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Machine learning algorithms can classify outdoor terrain types during running using accelerometry data

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A R T I C L E I N F O

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Accelerometer

A B S T R A C T

Background: Running is a popular physical activity that benefits health; however, running surface characteristics may influence loading impact and injury risk. Machine learning algorithms could automatically identify running surface from wearable motion sensors to quantify running exposures, and perhaps loading and injury risk for a runner.
Research question: (1) How accurately can machine learning algorithms identify surface type from three-dimensional accelerometer sensors? (2) Does the sensor count (single or two-sensor setup) affect model accuracy?
Methods: Twenty-nine healthy adults (23.3 ± 3.6 years, 1.8 ± 0.1 m, and 63.6 ± 8.5 kg) participated in this study. Participants ran on three different surfaces (concrete, synthetic, woodchip) while fit with two three-dimensional accelerometers (lower-back and right tibia). Summary features (n = 208) were extracted from the accelerometer signals. Feature-based Gradient Boosting (GB) and signal-based deep learning Convolutional Neural Network (CNN) models were developed. Models were trained on 90% of the data and tested on the remaining 10%. The process was repeated five times, with data randomly shuffled between train-test splits, to quantify model performance variability.
Results: All models and configurations achieved greater than 90% average accuracy. The highest performing models were the two-sensor GB and tibia-sensor CNN (average accuracy of 97.0 ± 0.7 and 96.1 ± 2.6%, respectively).
Significance: Machine learning algorithms trained on running data from a single- or dual-sensor accelerometer setup can accurately distinguish between surfaces types. Automatic identification of surfaces encountered during running activities could help runners and coaches better monitor training load, improve performance, and reduce injury rates.

1. Introduction

Running is an easily accessible and popular physical activity performed worldwide that is associated with numerous health benefits; however, injuries can occur. On average, the incidence of lower-limb injury ranges from 19.4 to 79.3% [1]. During running, the lower-limbs are repeatedly loaded during ground contact, leading researchers to posit that vertical acceleration profiles may be related to injury through various stress mechanisms. Recently, Boey et al. [2] demonstrated that surface conditions affect vertical acceleration parameters; however, it is unclear if surface-induced changes in acceleration could lead to increased running injuries.

Runners can traverse multiple terrain types in a given training session. Currently, it is difficult to estimate training mileage by surface type. Machine learning algorithms, using wearable sensor data as inputs, could represent a simple way to determine the training load experienced on different surfaces by automatically classifying surface types. Two machine learning approaches have been used in the context of human activity recognition. Feature-based (traditional) methods require discrete inputs extracted from the underlying signal via a feature

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engineering procedure (e.g. extraction of the mean or maximum value of a time-series segment). Of these, Gradient Boosting (GB) approaches, often provide the most accurate solutions to human activity recognition problems [3]. For example, Procter et al. [4] implemented a GB model that could accurately distinguish between travel modes (walk, cycle, motorized vehicle, train, and stationary) using a waist-worn accelerometer. Recently, deep learning methods, such as Convolutional Neural Networks (CNNs), have become popular. Mehrizi et al. [5] used deep learning to predict lower-back joint load in lifting tasks. Hu et al. [6] developed CNN models able to distinguish subtle differences in movement patterns induced by walking on irregular and flat brick surfaces (accuracy of 96.3%). The study used a single sensor placed on the lower-back. In the context of running, placing sensors on the lower-limbs may better capture vertical loading patterns and therefore improve classification.

It remains unclear whether feature-based or deep learning methods can identify running surfaces based on subtle differences in acceleration patterns recorded by wearable devices. Therefore, the primary aim of this study is to determine how accurately machine learning algorithms can classify outdoor terrain types using wearable sensor acceleration data extracted during a running task. The secondary aim of this study is to determine how sensor location affects classification accuracy. We hypothesized that (1) deep learning CNN models would outperform feature-based GB models, and (2) multiple sensor inputs, in comparison to using only one sensor, would improve surface classification accuracy.

