

Prediction of running anteroposterior ground reaction forces from the vertical component through a deep learning approach

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Abstract — Studying ground reaction forces is essential for in-situ running analysis, as they provide critical insights into both performance optimization and the etiology of running-related injuries. However, the use of current measurement systems in ecological or field conditions remains limited: their restricted measurement areas constrain data collection to only a few steps, and their high cost hinders widespread adoption. Recently, a size-adjustable instrumented track has been developed to measure the vertical component of ground reaction forces outside the laboratory environment. Building on this advancement, the present study aims to develop a neural network approach for predicting the anteroposterior component from the measured vertical component and to evaluate the impact of prediction errors on joint kinetics. A public dataset comprising 9,500 running steps was used to train, validate, and test the prediction model. The results demonstrated that a convolutional neural network can accurately predict the anteroposterior component of the ground reaction force (relative root mean square error = 7.44%). While these AP-GRF prediction errors had only a minor impact on ankle moment calculations, estimates at the knee and hip were more substantially affected. These findings suggest that the proposed model may be effectively applied in conjunction with the size-adjustable instrumented track.

Keywords: Ground Reaction Force, Deep Learning, Prediction, Running

1. Introduction

Ground reaction forces (GRF) are among the most critical biomechanical variables for understanding human locomotion. They are commonly used in clinical studies to investigate gait analysis^{1,2}, and also in sports-related studies to assess performance³ and the effects of environmental parameters⁴⁻⁶. GRF represent the external forces exerted by the ground on the body at each step and are traditionally decomposed into three orthogonal components: vertical (vGRF), anteroposterior (AP-GRF), and mediolateral (ML-GRF). In running, the vertical and anteroposterior components are of particular interest given their close association with running technique^{7,8}, their influence on running economy^{9,10} and their involvement in injury-related biomechanical parameters^{11,12}. GRF parameters commonly investigated include loading rate, impact peak, and vertical impulse for the vertical component, as well as braking and propulsive impulses and peak forces for the anteroposterior component. Beyond their descriptive value, GRF are also essential inputs for inverse dynamics analyses, where they are combined with kinematic data to compute joint moments and loading patterns. These joint-level estimates are widely used to better understand how mechanical stress on structures¹³⁻¹⁶ are related to running-related injuries.

While force plates and instrumented treadmills provide reliable measurements of GRF, their application is typically restricted to controlled laboratory environments. These systems are not only expensive and space-limited but also fail to capture the natural variability of running mechanics in ecological settings. To overcome these limitations, researchers developed innovative devices to measure GRF during in-field activities. For instance, instrumented studs have been introduced to measure vertical GRF during on-field football practice ¹⁷.

In response to the practical limitations of direct GRF measurement devices, alternative approaches have emerged to estimate GRF indirectly using biomechanical data. For example, several studies have attempted to estimate three-dimensional GRF from center of mass acceleration according to the second Newton law ^{18,19} or from center of pressure data ²⁰. Similarly, other studies have applied the linear and angular momentum theorems using kinematic data as inputs to estimate GRF ²¹. Deep learning approaches have also shown promising results in predicting GRF using input data from wearable accelerometers ^{22,23} or from pressure insoles ²⁴. These innovative methods could allow for GRF predictions outside of the lab, including complex environments such as downhill/uphill ²⁵. However, the accuracy of these predictions may be influenced by diverse factors such as individual running technique ²⁴ and running speed ²⁵ highlighting the need for adaptable and robust predictive models.

Recently a size-adjustable instrumented track has been developed and validated to measure vGRF *in situ* over large distances ²⁶. This low-cost and innovative device significantly improves accessibility to force data during real-world running conditions. However, to provide a more comprehensive *in situ* running analysis, the measurement of the AP-GRF force is critical. Indeed, capturing this component is essential for calculating joint moments and other key biomechanical parameters, such as braking and propulsive impulses. More broadly, the integration of accurate field-based measurement systems holds substantial potential to advance scientific knowledge by enabling the collection of biomechanical data under conditions that closely reflect real-world practice.

The objective of this study is to evaluate the performance of a deep learning approach in predicting the anteroposterior component of GRF (AP-GRF) from the measured vertical component (vGRF) during running at various speeds. In addition, the influence of AP-GRF prediction accuracy on lower limb joint moment estimation will also be examined.

