2024-1 | 49th congress of the Société de Biomécanique
29-31 octobre 2024, Compiègne, France

Multidisciplinary Biomechanics Journal

Can machine learning accurately classify running speed levels based on vGRF Determinants?

Firas Gabsi[a], Taysir Rezgui[a*], Aida Chebbi[b], Sami Bennour[c], Mike Hahn[b]

a Laboratory of Applied Systems and Mechanics, University of Carthage, Tunisia Polytechnic School, Tunisia
b Neuromechanics Laboratory, Department of Human Physiology, University of Oregon, USA
c Laboratory of Mechanics of Sousse, University of Sousse, National School of Engineers of Sousse, Tunisia
* Corresponding author: taysir.rezgui@ept.ucar.tn

Received date: 07/04/2024
Accepted date: 28/06/2024
Publication date: 31/01/2025

Keywords: ground reaction forces, running, speed levels, machine learning

© 2025 The Authors
Licence CC-BY 4.0
Published by Société de Biomécanique

1. Introduction

Running is a popular physical activity that offers several health benefits. However, it carries a relatively high risk of injury, with 50-75% of runners experiencing injuries annually, during races and training. Speed is a critical component of running performance. As running speed increases, significant changes occur in joint and muscle dynamics (Orendurff et al. 2018, Khassetarash et al. 2020). In fact, ground reaction forces (GRF) exhibit distinct peaks, with excessive amplitude and occurrence time often associated with injuries, and highly correlated to gender (Yu et al. 2021) and running environment (Vernillo et al. 2020).

Given the prevalence of running-related injuries, recent advancements in smart wearable sensors present promising approaches for real-time monitoring that can lead to performance improvement and to reduce injury risks by adjusting running strategies. IMU are increasingly used due to their portability and accuracy to provide objective assessment in running kinematics and posture. However, smart insoles that embedded pressure sensors, seems gain attention to monitor running dynamics. Since loadsols typically measure vertical GRF (vGRF), this study aims to evaluate the contribution of these measurements to running speed monitoring using machine learning models, as there are no existing scientific studies on this topic (Yu et al. 2021, Xiang et al. 2022).

2. Methods

2.1 Data Collection and Processing

A public database including measurements at various running speeds (Fukuchi et al. 2017) is used in this study. 28 athletes performed 30s running trials at different speeds: 2.5 m/s, 3.5 m/s and 4.5 m/s and GRF data were collected using an instrumented treadmill. Raw vGRF data were filtered to eliminate vibration noise. A MATLAB script was developed to extract running cycles upon vGRF exceeding 50 N. Data were time-normalized to represent 100% of the stance phase and normalized to body weight. A total of 7004 running cycles were generated and distributed as follows: 2186 cycles for the slow speed (Class 1), 2322 cycles for the moderate speed (Class 2), and 2186 cycles for the fast speed (Class 3).

2.3. Feature Extraction

Common vGRF determinants used to assess running performance, presented in figure 1, include active (AP) and passive (IP) forces, loading rate (VALR), and time to peak values (TAP, TIP). In the absence of IP during forefoot striking, literature suggests that the impact peak occurs at 13% of stance phase. Additionally, the running cycle duration (GC) and stance phase duration (ST) are calculated. Two sets of features were defined: set 1 (IP, AP, VALR, TIP, TAP) and set 2 (IP, AP, VALR, TIP, TAP, GC, ST).

To cite this article: Firas Gabsi, Taysir Rezgui, Aida Chebbi, Sami Bennour, Mike Hahn, Can machine learning accurately classify running speed levels based on vGRF Determinants?, *Multidisciplinary Biomechanics Journal*, 2024, vol. 1, p. 459-461, DOI: 10.46298/mbj.14567.

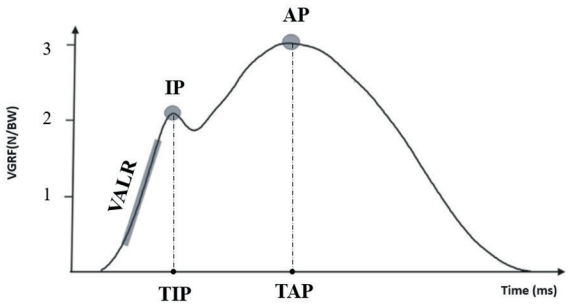

Figure 1. vGRF determinants in running: time stance (%) vs force value (%BW)

2.4. Machine Learning Process

After min-max scaling to prevent the dominance of features with large amplitudes, data were divided into 80% for training, 10% for test, and 10% for validation. Data were randomly assigned to each subset to ensure that the splits were representative of the overall running conditions.