2. Methods

2.1. Participants

Twenty-nine (15 male) participants were included in this study. All participants were injury free at the time of testing and reported that they did not suffer from any injury within three months of the data collection. Participants of three different training levels were recruited: (1) untrained (n = 10) participants, who had no running experience and did less than two hours of sports per week, (2) recreational runners (n = 9) who ran between 10 and 30 km per week for at least six months, and (3) well-trained runners (n = 10) who ran more than 50 km per week under supervision of a coach for at least two years. Participants' mean ± standard deviation age, height, and weight were 23.3 ± 3.6 years, 1.8 ± 0.1 m, and 63.6 ± 8.5 kg, respectively. The study was approved by the KU Leuven Medical Ethics committee and was performed in accordance with the Declaration of Helsinki. All participants provided written informed consent.

2.2. Data collection

Participants performed a warm-up run on a 400 m synthetic track (1–3 laps). Thereafter, 2–4 running trials of 8 s were performed on a straight 90 m segment of each outdoor surface (concrete road, synthetic track, woodchip trail) (Fig. 1). Surface presentation was randomized. A practice trial was provided to familiarize participants to each surface. To avoid fatigue effects, participants were allowed to rest for up to 5 min between surface conditions.

Two three-dimensional accelerometers (X50-2, Gulf Coast Data Concepts, LLC, United States: ± 50 g range, sampling frequency of 1024 Hz, 33 g weight, 13-bit resolution (0.016 g/count)) were used to measure accelerations during running. The first accelerometer was positioned at the midline of the lower-back (over the L3-L5 spinous processes of the trunk). The second accelerometer was positioned at the right tibia (at the distal antero-medial aspect 8 cm above the medial malleolus so that the vertical axis of the accelerometer was parallel to the long axis of the shank). Both accelerometers were placed on the skin with double-sided tape and fixated with extra tape. Adhesive spray was applied to the skin prior to placement to minimize the chance of the accelerometers coming loose due to moisture from perspiration.

2.3. Initial data processing

The first 2 s of each trial were excluded to reduce running transition effects. Next, a sliding window of 4 s (5–6 gait cycles), was used to segment the remaining data (6 s). For the sliding window, a fixed step length of 1 s was applied to augment the data. Thus, 324 trials were augmented to 972 time series which were subsequently analyzed. Each sensor's tri-axial accelerometer outputs were scaled from 0 to 1 according to the minimum and maximum value in the set of available trials for each subject. Processes were performed in Matlab (v2017a, The Mathworks Inc., Natick, USA).

2.4. Feature-based models

2.4.1. Model architecture

GB classifiers attempt to make a prediction in the form of an ensemble of weak prediction tree-based models, with each subsequent model improving the prediction of the previous model. GB models were implemented using the Scikit-Learn [7] wrapper for the XGBoost module [8] in Python (Python Software Foundation, https://www.python.org/). For each model, the following hyperparameters were tuned to optimize performance: number of trees, maximum tree depth, and learning rate.

2.4.2. Feature engineering

For each trial, each sensor's tri-axial accelerometer outputs (antero-posterior, medio-lateral, vertical, as well as the overall resultant acceleration vector) were used to extract features. A total of 208 features were investigated, comprising of statistical (e.g. mean and standard deviation), autocorrelation (step and stride regularity [9]), sample entropy [10], smoothness [11], body load [12], and wavelet-derived energy features [13]. Features were computed in Matlab and exported as a comma separated spreadsheet.

2.4.3. Feature reduction

For each GB model, feature reduction, via univariate feature selection [14], was performed. The top 20 features were extracted for each

