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COMPUTER METHODS IN BIOMECHANICS AND BIOMEDICAL ENGINEERING
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RAPID COMMUNICATION

Machine learning-based prediction of hip joint moment in healthy subjects, patients and post-operative subjects

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ABSTRACT
The application of machine learning in the field of motion capture research is growing rapidly. The purpose of the study is to implement a long-short term memory (LSTM) model able to predict sagittal plane hip joint moment (HJM) across three distinct cohorts (healthy controls, patients and post-operative patients) starting from 3D motion capture and force data. Statistical parametric mapping with paired samples *t*-test was performed to compare machine learning and inverse dynamics HJM predicted values, with the latter used as gold standard. The results demonstrated favorable model performance on each of the three cohorts, showcasing its ability to successfully generalize predictions across diverse cohorts.

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KEYWORDS
Machine learning; hip joint moment; long short-term memory model; deep learning; motion analysis

1. Introduction

Motion analysis techniques are commonly utilized to generate inputs for in silico musculoskeletal models to understand the internal joint force environment (Holder et al. 2020; Perrone et al. 2023). In the last years, machine learning (ML) has emerged as a new approach in this context, leveraging open-source libraries and providing quicker inference with respect to in silico biomechanical models (Low et al. 2022). Since most biomechanical variables are represented by time series, deep learning models such as long short-term memory (LSTM) models are among the most implemented (Hochreiter and Schmidhuber 1997; Ma et al. 2020). There are several studies in the literature leveraging machine learning in motion analysis settings to compute biomechanical variables. However, most of these studies employ datasets comprising only individuals from a single cohort, which could be either healthy people (Giarmatzis et al. 2020; McCabe et al. 2023), patients affected by musculoskeletal disorders (Ardestani et al. 2014; Tan et al. 2022) or post-operative patients (Burton et al. 2021). Although there are a few investigations including two of these cohorts (Rane et al. 2019; Mundt et al. 2020b), these studies limited their analysis to gait tasks and have not investigated other motion tasks that could potentially highlight a broader spectrum of disparities between such cohorts in terms of biomechanical variables.

The purpose of the study is to develop a pipeline that utilizes a ML model to predict sagittal plane hip joint moment (HJM) in healthy controls, people affected by femoroacetabular impingement syndrome (FAIS) and post-operative patients with FAIS. Single-leg squat (SLS) is the chosen motion task in this analysis as sagittal plane HJM serves as a recognized biomarker for FAIS during this specific activity (Malloy et al. 2019). We hypothesize that the LSTM model will produce similar sagittal plane HJM outputs to the ones calculated using a traditional inverse dynamics approach for each of the three groups. We feel that assessing the performance of ML models across distinct populations where task-related differences are pronounced (Malloy et al. 2019) is a key point for validating this type of framework that needs to be further investigated.

2. Methods

A total of 29 patients diagnosed with femoroacetabular impingement syndrome (FAIS), 24 healthy controls and 15 post-operative FAIS patients underwent three-dimensional motion capture testing during SLS trials (Malloy et al. 2019). A twenty-camera system collected data at 100 Hz with simultaneous force plate data acquisition at 1000 Hz. All participants provided institutional review board approved written informed

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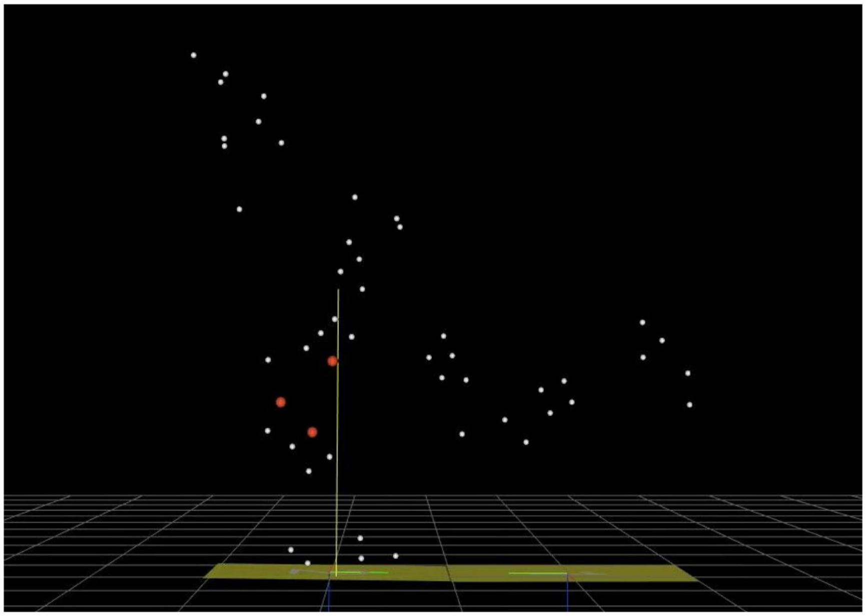

Figure 1. Image showing one of the study participants performing a single leg squat in the Mokka interface. To calculate knee joint angles (KJA), the positions of the three red markers (lateral thigh, lateral femoral epicondyle and lateral shank) were used.