2. Methods

2.1. Participants

A public dataset recorded by Van Hooren & Meijer, (2024) was used in this study to train and test the prediction model. The dataset includes data from 19 participants (mean $\pm$ SD: 23.6 $\pm$ 3.7 years; 1.75 $\pm$ 0.09 m; 67.2 $\pm$ 10.4 kg), including ten males and nine females free of any moderate (for previous 3 months) or minor (for previous 1 month) musculoskeletal injuries.

2.2. Data Collection

Van Hooren & Meijer, (2024) used an instrumented split-belt treadmill (CAREN, Motek, The Netherlands) to collect GRF data. This system enabled continuous GRF measurement for every step during each 1-minute running trial and allowed precise control of running speed. A 12-camera three-dimensional motion capture system (VICON NEXUS v2.1, Oxford Metrics Group, Oxford, UK, 100 Hz) was used to measure kinematic outcomes. Prior to data collection, participants completed an 8-minute run at a fixed speed of 2.78 m·s⁻¹ to familiarize themselves with treadmill running. Each participant subsequently ran at five distinct speeds (2.78, 3.00,

3.33, 4.00, and 5.00 m·s⁻¹), with the order of the speed conditions randomized to minimize potential order effects.

2.3. Data Processing

GRF data were first pre-processed using a zero-lag, fourth-order Butterworth low-pass filter with a cut-off frequency of 20 Hz, thus enabling to remove noise from the treadmill components²⁸. Steps were identified using a 20 N threshold^{29,30}, time-normalized to 100 data points (0–100% of the stance phase), and normalized to body weight, ensuring a consistent and reproducible processing procedure across participants. To reduce potential errors associated with step segmentation at the beginning and end of stance, the first and last data points of GRF were removed. For each subject and speed condition, 100 steps were randomly selected, resulting in a total dataset of 9,500 steps.

A leave-one-subject-out (LOSO) cross-validation procedure was employed to quantify the predictive performance of the model. This approach consisted of training the neural network on data from all participants except one, with the excluded participant serving as the test subject³¹. Within each fold, the model was trained on the complete data from all remaining participants (N-1) without a separate internal validation set, and the number of training epochs was fixed a priori and kept constant across all folds. Tested subject data remained entirely unseen during training, ensuring unbiased evaluation. The procedure was repeated iteratively so that each participant was used once as the test subject. This validation strategy provides a transparent and robust estimate of model accuracy and more accurately reflects the true generalizability of the proposed method³². Totally nineteen models are tested.

2.4. Model structure

The predictive model used in this study was inspired by the work from Dorschky et al., (2020), who developed a convolutional neural network (CNN) capable of accurately estimating sagittal plane joint angles, joint moments, and GRF using inertial measurement unit data. In our case, the CNN was adapted to predict AP-GRF from the vertical component. Accordingly, the vGRF normalized by bodyweight was incorporated into the neural network as a single input channel represented by a 98-point vector. The network output consisted of the bodyweight-normalized AP-GRF, also represented as a 98-point vector. The model was implemented in Python 3.9 and built using the TensorFlow backend³³.

The CNN architecture consisted of two convolutional layers with 64 and 128 filters, respectively, each followed by max-pooling layers to reduce dimensionality. The output was then flattened and passed through a fully connected layer comprising 512 neurons, with L2 regularization applied to mitigate overfitting. The final output layer contained 98 neurons with a linear activation function, suitable for regression tasks. The model was compiled using the Adam optimizer and mean squared error (MSE) as the loss function. Training was conducted over 500 epochs with a batch size of 64.

2.5. Joint moment calculation evaluation

Joint moments were computed using inverse kinematics and inverse dynamics analyses performed in OpenSim software³⁴. Inverse kinematics was used to compute joint angles from motion capture data, while inverse dynamics combined kinematics and external forces to compute net joint moments throughout the movement. Two types of external forces were used as inputs for the inverse dynamics analysis, differing only in the source of the AP-GRF: (1) measured AP-GRF obtained from the instrumented treadmill in data collection procedure, and

(2) predicted AP-GRF generated by the CNN model based on vGRF data. Joint moments were time-normalized to 100 data points, representing 0–100% of the step time, and were also normalized to body weight. Comparisons were performed on a total of 500 steps per subjects, corresponding to 100 steps per running speed for each subject.