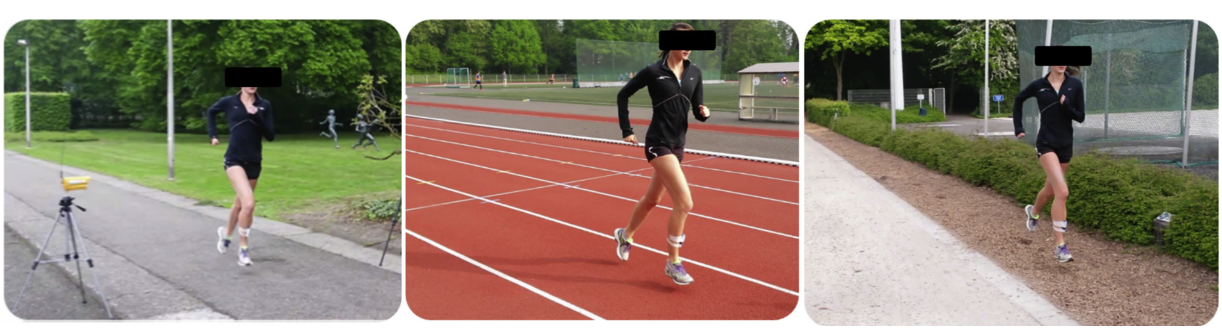

Fig. 1. Experimental set-up showing the concrete, synthetic, and woodchip surfaces. Sensors used in the present study: Lower-back (not visible) and right tibia.

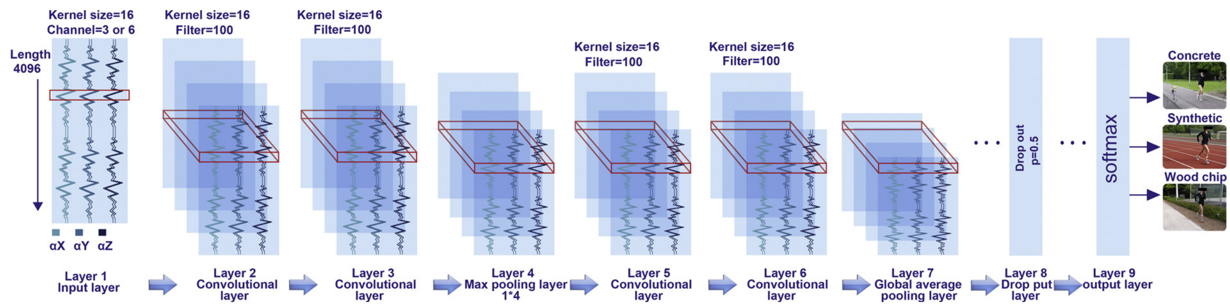

Fig. 2. Convolutional Neural Network architecture.

model. Models with all features and with reduced features were analyzed.

2.5. Deep learning models

2.5.1. Model architecture

CNNs are deep neural networks that are able to extract features directly from the underlying signal due to the presence of one or more convolutional layers [15]. CNN models with an architecture based on the work of Ackermann [16] were developed (Fig. 2). The CNN models started with the data input layer. Therefore, each model received an $n \times m \times 4096$ tensor, where n and m represent the number of trials and acceleration channels, respectively. The input layer was followed by the first two convolution layers which included 100 filters of size 16. The purpose of having two convolution layers was to perform dimensionality reduction, feature extraction, and extract local connectivity [15]. Rectified linear units (ReLUs) were used as the activation function [17]. Compared to other activation functions (e.g. sigmoid and tanh), ReLUs greatly accelerate the convergence of stochastic gradient descent and do not suffer from saturation. A maximum pooling layer of size 4 was applied after the second convolution layer to further reduce the data dimensionality and increase the spatial invariance of the features [18]. Then, two further convolutional layers with 100 filters of size 16 were included for additional feature extraction. A global averaging pooling layer and a dropout layer (probability of 0.5) were added to reduce overfitting [19]. Finally, a fully connected layer with 3 neurons (for the 3 types of running surfaces) was developed with softmax as the activation function. The output of the softmax function represents the class probability for each running surface.

2.5.2. Model settings

The CNN models were configured as follows: the categorical cross-entropy function [20] was applied as the loss function, Adaptive Moment Estimation (Adam) was used as the update rule due to its optimization convergence rate [21], and accuracy was used to evaluate the model training. Model weights were initialized randomly using default Keras settings (kernel initializer: glorot uniform, bias initializer: zeros). The CNN models were developed in Python with Keras [22] and a tensorflow backend [23].

2.6. Model sensor configurations

Three GB and CNN models were developed for the current study: a two-sensor model with combined data from both inertial measurement unit sensors as inputs, a lowback-sensor model, and a tibia-sensor model.

2.7. Model training

The feature-based models were trained on a standard consumer grade computer. The CNN models were trained on Google's (Google LLC, Mountainview, USA) colaboratory GPU (GPU: 1xTesla K80, 2496 CUDA cores, 12GB RAM). The CNN models were trained for a maximum of 2000 iterations with a batch size of 124. A Keras early stopping callback was added to avoid overfitting (patience of 500 epochs). Learning rate was adjusted during training using a Keras callback.

