ESTIMATING LOWER LIMB JOINT MOMENTS IN GAIT USING COMMON MACHINE LEARNING APPROACHES

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The aim of this study was to investigate the efficacy of common machine learning algorithmic approaches to estimate lower limb joint moments during fast walking gait. Kinematic and ground reaction force data on 19 participants were captured with a force-plate and motion caption capture system. Inverse dynamics was used to calculate the right lower limb joint moments and common machine learning algorithmic approaches, such as Random Forest (RF), Linear Regression (LR), Neural Network (NN), AdaBoost (AB) and Gradient Boosting, were used to predict the corresponding joint moments using only the kinematic data. High coefficient of determination values (R^2>0.9) for predicting moments using random forest, neural network and AdaBoost are observed in for the ankle, knee and hip joints in frontal, sagittal and transverse planes. The other approaches had R^2 values between ranged 0.71 and 0.97. This suggests that common machine learning algorithms may be a feasible approach to estimate joint moments during fast walking in a clinical setting for monitoring sport injury prevention and management.

KEYWORDS: data science, machine learning, joint moments, fast walking, gait

INTRODUCTION: The measurement of joint moments during gait traditionally using force-transducers instrumentation is costly and potentially limits its adoption (Hong et al., 2017). There are studies that indirectly estimate joint moments during gait without the use of force transducers (Rokhmanova et al., 2022; Johnson et al., 2018; Onal et al., 2019). The use of machine learning in data science for such estimations is an emerging area of investigation (Burdack et al., 2019). However, this type of investigation typically requires 'large data' to optimize ecological validity (Ferber et al., 2016). Recently, machine learning approaches have been applied to small or minimal data set that require models with low complexity to avoid overfitting the model to the data (Rokhmanova et al., 2022; Lim et al., 2020). Commonly used machine learning (ML) approaches are Random Forest (RF), Linear Regression (LR), Neural Network (NN), AdaBoost (AB) and Gradient Boosting (GB) (Donisi et al., 2021).
In laboratory-based gait measurements of the lower limb, the motion is constrained within a small spatial volume and the activities are repetitive (Ong et al., 2017). This is potentially advantageous in a simple model, where faster computation time with fewer relevant features/predictors are required during the modelling process, as compared to a complex movement model (e.g., dancing and cutting maneuvers). However, there is a dearth of knowledge on investigating the efficacy of estimating or predicting joint moments using commonly used machine learning algorithmic approaches.
Therefore, the aim of this pilot study was to investigate the efficacy of common machine learning algorithmic approaches to estimate joint moments in overground fast walking. It was hypothesized that the predicted lower limb joint moments would have good correspondence with the measured for joint moment in the three orthogonal anatomical planes using common machine learning algorithmic approaches.

METHODS: Nineteen healthy participants (age = 33.78 $\pm$ 6.20 yr, height = 1.60 $\pm$ 0.06 m, mass = 55.56 $\pm$ 7.56 kg) were included in the study. The study was approved by the institutional review board and written consent was obtained from the participants prior to the study.
Kinematic variables during walking were collected using a six-camera, motion capture system

(Motion Analysis Corporation, California) sampling at 100 Hz. The ground reaction force data were collected from two floor-mounted Kistler force plates ((Kistler 9289A plates) position in the middle of the 10 m walkway and sampling at 1000 Hz. Both the kinematic and GRF datasets were low-pass filtered with a 4th-order Butterworth filter using a cut-off frequency of 6 Hz to remove noise Each participant, in their own shoes, accomplished five trials where they were instructed to walk as “fast as you feel comfortable going.” In addition, practice trials were allowed until the participants walked comfortably and could contact the force plates with the right foot without altering their gait.
Markers were placed on the iliac crests as well on the lateral aspects of femur greater trochanter, femur medial epicondyle, fibula apex of medial malleolus, head of 5th metatarsal of the right lower limb. kinematic and kinetic data for 5 successful strides for each participant were collected. The joint moments of hip, knee and ankle of the right lower limb were calculated using inverse dynamics via Visual 3D software. To analyze the predictive capability of the ML approaches, where the markers’ spatial 3D linear kinematic data set was divided with a 60-20-20 split into training-validation-test data, Python 3.7.4 via the Orange data mining toolkit was used to facilitate the analysis (Demšar et al., 2013) using its default configuration tuning values. Moments were normalized by body mass (kg) and all data was time -normalized o 101 points representing 0–100% stance phase. The data were trained and evaluated using the Random Forest (RF), Linear Regression (LR), Neural Network (NN), AdaBoost (AB) and Gradient Boosting (GB) techniques. Root mean square error (RMSE), mean absolute of errors (MAE), and coefficient of determination (R2) were calculated, incorporating 10-fold cross-validations, to investigate the efficacy of the common ML approaches in predicting the lower limb joint moments.