2.6. Model evaluation

First, the accuracy of the prediction model was evaluated by computing the Root Mean Square Error (RMSE) (1), the relative RMSE (rRMSE) (2) and the Pearson correlation coefficient between the measured and predicted data for each subject.

$$RMSE = \left(\sqrt{\frac{\sum_{i=1}^n (y_{pred,i} - y_{measured,i})^2}{n}} \right) \quad (1)$$

$$rRMSE = \frac{RMSE}{amplitude} \times 100 \quad (2)$$

In Equation (1), $y_{pred,i}$ represents the predicted AP-GRF value for each step i , $y_{measured,i}$ the corresponding measured reference AP-GRF value for each step i , and n the number of data points. In Equation (2), the amplitude is defined as the difference between the maximum and minimum values of the measured AP-GRF signal.

Minimal and maximal values of AP-GRF for each step were also compared based on Bland-Altman plots³⁵. Bias and limits of agreement (LOA) were computed to assess the agreement between predicted and measured AP-GRF signals. Bias was defined as the mean difference between the two measurements. LOA were calculated as the bias $\pm$ 1.96 times the standard deviation of the differences³⁶. A two-way mixed model intraclass correlation coefficient (ICC_{3,1}) was calculated, along with the corresponding 95% confidence interval, for both minimum and maximum values. ICC values were interpreted according to the following criteria: values below 0.5 indicated poor reliability; values between 0.50 and 0.75 reflected moderate reliability; values from 0.75 to 0.90 indicated good reliability; and values exceeding 0.90 were considered to reflect excellent reliability.³⁷

Secondly, the influence of the predicted AP-GRF on lower-limb joint moment estimation was evaluated by comparing the peak hip extension, peak knee extension, and peak ankle plantarflexion moments computed using both measured and predicted AP-GRF inputs. In addition to peak AP-GRF analysis, the intraclass correlation coefficient ICC_{3,1} with its corresponding 95% confidence interval was calculated to assess measurement consistency, while ICC_{A,1} was computed to evaluate absolute agreement for each of the three peak joint moments.

3. Results

In total, nineteen models were trained, corresponding to one model per participant, with each participant serving once as the independent test dataset.

The predicted AP-GRF values were strongly correlated with the measured AP-GRF forces ($p < .001$), with a mean Pearson correlation coefficient of 0.98 ± 0.011 (Table 1). The mean RMSE between measured and predicted AP-GRF was 32.00 ± 10.69 N, corresponding to a mean relative RMSE (rRMSE) of 7.44 ± 2.34 % of the force amplitude.

Table 1 : Mean ($\pm$ SD) results for RMSE (in Newton), rRMSE (in %) and Pearson correlation for all subjects tested averaged for all tested speeds.

Subjects	Pearson r	RMSE (N)	rRMSE (%)
01	0.988 ± 0.011	38.88 ± 18.23	7.35 ± 2.49
02	0.986 ± 0.008	27.75 ± 8.77	6.03 ± 1.55
03	0.989 ± 0.008	34.98 ± 10.80	7.61 ± 1.73
04	0.98 ± 0.014	42.98 ± 12.26	10.86 ± 3.84
05	0.981 ± 0.013	36.31 ± 13.06	7.0 ± 2.06
06	0.985 ± 0.012	34.60 ± 11.40	6.48 ± 1.82
07	0.988 ± 0.011	29.29 ± 10.42	6.61 ± 2.42
08	0.99 ± 0.01	25.14 ± 7.61	6.38 ± 3.24
09	0.971 ± 0.018	37.33 ± 9.42	9.75 ± 3.71
10	0.984 ± 0.008	30.51 ± 7.4	7.18 ± 2.04
11	0.988 ± 0.01	23.97 ± 8.91	6.95 ± 2.1
12	0.975 ± 0.014	30.81 ± 11.75	8.04 ± 2.22
13	0.981 ± 0.014	34.41 ± 10.06	8.90 ± 2.16
14	0.986 ± 0.009	32.2 ± 10.73	6.64 ± 2.13
15	0.99 ± 0.005	31.21 ± 10.45	6.73 ± 1.92
16	0.989 ± 0.006	32.51 ± 11.27	7.05 ± 1.77
17	0.987 ± 0.008	24.67 ± 8.7	7.38 ± 2.32
18	0.992 ± 0.006	27.76 ± 13.70	5.96 ± 2.06
19	0.975 ± 0.014	32.72 ± 8.25	8.38 ± 2.81
Mean ($\pm$ SD)	0.984 ± 0.011	32.0 ± 10.69	7.44 ± 2.34

Regarding the subject- and speed-dependency of AP-GRF prediction accuracy, Figure 1 presents the rRMSE for each step tested across all subjects, with point colors representing running speed to highlight its effect on prediction performance. Figure 2 displays the mean measured and predicted AP-GRF for the subjects with the highest and lowest prediction accuracy across different speeds.