2.8. Model performance analysis

For both GB and CNN models, data were shuffled randomly and a 90/10 splitting procedure was performed to obtain the training (874 trials) and test (98 trials) sets, respectively. The reshuffling procedure was performed with 5 different seeds to ensure robustness of performance and to estimate performance variability. Model performance was evaluated using the test data sets. Evaluation was conducted using the following metrics overall and for each surface class: (1) accuracy, (2) precision (number of true positives over the number of true positives plus the number of false positives), (3) recall (number of true positives over the number of true positives plus the number of false negatives), and (4) F1 score (harmonic mean of precision and recall).

3. Results

Sample signals for the lower-back and tibia sensors for a representative subject over each surface are shown in Fig. 3.

3.1. Gradient boosting models

All GB classifiers revealed strong performance on the test sets (Table 1). For the two-sensor GB classifier with all 208 features, the testing accuracy was 97.0 ± 0.7%. Accuracy was decreased for both the tibia (100 features) and lowback (108 features) models to 93.9 ± 1.9% and 94.0 ± 2.8%, respectively. A confusion matrix for the best performing two-sensor GB model is shown in Fig. 4(a).

Feature reduction decreased model performance. Using only the 20 best features, the testing accuracy was reduced for the two-sensor (88.1 ± 2.1%), tibia (86.7 ± 2.7%), and lowback (90.9 ± 2.4%) models. The relative importance of the top 10 features for each feature-reduced model are shown in Table 2.

3.2. CNN models

For the CNN models, the two-sensor, lowback-sensor, and tibia-sensor models revealed average test accuracies of 95.6 ± 3.2, 91.4 ± 10.1, and 96.1 ± 2.6%, respectively, across all surfaces. A detailed performance analysis is presented in Table 1. A confusion matrix for the best performing CNN model is shown in Fig. 4(b).

4. Discussion

4.1. Summary

This study investigated the ability of machine learning algorithms to automatically classify three different outdoor surfaces using running

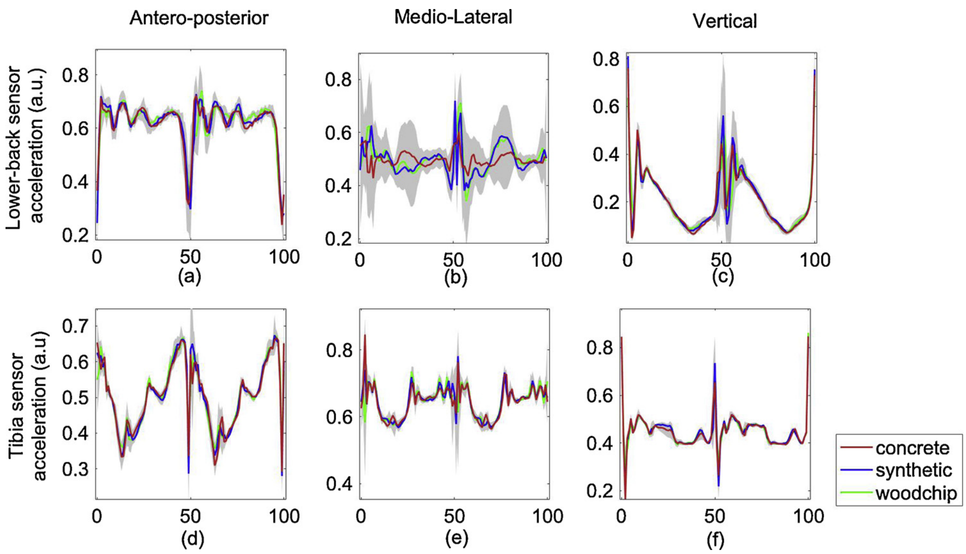

Fig. 3. Representative mean signals from the lower-back and tibia sensors over the three walking surfaces for one of the participants in the study. For visualization purposes, data were trimmed, aligned, and normalized to 100% over a section of three peaks from the vertical axis sensors. Shaded bands represent standard deviation.

acceleration data extracted from inertial measurement unit sensors. The feature-based GB models and the deep learning CNN models were able to accurately classify running surfaces. Sensor location and sensor count had only modest effects on model performance. The results show that acceleration data from inertial measurement units can accurately classify the outdoor running surfaces examined in this study.