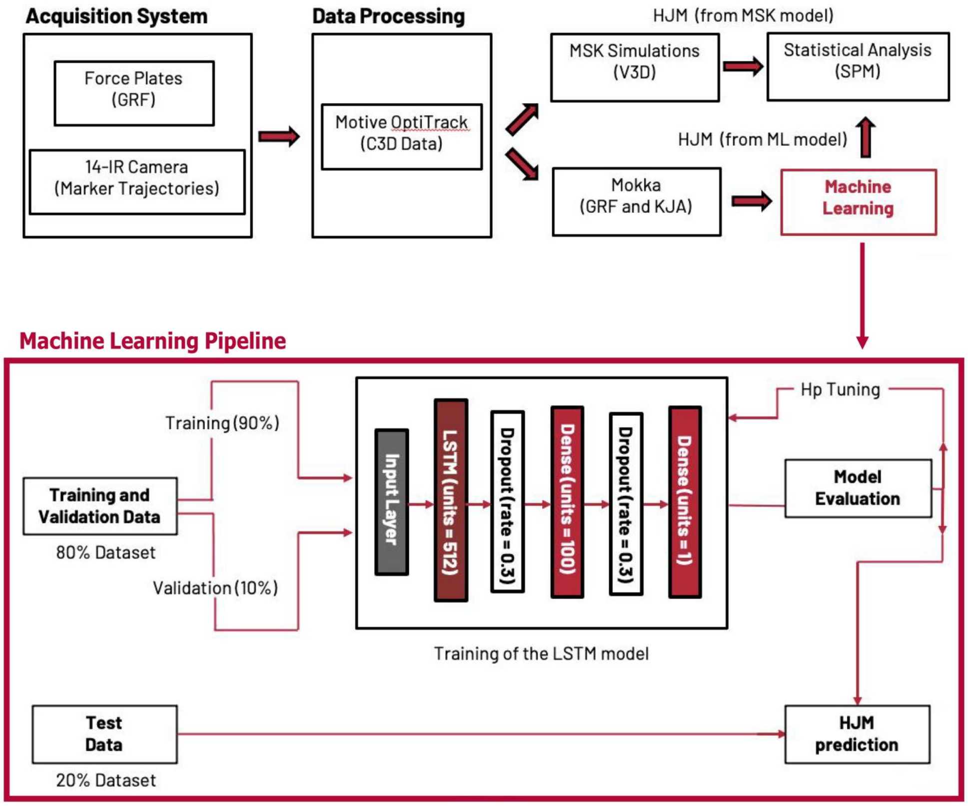

Figure 2. Pipeline followed during the whole study, with a specific focus on the machine learning section (red box). Ground reaction forces and knee joint angles time series were used as input data for the machine learning pipeline. This consisted in performing hyperparameter (hp) tuning of a long short-term memory (LSTM) model using 10-fold cross validation and then making predictions on the test set using the best model configuration found. The hyperparameters optimized include LSTM hidden units, dropout rates, and fully connected layer size, resulting in 512 LSTM units, 0.3 dropout rates, and 100 fully connected units. We performed stratified splitting with a 4:1 ratio for control, FAIS, and postoperative FAIS participants in the training and test sets. To completely blind the training set to individual participants, if a participant had a trial in the test set, all their trials were excluded from the training set. Finally, hip joint moment (HJM) predictions from the machine learning model were compared to the gold standard biomechanics HJM time series using statistical parametric mapping.

Table 1. nRMSE, r, and nMAE obtained on the training set and on the test set.

	Training set	Test set
nRMSE (%)	10.03	9.62
r	0.95	0.94
nMAE (%)	17.61	15.55

consent prior to any participation. Each participant completed 6 task repetitions, resulting in a dataset of 334 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 SLS trials (Figure 1). We used KJA as inputs rather than hip joint angles (HJA) because they can be more easily derived from marker positions through geometric relationships, whereas HJA calculation necessitate knowing hip joint center position, which is less accessible. Figure 2 shows the workflow followed in the current study. A long short-term memory (LSTM) model was chosen as the machine learning model to make predictions of HJM starting from GRF and KJA. Model parameters were selected performing a grid hyperparameter search through 10-fold cross validation by evaluating the mean squared error (MSE) as loss function. The model was trained using the Adam optimizer, with a learning rate of 0.0001, for 200 epochs. Error metrics used to assess model performance include coefficient of correlation (r), root mean squared error normalized to the range of the data (nRMSE) and the mean absolute error normalized to the range of the data (nMAE) on each of the three test cohorts. We further analyzed performance during distinct SLS cycle phases (0–33%, 33–66%, 66–100%) for the entire test set and individual cohorts, motivated by prior findings that have specifically identified differences among cohorts in terms of HJM minima (second phase) (Malloy et al. 2019). The HJM predicted by the deep learning model were compared with the HJM generated using inverse dynamics through statistical parametric mapping (SPM) in python (Pataky 2010). Paired samples t-test were performed with an alpha level of 0.05 to define statistical significance. Finally, LSTM predictions were compared to predictions from a baseline recurrent neural network (RNN) model.