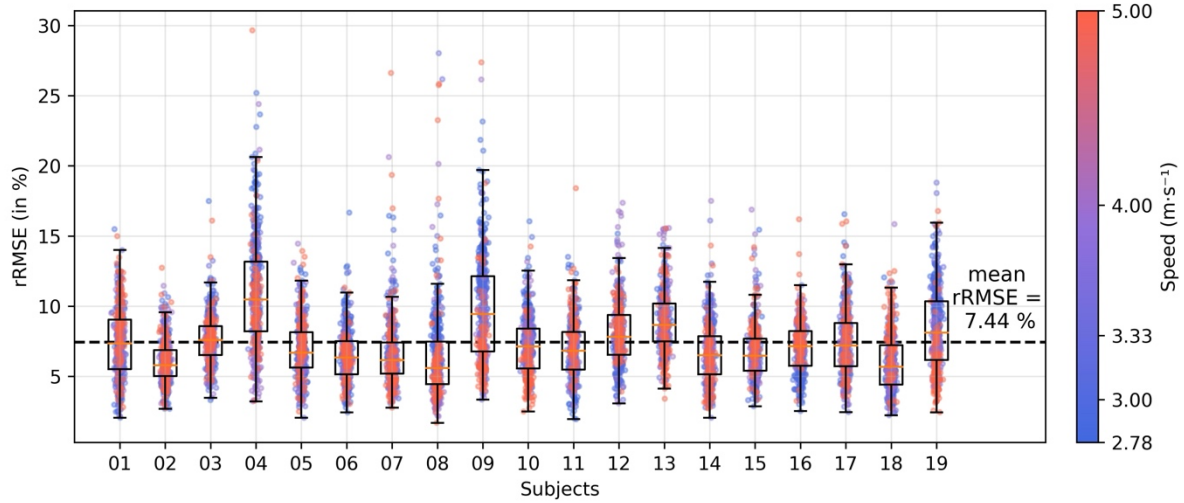


Figure 1 : A box-and-whisker plot illustrates the distribution of the rRMSE for each participant, calculated between the measured and estimated waveforms AP-GRF. The color bar on the right represents the corresponding running speed of each step tested. AP-GRF indicates anteroposterior ground reaction forces; rRMSE, relative root mean squared error.

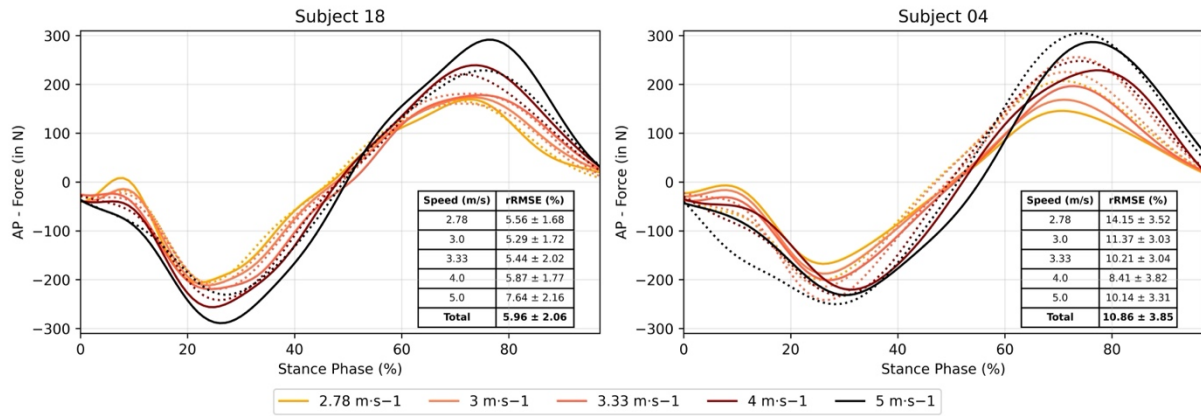


Figure 2 : Mean measured AP-GRF (solid lines) and predicted AP-GRF (dashed lines) are shown for each running speed condition, comparing the most accurate (on left) and least accurate (on right) subject-independent models based on rRMSE results. AP-GRF indicates anteroposterior ground reaction forces; rRMSE, relative root mean squared error.