4.2. Classification of outdoor-running surfaces

The primary aim of this work was to determine if machine learning algorithms could classify different running surfaces. Both model types performed well; however, contrary to our first hypothesis, the accuracy of the deep learning CNN models was similar to that of the feature-based GB models.

A notable strength of this study is that the differences in terrain characteristics of the surfaces investigated were minor, making classification accuracy using accelerometer signals alone difficult, even for the human observer. Human activity recognition studies often aim to classify vastly different movements. For example, the work of Rueda et al. [24] compared activities like sitting, ascending stairs, and vacuum cleaning, which should be easy to classify. Similarly, Jatoba et al. [25] used tree-based methods to classify daily activities such as lying, standing, jogging, walking, and stair negotiation; achieving an average accuracy of approximately 80%. However, some other studies have also explored deep learning to uncover more subtle differences in human motion patterns. In one study, Klucken et al. [26] used machine learning classifiers to differentiate the gait of persons with versus without Parkinsons disease with an overall classification rate of 81%. In another study, Hu et al. [6] confirmed that a deep learning network with long short-term-memory (LSTM) units utilizing a single inertial measurement unit can detect surface- and age-related differences in walking with a high-level of accuracy (96.3 and 94.7%, respectively). Here, we achieved similar performance with a CNN architecture that is much less computationally costly to train than a comparable LSTM model. Also, most of the previous studies were performed in a well-controlled indoor laboratory environment, whereas the current work was conducted over real-world outdoor surfaces. Previous studies have shown that some algorithms trained with indoor data may not perform as well when tested with outdoor data [27]. Although generalizability to other outdoor surfaces remains uncertain, those tested in this study are commonly used during outdoor running, and thus the current study improves on the ecological validity of past studies.

4.3. Sensor location and sensor count

The secondary aim of this study was to investigate how sensor location affected model performance. Contrary to our hypothesis, fusing data from both sensors only had a modest effect on model performance. For the GB model, sensor fusion resulted in higher prediction accuracy; however, for the CNN models, higher prediction accuracy was obtained

Table 1
Model performance analysis.

		GB				CNN			
Sensors	Surface	Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1
Two	Concrete	96.7 (1.2)	95.8 (2.3)	94.5 (4.0)	95.1 (1.9)	95.1 (4.0)	93.0 (7.0)	92.6 (8.8)	92.6 (6.0)
	Synthetic	95.5 (1.0)	94.0 (4.1)	92.7 (2.4)	93.2 (1.4)	94.1 (5.0)	91.0 (9.6)	92.1 (7.3)	91.4 (7.1)
	Woodchip	98.8 (0.8)	97.1 (2.6)	99.4 (1.2)	98.2 (1.1)	97.8 (1.3)	97.5 (1.4)	95.7 (2.8)	96.6 (2.1)
	Average	**97.0 (0.7)**	95.6 (1.0)	95.5 (1.0)	95.5 (1.0)	95.6 (3.2)	93.8 (4.7)	93.5 (4.8)	93.5 (4.7)
Lower-back	Concrete	94.3 (3.7)	93.2 (6.3)	89.6 (6.3)	91.3 (5.6)	91.8 (8.2)	87.3 (12.9)	88.2 (12.8)	87.7 (12.6)
	Synthetic	93.3 (4.0)	91.1 (5.1)	88.4 (7.5)	89.7 (6.2)	93.7 (8.2)	91.5 (12.7)	89.7 (11.6)	90.6 (12.1)
	Woodchip	95.3 (2.9)	90.4 (5.5)	96.3 (3.6)	93.2 (4.1)	93.9 (6.6)	91.0 (10.7)	90.8 (10.1)	90.8 (9.9)
	Average	94.3 (3.5)	91.5 (5.2)	91.5 (5.2)	91.4 (5.2)	91.4 (10.1)	93.0 (5.0)	94.7 (2.9)	92.3 (4.5)
Tibia	Concrete	93.7 (2.8)	90.9 (4.1)	90.3 (6.5)	90.5 (4.3)	95.9 (4.0)	92.4 (9.0)	96.3 (2.6)	94.2 (5.4)
	Synthetic	92.2 (2.1)	88.8 (5.5)	88.4 (5.2)	88.4 (3.1)	94.7 (3.3)	94.7 (2.9)	89.0 (8.7)	91.7 (5.5)
	Woodchip	95.7 (2.4)	93.6 (5.6)	93.9 (4.3)	93.6 (3.5)	97.6 (1.2)	95.9 (3.2)	97.0 (2.1)	96.4 (1.7)
	Average	93.9 (1.9)	91.1 (2.7)	90.8 (2.8)	90.8 (2.8)	**96.1 (2.6)**	94.3 (3.4)	94.1 (3.8)	94.1 (3.8)