3. Results

There were no differences in subjects demographics among groups (supplementary Table 1). A summary

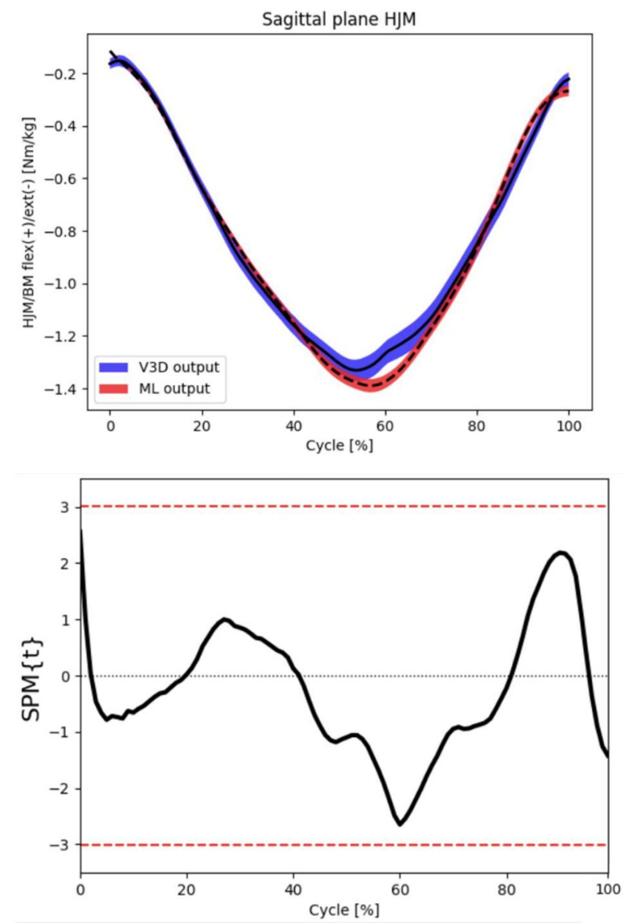

Figure 3. Mean and standard error of gold standard (blue) and machine learning predicted (red) hip joint moment (HJM) time series (on the top) and SPM graph showing that there are no statistically significant differences between real and predicted hip joint moment (HJM) time series (on the bottom). Both graphs refer to the whole test set.

of the evaluation metrics for the test set is displayed in Table 1. Figure 3 displays a visual comparison of biomechanical and ML-predicted HJM values for the entire test set, while Figure 4 provides a cohort-specific comparison within the test set. Error metrics assessing the LSTM model's in different subgroups and during different phases of the SLS cycle are reported in Table 2. Supplementary Table 2 and supplementary Figure 1 compare the performances of the LSTM model and the RNN baseline.

4. Discussion

The LSTM model predicted HJM time series demonstrated agreement with the predictions from Visual3D (Figure 3). In terms of the subgroup-based analysis, the model performs better on healthy controls and patients than on post-operative patients (Table 2), possibly due to limited post-operative training data.