The $ICC_{(3,1)}$ for maximum AP-GRF values was 0.79 (95% CI: 0.78–0.80, $p < .001$), and 0.76 (95% CI: 0.76–0.77, $p < .001$) for minimum values, indicating good reliability in both cases. As shown in Figure 3, the bias for the maximal and minimal values of the AP-GRF were -1.7 N (95% CI: $[-77.0, 73.7]$) and 5.1 N (95% CI: $[-62.3, 72.5]$), respectively. These values correspond to 1.9% (95% CI: $[-36.1, 39.9]$) and -0.2% (95% CI: $[-31.0, 30.0]$) relative to the peak force measured.

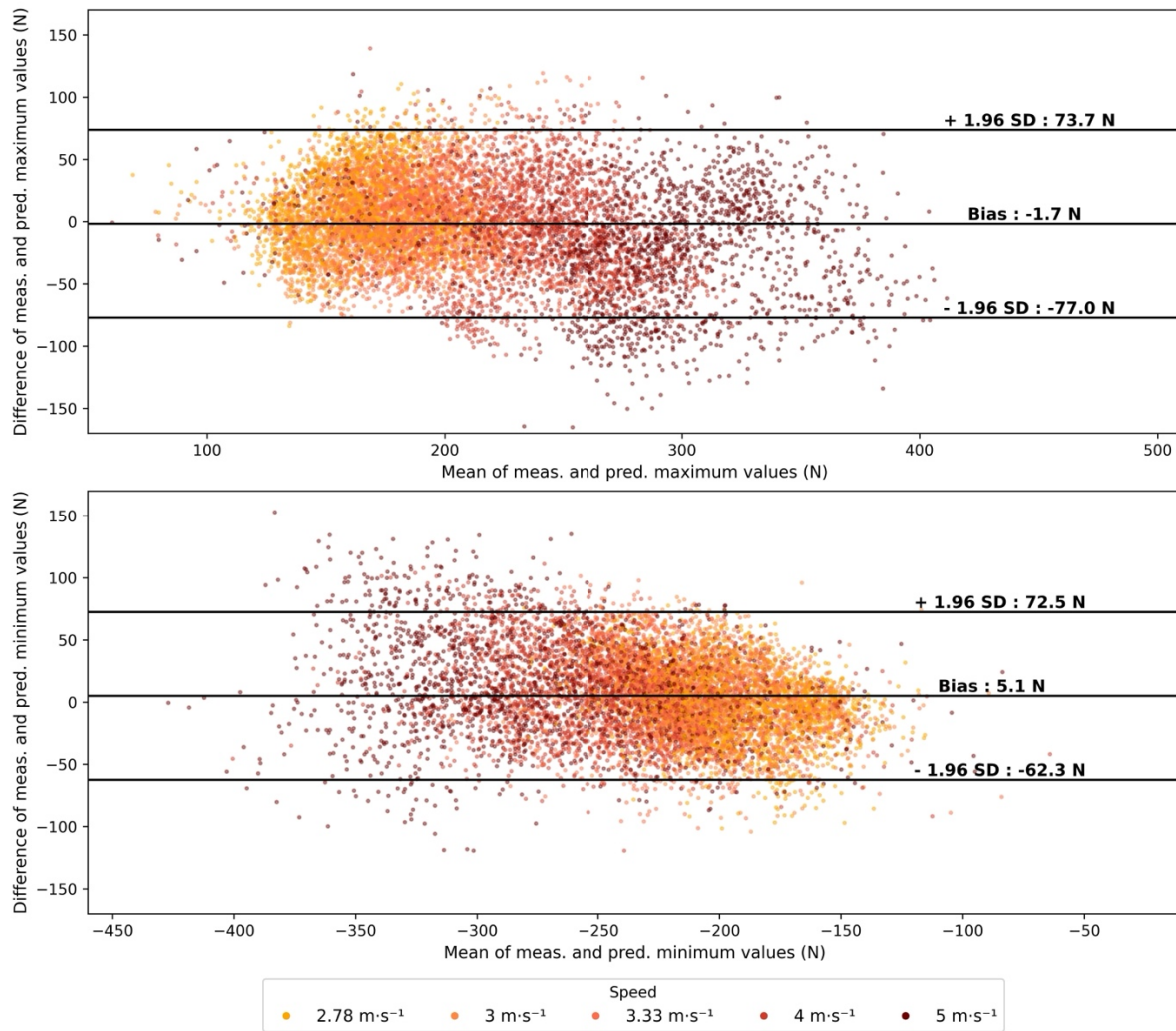


Figure 3 : Bland–Altman plot for maximal (top) and minimal (bottom) values of measured and predicted anteroposterior ground reaction forces. Each color represents a different running speed.