Notes: Mean (standard deviation) % shown. The two-sensor model comprises combined inputs from the lower-back and tibia sensors. See Section 2 for more details. Highest average accuracies for Gradient Boosting (GB) and Convolutional Neural Network (CNN) models shown in bold.

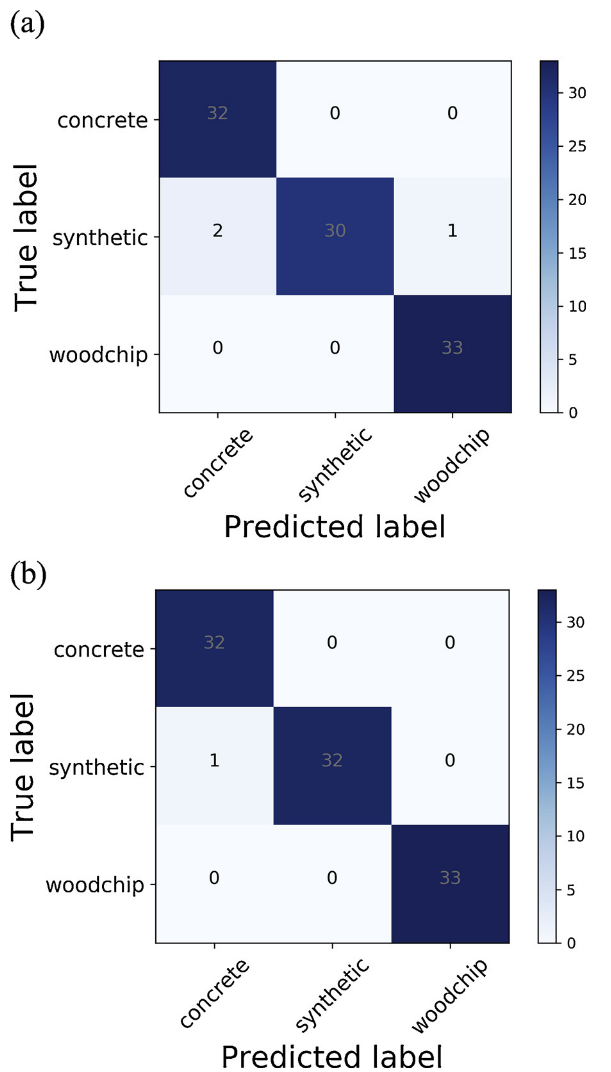

Fig. 4. Confusion matrix plots for the (a) Gradient Boosting and (b) Convolutional.
Neural Network model based on the best performing test set during model evaluation.

Table 2
Top 10 features selected by the feature reduction methods for each model.

two-sensor model	lowback-sensor model	tibia-sensor model
sampEnVT-Tibia (7.1)	sampEnVT-LowBack (6.3)	sampEnVT-Tibia (7.4)
sampEnML-Tibia (6.8)	sampEnML-LowBack (6.0)	sampEnML-Tibia (6.9)
sampEnAP-Tibia (6.7)	sampEnAP-LowBack (6.0)	sampEnAP-Tibia (6.8)
sampEnRV-Tibia (6.3)	sampEnRV-LowBack (6.0)	sampEnRV-Tibia (6.1)
StrFreq-Tibia (6.1)	SFreq-LowBack (5.8)	StrFreq-Tibia (5.9)
StrRegVT-Tibia (5.8)	SRegVT-LowBack (5.7)	StrRegVT (5.4)
StrRegML-Tibia (5.8)	SRegML-LowBack (5.6)	StrRegML (5.4)
StrRegAP-Tibia (5.6)	SRegAP-LowBack (5.6)	StrRegAP (5.3)
StrRegRV-Tibia (5.0)	SRegRV-LowBack (5.4)	StrRegRV (5.0)
xVT-Tibia (4.9)	StrRegVT-LowBack (5.1)	xVT (4.7)