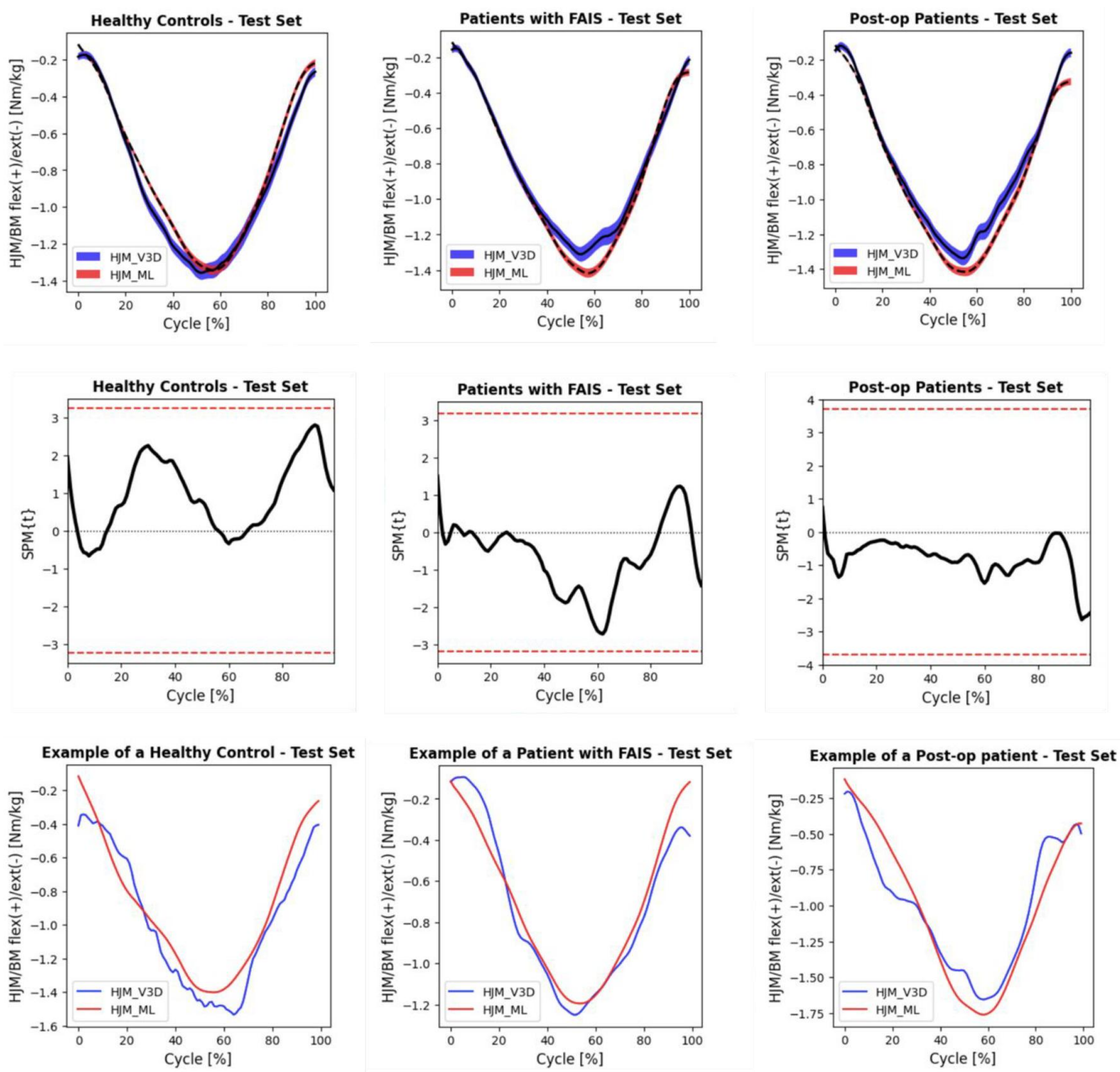

Figure 4. Comparison of the gold standard and ML predicted HJM averages and standard errors for each cohort (first row), of the results from SPM across cohorts (second row) and of a sample from biomechanics and ML predictions for all three cohorts (third row).

Table 2. nRMSE, r, and nMAE obtained during different SLS cylce phases across different subgroups (healthy, femoroacetabular impingement syndrome (FAIS) and post-operative). Phase represents the percentage of SLS cycle.

	Healthy			FAIS			Post-Operative		
Phase	0–33%	33–66%	66–100%	0–33%	33–66%	66–100%	0–33%	33–66%	66–100%
nRMSE (%)	7.74	10.72	8.95	7.37	10.84	10.21	9.65	14.14	11.76
r	0.96	0.76	0.97	0.96	0.78	0.95	0.97	0.71	0.88
nMAE (%)	12.23	16.40	14.29	12.45	16.3	15.01	13.49	18.02	14.24

Nevertheless, model performance metrics for the post-operative group align with existing literature (Rane et al. 2019; De Brabandere et al. 2020). Concerning the SLS phase-specific analysis, the second phase (from 33% to 66% of SLS cycle) is the one where the model achieves the lowest performances (Table 2). However, the model still produces satisfactory outcomes (Figure 4). Comparing the results of the current study with the literature, other studies reported values of R^2 between 0.8 and 0.9 (Rane et al. 2019), which are comparable to ours. Commonly used performance metric nRMSE typically hovers around 10-11% (Mundt et al. 2021), aligning with our result of 9.62%. Our nMAE of 15.55% matches findings from other motion analysis studies (De Brabandere et al. 2020). As a limitation, this study exclusively examined the sagittal plane HJM, in contrast to broader scopes in prior (De Brabandere et al. 2020; Giarmatzis et al. 2020). However, this focus was chosen given the significance of HJM as a biomarker for FAIS during SLS, as already previously explained. In conclusion, our study introduces a machine learning model that effectively predicts sagittal plane HJM across diverse cohorts, including healthy controls, patients, and post-operative subjects.

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Disclosure statement

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