RESULTS: The fast walking rate was 4.1±0.6 km/h. High coefficient of determination values (R^2>0.9) for predicting moments using random forest, neural network and AdaBoost were observed for the ankle, knee and hip joints in frontal, sagittal and transverse planes. The other algorithmic approaches had R^2 values ranging between 0.71 and 0.97. The predicted joint moments using the common ML approaches showed similar trends with those computed using inverse dynamics as seen in Figure 1 depicting the aggregated ensemble curves associated with the test data sets.

DISCUSSION: The aim of this study was to investigate the efficacy of common ML algorithm approaches to estimate lower limb joint moments. The main finding was that good R^2 values were observed in predicting joint moments in the frontal, sagittal and transverse planes. Therefore, our hypothesis was accepted.
The R^2 values for predicting joint moments in the ankle, knee and hip associated with the frontal, sagittal and transverse planes were generally more than 0.9. Joint moment (predicted measures) and kinematic data (predictors) are not linearly related. Thus, lower but strong R^2 values of around 0.71 were observed for LR algorithms compared with RF algorithm which better supports non-linearity (Medina-Ortiz et al., 2020). Also, when there are a small number of features with high noise data-sets, which is associated with our study, decision trees/RF may outperform linear regression models. In general cases, decision tree techniques such as RF will have better average accuracy. For the ankle frontal moments (i.e., eversion/inversion) where R^2= 0.716 was observed, the movement is comparatively subtle and hence relatively more challenging to estimate. Similar trends were observed for the hip and knee moments in the transverse plane (external/internal rotation) with R^2 values of 0.824 and 0.707 respectively for prediction using LR. Additional approaches such as feature (predictor parameters) optimization and tuning may be used to improve the performance of estimating joint moments (Dorschky et al., 2023).
In this study, the predictive algorithms were tuned using the default configurations of the Orange toolkit. Tuning is the process of maximizing a predictive model's performance without overfitting or creating too high of a variance. In machine learning, this is accomplished by selecting appropriate “hyperparameters”. Hyper-parameter refers to parameters that cannot be updated during the training of machine learning.