Notes: Feature (percentage of importance) shown for each model. Abbreviations: antero-posterior (AP), medio-lateral (ML), vertical (VT), resultant (RV); average (x), sample entropy (sampEn), step frequency (SFreq), step regularity (SReg), stride regularity (StrReg), and .

for the tibia model.

This finding shows that data fusion may not be necessary in this context. Single-sensor models, both lowback and tibia models, could be used. This result suggests that the motion pattern of the lower-limb is transmitted to the lower-back without losing much fidelity. This result is surprising as the foot and distal limb absorb, modulate, and control the foot-ground interaction, and thus should be more closely related to surface characteristics [28] than motion captured at the lower-back. The lowback sensor, which may be estimating whole body center of mass motion, also provides valuable information to the models. We would recommend determining sensor location based on site-specific needs or the availability of equipment.

4.4. Feature reduction

Feature reduction decreased model performance. Limiting analysis to a subset of available features reduces model complexity; however, missing information may have hindered performance. Given the relatively small computation cost related to running feature-based models (quick training even on a standard consumer computer), we suggest including all explored features in model training.

4.5. Features selected by the feature-based algorithms: A closer look

The feature-based classifiers used 208 features that were expected to quantify running biomechanics on different surfaces. The feature-based GB models revealed that sample entropy dominated importance in the two-sensor, lowback, and tibia models. Sample entropy is a non-linear measure known to detect changes in complex movement patterns that may not be detectable using more traditional features [10]. Differences in sample entropy, especially on the woodchip surface, may reflect adaptations to the braking and propulsive accelerations or slipping/friction-based accelerations (runners may sometimes slip on the loose woodchips). In previous work on the same dataset, there were no significant changes in sample entropy across surfaces for the lowback-sensor [29]. Here, it appears the GB algorithm was able to detect enough differences to correctly classify surfaces.

4.6. Feature-based vs deep learning model comparison

For feature-based models, features must be carefully selected. Model performance can depend on the number and importance of features fed to the model [14]. It is possible that additional unidentified features could have improved performance, highlighting that these methods are limited by domain knowledge and the ability of extracting features from raw data. An advantage of CNN models over feature-based methods is that no feature engineering is required. The model is able to extract and learn features automatically, through one or more convolutional layers, reducing the possibility of losing important information in the signal. However, deep learning models benefit from training via large sample sizes, allowing the model to generalize to unseen data [15]. A larger sample size than used in the current study could have improved the results. Nonetheless, our sample size is in the same range as similar previous studies [30].

4.7. Limitations

Study limitations warrant discussion regarding participant sample, protocol, hardware, and data processing. First, although the sample included individuals with different running experience, generalizability of this study to individuals with health conditions or of older age remains uncertain. Regarding hardware and protocol, it is unclear whether similar performance would be obtained if participants independently donned the sensors without adhesion or location control. In addition, other sensor signals beyond accelerometry (e.g., in-sole sensors) may also improve performance. Lastly, regarding data processing, the training and test sets contained different trials from the same subjects. Therefore, subject-specific features may have been learned by the models. In practice, a runner could present different surfaces to their device as part of a calibration process in order to obtain optimal classification results. Future work is planned with a larger sample size to confirm the results presented herein.

4.8. Conclusion

Feature-based and deep learning algorithms can readily identify different surfaces during running using accelerometer data from two sensors or a single sensor placed on the lower-back or tibia. These algorithms could be implemented into wearable devices in order to monitor the types of surfaces runners are exposed to during training sessions. This information could be used to monitor a runner's mileage by surface with the aim of maximizing running performance while reducing or preventing overuse injuries.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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