Grummett, K. J. Pope, D. M. W. Powers, S. P. Fitzgibbon, T. Bastiampillai, M. Battersby, and T. W. Lewis. 2021. The Necessity of Leave One Subject Out (LOSO) Cross Validation for EEG Disease

- Diagnosis. In *Brain Informatics*, Mufti Mahmud, M. Shamim Kaiser, Stefano Vassanelli, Qionghai Dai, and Ning Zhong (Eds.). Springer International Publishing, Cham, 558–567.
- [27] Shangxiao Li, Jiahui Pan, Dongmei Wang, Shufang Yuan, Jin Yang, and Weiya Hao. 2025. Predicting Running Vertical Ground Reaction Forces Using Neural Network Models Based on an IMU Sensor. *Sensors* 25, 13 (2025). doi:10.3390/s25133870
- [28] Nathan Louis, Jason J. Corso, Tylan N. Templin, Travis D. Eliason, and Daniel P. Nicoletta. 2022. Learning to Estimate External Forces of Human Motion in Video. In *Proceedings of the 30th ACM International Conference on Multimedia* (Lisboa, Portugal) (MM '22). Association for Computing Machinery, New York, NY, USA, 3540–3548. doi:10.1145/3503161.3548377
- [29] Haoyan Ma, Xiang Li, Xia Yuan, and Chunxia Zhao. 2023. Two-phase self-supervised pretraining for object re-identification. *Knowledge-Based Systems* 261 (2023), 110220. doi:10.1016/j.knsys.2022.110220
- [30] Rachel Mason, Liam T Pearson, Gillian Barry, Fraser Young, Oisín Lennon, Alan Godfrey, and Samuel Stuart. 2023. Wearables for Running Gait Analysis: A Systematic Review. *Sports Med.* 53, 1 (2023), 241–268.
- [31] Anderson Souza Oliveira, Morteza Yaserifar, and Cristina-Ioana Pîrșcoveanu. 2026. The Use of Machine Learning to Estimate Ground Reaction Forces During Running: A Scoping Review of the Current Practices. *Sensors* 26, 8 (2026). doi:10.3390/s26082502
- [32] Hari Prasanth, Miroslav Caban, Urs Keller, Grégoire Courtine, Auke Ijspeert, Heike Vallery, and Joachim von Zitzewitz. 2021. Wearable Sensor-Based Real-Time Gait Detection: A Systematic Review. *Sensors* 21, 8 (2021). doi:10.3390/s21082727
- [33] Thomas Provot, Samaneh Choupani, Maxime Bourgain, Laura Valdes-Tamayo, and Delphine Chadeaux. 2023. Using Wearable Accelerometers to Develop a Vertical Ground Reaction Force Prediction Model during Running: A Sensitivity Study. *Vibration* 6, 3 (2023), 680–694. doi:10.3390/vibration6030042
- [34] Jim Richards, Ambreen Chohan, and Renuka Erande. 2013. Chapter 15 - Biomechanics. In *Tidy's Physiotherapy (Fifteenth Edition)* (fifteenth edition ed.), Stuart B. Porter (Ed.). Churchill Livingstone, 331–368. doi:10.1016/B978-0-7020-4344-4.00015-8
- [35] Sebastian Scheurer, Salvatore Tedesco, Brendan O'Flynn, and Kenneth N. Brown. 2020. Comparing Person-Specific and Independent Models on Subject-Dependent and Independent Human Activity Recognition Performance. *Sensors* 20, 13 (2020). doi:10.3390/s20133647
- [36] E. Shahabpoor and A. Pavic. 2018. Estimation of vertical walking ground reaction force in real-life environments using single IMU sensor. *Journal of Biomechanics* 79 (2018), 181–190. doi:10.1016/j.jbiomech.2018.08.015
- [37] Dharmendra Sharma, Pavel Davidson, Philipp Müller, and Robert Piché. 2021. Indirect Estimation of Vertical Ground Reaction Force from a Body-Mounted INS/GPS Using Machine Learning. *Sensors* 21, 4 (2021). doi:10.3390/s21041553
- [38] Giovanni Spallone, Letizia Mancini, Arianna Carnevale, Stefano Campi, Alessandro de Sire, Emiliano Schena, Pieter D'Hooghe, Michael T. Hirschmann, Rocco Papalia, and Umile Giuseppe Longo. 2025. Step-by-step insight into gait analysis: A narrative review unlocking knee biomechanics. *Knee Surgery, Sports Traumatology, Arthroscopy* (2025), 1–18. doi:10.1002/ksa.70067
- [39] Jake Stuchbury-Wass, Mathias Ciliberto, Kayla-Jade Butkow, Qiang Yang, Yang Liu, Ezio Preatoni, Dong Ma, and Cecilia Mascolo. 2026. Ear-Worn Inertial Sensors Can Predict Gait Metrics and Reconstruct Vertical Ground Reaction Force Curves During Running. *Journal of Applied Biomechanics* (2026), 1–10. doi:10.1123/jab.2025-0337
- [40] Jake Stuchbury-Wass, Yang Liu, {Kayla Jade} Butkow, Josh Carter, Qiang Yang, Mathias Ciliberto, Ezio Preatoni, Dong Ma, and Cecilia Mascolo. 2025. WalkEar: Holistic Gait Monitoring using Earables. In *Proceedings - 2025 IEEE International Conference on Pervasive Computing and Communications, PerCom 2025* (2025 ed.) (IEEE International Conference on Pervasive Computing and Communications (PerCom)). IEEE, USA United States, 99–109. doi:10.1109/PerCom64205.2025.00029 23rd IEEE International Conference on Pervasive Computing and Communications, PerCom 2025 ; Conference date: 17-03-2025 Through 21-03-2025.