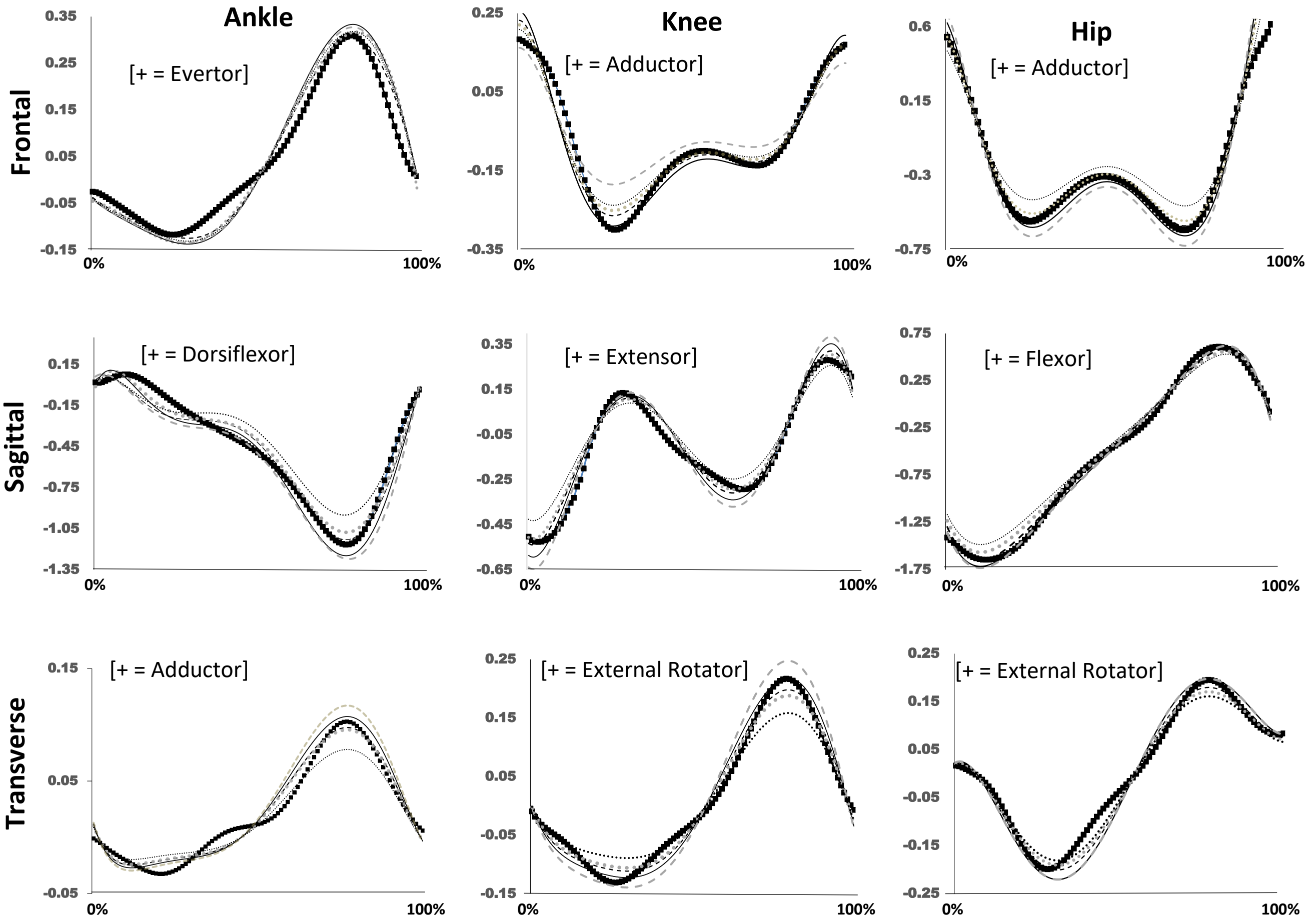

Figure 3: Ensemble curves, associated with the test data, along the % duration of the stance phase for the right limb's ankle, hip and ankle joint moments (Nm/kg) computed by i) inverse dynamics (in square-dotted line ▪▪▪) and predicted using ii) Random Forest (RF) (in black dashed line _ _ _ _), iii) Linear Regression (LR) (in black dotted line …..), iv) Neural Network (NN) (in black solid line _____), v) AdaBoost (AB) (in grey dashed line _ _ _ _) and vi) Gradient Boosting (GB) (in grey dotted line ••••) algorithmic approaches for moments (Nm/kg) in the frontal, sagittal and transverse planes.

The present predictive approaches can be further improved using commonly used tuning approaches such as Bayesian Optimisation, Evolutionary Algorithms, Gradient-Based Optimisation, Grid Search, Keras' Tuner, Population-based Optimisation, ParamILS, Random Search. (Vincent & Jidesh, 2022; Yu & Zhu, 2020). This will be useful in improving the ML predictive performance in the context of monitoring injury prevention and management (Liew et al., 2021).
The good R^2 results as well as the predictive trends resembling actual data calculated using inverse dynamics suggest that ML approaches potentially can be used in a clinical setting to complement assessments such as gait asymmetry detection as well as gait disorder detection associated with injury, will allow more accessibility to the community in the management of lower limb injury (Ghaffar et al., 2016).
This study was conducted under fast walking condition. However, we have not evaluated higher gait speed conditions such as running and sprinting which are also commonly encountered. More studies can be done to gain additional insights into these conditions where the traditional mocap setup has the capabilities to measure gait-related kinetics and kinematics accurately and precisely.

CONCLUSION: The results suggest that common ML algorithms may be used to estimate joint moments in a clinical setting. These observations of joint moments can provide meaningful feedback for injury prevention and management protocols. We are not suggesting that ML algorithmic approaches replace sophisticated motion capture systems. When more detailed quantitative joint moments measurements are required, higher speed optical camera systems integrated with force plates should be used.

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