The impact of the predicted AP-GRF on lower-limb joint moments is illustrated in Figure 4, which presents the mean ($\pm$ SD) sagittal-plane joint moment curves computed using predicted and measured AP-GRF. The figure displays the joint moment curves corresponding to the most accurate and least accurate AP-GRF predictions, as well as the mean curves across all subjects. Table 2 summarizes the differences in peak joint moments between the two conditions for the hip, knee, and ankle joints. The mean differences for peak hip and knee extension moments and peak plantarflexion moment were 0.06 ± 0.75 , 0.29 ± 0.27 , and 0.00 ± 0.07 N·m·kg⁻¹, respectively. Both ICC_{3,1} and ICC_{A,1} indicated similar levels of agreement: moderate for the peak hip extension moment (ICC_{3,1} = 0.59, ICC_{A,1} = 0.59), good for the peak knee extension moment (ICC_{3,1} = 0.89, ICC_{A,1} = 0.79), and excellent for the peak ankle plantarflexion moment (ICC_{3,1} = 0.996, ICC_{A,1} = 0.996).

Table 2 : Mean ($\pm$ SD) values of body mass–scaled peak joint moment magnitudes (in N.m.kg⁻¹) derived from measured and predicted anteroposterior AP-GRF, along with the corresponding intraclass correlation coefficients (ICC_{3,1}) and (ICC_{A,1}).

	Measured	Predicted	Difference	ICC _(3,1)	ICC _(A,1)
Peak hip extension moment (N·m·kg⁻¹)	3.04 $\pm$ 0.84	2.98 $\pm$ 0.83	0.06 $\pm$ 0.75	0.592 [0.55,0.63]	0.591 [0.55,0.63]
Peak knee extension moment (N·m·kg⁻¹)	2.58 $\pm$ 0.57	2.29 $\pm$ 0.58	0.29 $\pm$ 0.27	0.887 [0.87,0.9]	0.789 [0.21,0.92]
Peak ankle plantarflexion moment (N·m·kg⁻¹)	3.11 $\pm$ 0.72	3.11 $\pm$ 0.73	0.0 $\pm$ 0.07	0.996 [0.99,1.0]	0.996 [0.99,1.0]

