Machine Learning-Based Prediction of Hip Joint Moment during a Single Leg Squat: A Proof of Concept Study

Mattia Perrone[1], Steven P. Mell[1], John Martin[1], Shane J. Nho[1], Philip Malloy[1, 2]

[1]Rush University Medical Center, Chicago, IL, [2]Arcadia University, Glenside, PA
Email of Presenting Author: mattia_perrone@rush.edu

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INTRODUCTION: Motion analysis research is essential to understanding the biomechanics of the human body in the context of health, disease, and physical performance. Traditionally, motion analysis biomechanics research has been primarily laboratory based, where motion capture cameras are used to quantify the position of body segments (kinematics) and force plates are used to measure reaction forces (kinetics). In the context of musculoskeletal conditions, motion analysis techniques are applied to determine how disease impacts the biomechanical function of different joints during functional tasks. In particular, kinematic and kinetic data are commonly utilized to generate inputs for in silico musculoskeletal models to quantify joint contact forces. However, this approach can be time consuming and prone to error based on model input assumptions. Machine learning has emerged as a new method to address limitations that can arise in motion capture workflows. The purpose of the study is to develop a proof-of-concept pipeline that utilizes a machine learning model to predict sagittal plane hip joint moment with limited kinematic and kinetic measured data inputs, proposing an alternative to the classical musculoskeletal modeling workflow.

METHODS: A total of twenty-nine patients diagnosed with femoroacetabular impingement syndrome (FAI), twenty-four healthy controls and fifteen post-operative FAI patients underwent three-dimensional motion capture testing during single leg squat trials. A twenty-camera system collected data at 100 Hz with simultaneous force plate data acquisition at 1000 Hz. Each participant completed six task repetitions, resulting in a dataset of three-hundred thirty-four observations after discarding instances with marker dropout or synchronization issues among biomechanical variables. Data were processed in Motive and Visual3D software to compute sagittal plane hip joint moments (HJM). Mokka was also used to export values of ground reaction forces (GRF) and sagittal plane knee joint angles (KJA) from participants during the squat trials. The KJA was calculated as the projection angle of three laterally placed markers on the stance leg, located on lateral thigh, lateral femoral epicondyle and lateral shank. A Long Short-Term Memory (LSTM) model was chosen as the machine learning model to make predictions of HJM starting from GRF and KJA. The loss function used for the model is the mean squared error (MSE), and the model performance was assessed with the following:1) coefficient of correlation (r), 2) root mean square error normalized to the range of the data (nRMSE), and 3) the mean absolute error normalized to the range of the data (nMAE). Model parameters were selected performing a grid hyperparameter search assessing the loss function. Finally, the HJM time series predicted by the machine learning model were compared with the HJM generated from Visual3D using statistical parametric mapping (SPM) in python. **Figure 1** shows the workflow followed in the current study.

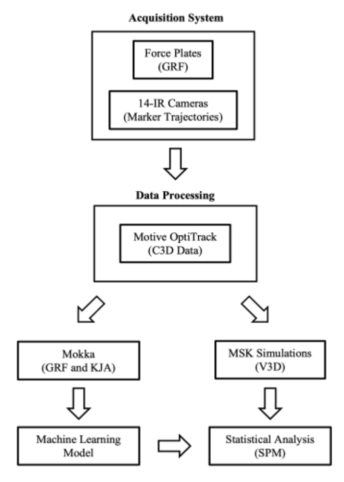

Fig. 1. Workflow used to validate the machine learning model

RESULTS: There was a strong correlation between the machine learning and Visual3D predicted HJM (r=0.94). Conversely, the nRMSE and nMAE values were low (nRMSE=9.62%; nMAE=15.55%). SPM revealed no statistical significant differences between the two HJM calculation approaches. **Figure 2** displays values of HJM time series found using the method described before, while **Table 1** also shows model performances when KJA and GRF alone are entered into the model as input data.

DISCUSSION: Model performance aligns with similar studies[1,2], reflecting consistent evaluation metric outcomes. As expected, better performances are obtained when the model receives in input both kinetic (GRF) and kinematic data (KJA). Next steps are to extend this approach other outputs and tasks.

SIGNIFICANCE: This study proposes a novel approach based on machine learning for the prediction of sagittal plane HJM compared to traditional inverse dynamics biomechanical workflows. To our knowledge, this approach is applied to a dataset including healthy controls, patients and post-operative patients for the first time in the current study, showcasing its robust performance.

REFERENCES: 1. Tan J.S. et al., 2022. Predicting knee joint kinematics from wearable sensor data in people with knee osteoarthritis and clinical considerations for future machine learning models. 2. Molinaro D.D. et al., 2022, Subject-independent, biological hip moment estimation during multimodal overground ambulation using deep learning. IEEE Transactions on Medical Robotics and Bionics.

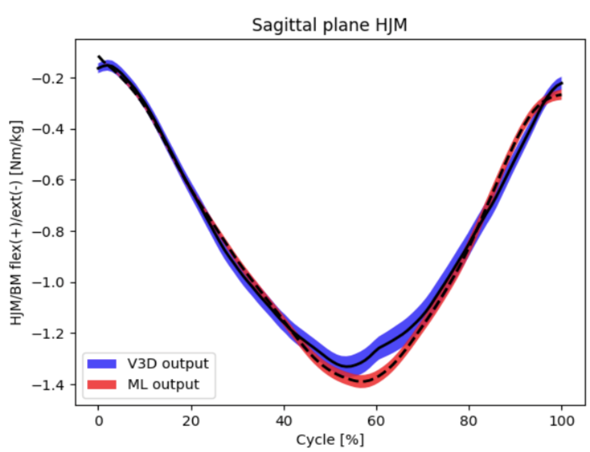

Table 1. Comparison of evaluation metrics when the model is trained just using kinetic (GRF) and/or kinematic data (KJA).

	GRF and KJA	KJA	GRF
nRMSE (%)	9.62	10.67	10.64
r	0.94	0.91	0.90
nMAE (%)	15.55	16.35	16.21

Fig. 2. Mean and standard error of inverse dynamics predicted HJM (blue) and machine learning predicted HJM (red)