According to literature, widely used algorithms for classification were employed: K Nearest Neighbors (KNN), Random Forests (RF), Artificial Neural Networks (ANN) and Support Vector Machines (SVM) with linear and Gaussian kernels. These algorithms are suitable for capturing the nuances of running dynamics in relation to variations in speed, including the complex interactions and non-linear relationships between features and speed levels. To assess the performance of these classifiers, accuracy and F1 score metrics were used.

3. Results and discussion

Table 1 illustrates the performance of the proposed models for classifying running speed. The Gaussian SVM and ANN classifiers exhibit the best performance for both feature sets. SVM demonstrates higher accuracy (90.8% and 94.1%) and ANN achieves the highest F1 score (97.1% and 98.1%). However, the Gaussian SVM boasts a faster execution time. In addition, features from set 2 outperform those from set 1, with a discrepancy with a difference of 2.9% and 3.3% for ANN and Gaussian SVM, respectively. This highlights that features from vertical ground reaction force may not be sufficient for monitoring running speed and subsequently potential injury risks during real-world environments. This funding aligns literature outcomes, affirming the significance of anteroposterior forces as speed increases (Hamill et al. 1983). This may be relevant for enhancing the performance of classification algorithms for speed monitoring. Additionally, the predominant classification errors were observed between high and normal speed classes, with the highest false discovery rate of 8.5% for fast, 3.4% for slow, and 15.3% for moderate speeds. In fact, five participants displayed a race pace (4.60 ±0.15 m/s), exceeding the predetermined speed values used in experiments.

Table 1. Algorithm performances for running speed classification based on GRF features.

Classifier	Features	Accuracy (%)	F1_score (%)
ANN	Set 1	90.2	97.1
	Set 2	93.1	98.1
RF	Set 1	89.5	89.9
	Set 2	92.6	94.6
KNN	Set 1	87.4	96.1
	Set 2	92.2	97.3
Linear SVM	Set 1	83.6	84.5
	Set 2	84.8	86.7
Gaussian SVM	Set 1	90.8	92.2
	Set 2	94.1	93.1

4. Conclusion

This study aims to assess the contribution of vGRF in the classification of running speed levels. A comparative analysis demonstrated that Gaussian SVM may offer a better compromise between accuracy and execution time, which is advantageous for real-time prediction and monitoring. In addition, vGRF features, that can be extracted from smart insole measurements, may not be sufficient for effective speed monitoring and injury prevention and additional information could be required. In future perspectives, we propose to consider athletes' individual abilities and ground inclination during running to improve speed class definitions and optimize the performance of machine learning algorithms.

Conflict of interest

The authors declare that they have no conflicts of interest to report regarding the present study

References

Fukuchi, Reginaldo K., Fukuchi, Claudiane A., et Duarte, Marcos,2017. A public dataset of running biomechanics and the effects of running speed on lower extremity kinematics and kinetics. *PeerJ*, vol. 5, p. e3298.

Hamill J., Bates B.T., Knutzen K.M., Sawhill J.A., 1983, Variations in ground reaction force parameters at different running speeds, *Human Movement Science*, Volume 2, Issues 1–2, Pages 47-56, ISSN 0167-9457.

Khassetarash, A., Vernillo, G., Martinez, A., Baggaley, M.,et al. (2020). Biomechanics of graded running: Part II-Joint kinematics and kinetics. *Scandinavian journal of medicine & science in sports*, 30(9), 1642–1654.

Orendurff, Michael S., Kobayashi, Toshiki, Tulchin-francis, Kirsten, et al. 2018, A little bit faster: Lower extremity joint kinematics and kinetics as recreational runners achieve faster speeds. *Journal of biomechanics*, vol. 71, p. 167-175.

Vernillo, G., Martinez, A., Baggaley, M., Khassetarash, et al., (2020). Biomechanics of graded running: Part I - Stride parameters, external forces, muscle activations. *Scandinavian journal of medicine & science in sports*, 30(9), 1632–1641.

Xiang L., Wang A., Gu Y., et al. 2022, Recent machine learning progress in lower limb running biomechanics with wearable technology: A systematic review. *Frontiers in Neurorobotics*, vol. 16, p. 913052.

Yu L., Mei Q., Xiang L., et al. 2021, Principal component analysis of the running ground reaction forces with different speeds. *Frontiers in bioengineering and biotechnology*, vol. 9, p. 629809.