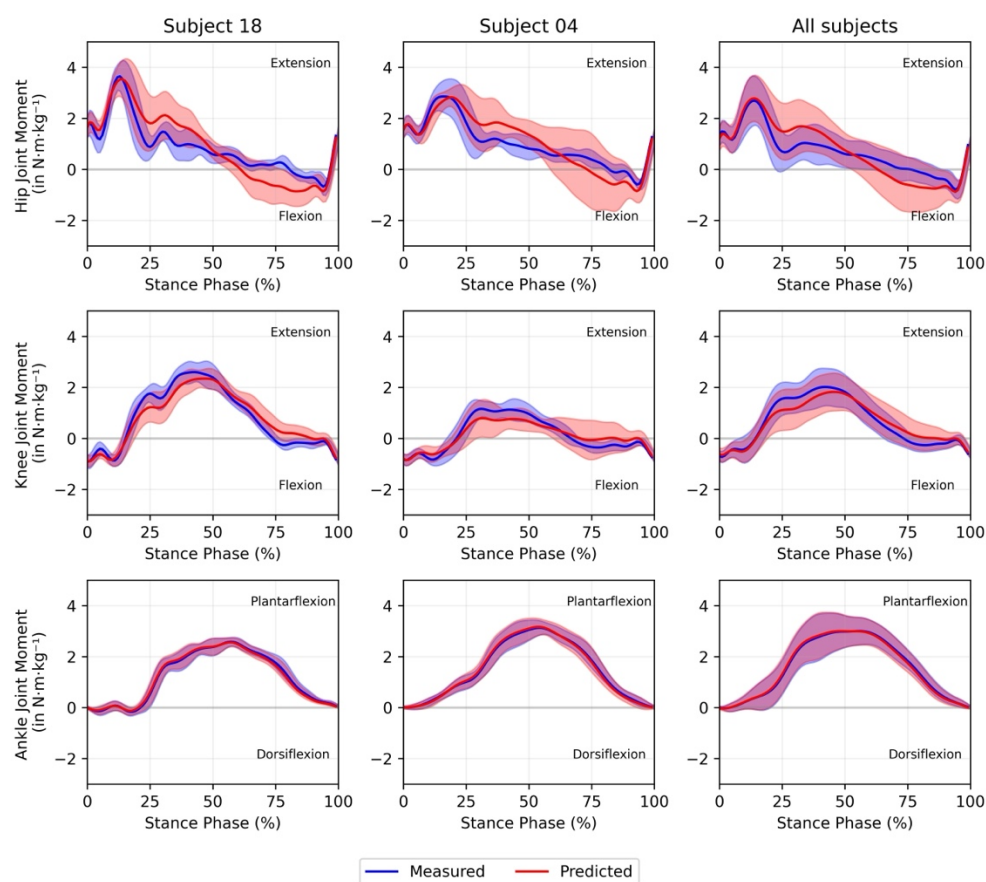


Figure 4 : Mean (SD) of sagittal-plane lower limb joint moments computed from predicted and measured anteroposterior ground reaction forces during the right stance phase. Results are shown for the subject with the most accurate prediction (left), the subject with the least accurate prediction (center), and the mean across all subjects (right).

4. Discussion

This study aimed to evaluate the performance of a deep learning approach to predict the AP-GRF using vGRF as input. The primary objective was to assess the accuracy of the predicted forces in comparison to reference measurements. Additionally, the study sought to quantify the impact of using predicted AP-GRF on the estimation of lower limb joint moments.

First, the results demonstrated a significant and strong correlation between the measured and predicted AP-GRF signals, with a mean Pearson $r = 0.984 \pm 0.011$ across all subjects ($p < 0.01$), confirming the effectiveness of the proposed method. This accuracy is further supported by the mean rRMSE of 7.44 % across all subjects and running speeds. These values are consistent with those reported in similar studies aiming to estimate GRF components using deep learning approaches. For instance, Scheltinga et al., (2023), reported AP-GRF prediction rRMSE values of $7.8 \pm 3.1\%$ and $7.8 \pm 3.2\%$ for two prediction methods using IMU data as input, while Dorschky et al., (2020) also achieved rRMSE values below 5%, relative to body weight.

Prediction accuracy was not consistently reproduced across subjects. For instance, some participants e.g., Subject 04 (rRMSE = $10.86 \pm 3.84\%$) and Subject 09 (rRMSE = $9.75 \pm 3.71\%$), exhibited lower overall accuracy and higher standard deviations, indicating reduced precision. Conversely, Subjects 18 (rRMSE = $5.96 \pm 2.06\%$) and 02 (rRMSE = $6.03 \pm 1.55\%$) showed consistently low mean rRMSE values across most running speeds. These isolated increases in error may reflect subject-specific gait variability that was not adequately captured during neural network training, suggesting that the movement patterns of certain tested subjects differed substantially from those represented in the training dataset.

Concerning discrete values of AP-GRF signal, maximum and minimum values obtained from predicted AP-GRF demonstrated a good agreement. Thus, the maximum and minimum peak of AP-GRF values tended to be underestimated by the neural network model. Although the mean differences were relatively small (-1.7 N and 5.5 N representing 1.9% and -0.2%, respectively), the limits of agreement were wider, suggesting some variability in prediction accuracy across steps. This trend suggests that the accuracy of peak values did not depend on the force amplitude. Wide variability may provide insight of the inter- and intra-individual step pattern difference when training neural network model, and this could reflect limitations in the current training strategy of the neural network, which might not fully capture subject-specific or context-dependent biomechanical patterns. For instance, Dorschky et al., (2020) demonstrated that augmenting training data with outputs from physics-based models can enhance prediction performance. Adding biomechanical parameters such as gait parameters or adapting model architectures could permit to better exploit temporal information. However, in our case, the vGRF signal used as input was a rich and complex source of indirect information that the model can learn from. Although speed is not explicitly provided as an input during CNN training, the amplitude of the vGRF signal is inherently influenced by running speed²⁹. As a result, the network is implicitly exposed to speed-related variations and can learn speed-dependent patterns indirectly through the vGRF data.