- [41] Timo Szttyler and Heiner Stuckenschmidt. 2016. On-body localization of wearable devices: An investigation of position-aware activity recognition. In *2016 IEEE International Conference on Pervasive Computing and Communications (PerCom)*. 1–9. doi:10.1109/PERCOM.2016.7456521
- [42] Tian Tan, Peter B. Shull, and Akshay S. Chaudhari. 2023. Self-Supervised Learning for IMU-Driven Biomechanical Estimation [Source code]. https://github.com/StanfordMIMI/SSL_IMU
- [43] Tian Tan, Peter B Shull, Jennifer L Hicks, Scott D Uhlich, and Akshay S Chaudhari. 2024. Self-Supervised Learning Improves Accuracy and Data Efficiency for IMU-Based Ground Reaction Force Estimation. *IEEE Trans Biomed Eng* 71, 7 (June 2024), 2095–2104.
- [44] Soroosh Tayebi Arasteh, Leo Misera, Jakob Nikolas Kather, Daniel Truhn, and Sven Nebelung. 2024. Enhancing diagnostic deep learning via self-supervised pretraining on large-scale, unlabeled non-medical images. *Eur Radiol Exp* 8, 1 (Feb. 2024), 10.
- [45] Joe Verghese, Cuiling Wang, Richard B Lipton, Roe Holtzer, and Xiaonan Xue. 2007. Quantitative gait dysfunction and risk of cognitive decline and dementia. *J Neurol Neurosurg Psychiatry* 78, 9 (Jan. 2007), 929–935.
- [46] Wenchao Yin, Wencheng Zhu, Hong Gao, Xiaohui Niu, Chenxin Shen, Xiangmin Fan, and Cui Wang. 2024. Gait analysis in the early stage of Parkinson's disease with a machine learning approach. *Frontiers in Neurology* 15 (2024). doi:10.3389/fneur.2024.1472956
- [47] Batın Yılmazgün, Jonas Weber, Thorsten Stein, Stefan Sell, and Bernd J. Stetter. 2025. Predicting 3D ground reaction forces across various movement tasks: a convolutional neural network study comparing different inertial measurement unit configurations. *Journal of Biomechanics* 192 (2025), 112888. doi:10.1016/j.jbiomech.2025.112888
- [48] Zehui Zhao, Laith Alzubaidi, Jinglan Zhang, Ye Duan, and Yuantong Gu. 2024. A comparison review of transfer learning and self-supervised learning: Definitions, applications, advantages and limitations. *Expert Systems with Applications* 242 (2024), 122807. doi:10.1016/j.eswa.2023.122807
- [49] Yeqing Zhu, Di Xia, and Heng Zhang. 2023. Using Wearable Sensors to Estimate Vertical Ground Reaction Force Based on a Transformer. *Applied Sciences* 13, 4 (2023). doi:10.3390/app13042136
- [50] Shaghayegh Zihajezadeh and Edward J. Park. 2016. Regression Model-Based Walking Speed Estimation Using Wrist-Worn Inertial Sensor. *PLOS ONE* 11, 10 (10 2016), 1–16. doi:10.1371/journal.pone.0165211