Nevertheless, running speed appeared to affect AP-GRF prediction accuracy in subjects who already demonstrated lower overall performance (Figure 1). Bland–Altman analyses further indicated that higher running speeds were also associated with larger differences in peak values (Figure 3). Although the neural network is indirectly influenced by speed through vGRF amplitude modulation, explicitly incorporating running speed as an input variable may further improve prediction robustness and warrants future investigation.

The comparison of joint moment values deduced from measured and predicted AP-GRF conditions showed minimal differences at the ankle (difference = 0.0 ± 0.07 N.m.kg⁻¹, ICC(3,1)

= 0.996), suggesting that ankle joint moment estimation was robust to AP-GRF prediction. Moderate differences were observed for the knee (difference = $0.29 \pm 0.27 \text{ N.m.kg}^{-1}$, ICC(3,1) = 0.887) and hip moments (difference = $0.06 \pm 0.75 \text{ N.m.kg}^{-1}$, ICC(3,1) = 0.592), indicating that inaccuracies in AP-GRF prediction can affect proximal joint moment estimations more substantially. Given the fact that joint moments are calculated using inverse dynamics propagated proximally along the kinematic chain, small discrepancies in the ground reaction force can propagate and accumulate, resulting in larger differences at the knee and hip levels. These findings suggest that, although the model predictions may be sufficient for estimating ankle joint kinetics, greater caution is warranted when interpreting hip and knee joint moments. Our results are consistent with previous studies demonstrating that uncertainties in ground reaction forces are amplified along the stance limb due to the recursive inverse dynamics procedure, leading to progressively larger effects on proximal joint moments, particularly for anteroposterior force components³⁸. This finding confirms previous systematic reviews highlighting the importance of accurate GRF measurements in inverse dynamics to minimize uncertainty propagation³⁹.

Although inverse dynamics can be performed using limited ground reaction force (GRF) data - as demonstrated by Forner-Cordero et al., who utilized only vertical GRF and center of pressure⁴⁰ - such simplifications inherently compromise the accuracy of joint moment estimations. Therefore, the accuracy of ground reaction force (GRF) estimation is critical for the reliable assessment of running-related injury (RRI) risk. The literature remains controversial: while numerous studies have reported associations between kinetic parameters—such as average loading rate^{41,42}, maximum instantaneous loading rate^{42,43}, peak braking forces⁴⁴, and knee or hip joint moments^{15,45}—and the risk of RRI other studies have highlighted inconsistencies in these findings, suggesting that such associations may not be generalizable across populations or running conditions¹². As these variables are derived directly from GRF data, even moderate estimation errors can propagate through inverse dynamics computations, leading to substantial inaccuracies in joint load estimation. This is particularly critical at proximal joints, such as the hip, where errors in estimating adduction moments may obscure clinically relevant indicators of RRI risk.

One limitation of this study is that the GRF used in this study were collected using an instrumented treadmill, which may not fully replicate overground running conditions. It is well-established that treadmill locomotion can alter running biomechanics, including stride pattern, impact forces, and propulsion characteristics, compared to natural, overground running⁴⁶. Additionally, instrumented treadmills are subject to motor-induced mechanical and electrical noise, which requires substantial filtering of the force signals—particularly in the anteroposterior (AP) and mediolateral (ML) components²⁸. Such filtering may introduce discrepancies between treadmill-derived GRF signals and those obtained from conventional force plates. Consequently, the vGRF and AP-GRF patterns used to train and evaluate the model may differ from those observed in more ecological conditions, potentially limiting the generalizability of the results to real-world applications. Future work should consider validating the model using GRF data collected in overground settings to assess its robustness and ecological validity.

This study aimed to evaluate the performance of a deep learning approach in predicting the anteroposterior component of the ground reaction force from the vertical component. The proposed convolutional neural network achieved accurate predictions across various speeds and subjects, with a mean rRMSE of 7.44%. The analysis also showed that the predicted AP-GRF can be effectively used to estimate lower limb joint moments, with minimal impact at the ankle and moderate differences at the knee and hip joints. However, both inter- and intra-subject variability in step patterns underscores the importance of dataset diversity and the selection of

appropriate model training strategies. While promising, these results must be interpreted considering the limitation of treadmill-based data, and future work should aim to validate the model under real-world running conditions.

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