

# Prediction of Deltoid Muscle Force in Reverse Total Shoulder Arthroplasty Using a Deep Learning Model

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## 1. Introduction

Reverse total shoulder arthroplasty (rTSA) has seen a substantial increase in clinical use over the past decade to treat osteoarthritis, rotator cuff tears, and complex shoulder fractures. Despite its effectiveness in restoring joint stability and function, roughly 9% of patients experience complications within two years postoperatively, including joint instability, fractures, implant loosening, and reduced mobility (Parada et al. 2021). Understanding the mechanical factors underlying these complications is essential for improving implant design and surgical planning.

The deltoid muscle is a primary contributor to shoulder joint force and stability, potentially contributing to bone fractures after rTSA (Khwaja et al. 2020). Since internal muscle forces cannot be measured in vivo, computationally expensive musculoskeletal models (MSM) are commonly used for their estimation. Deep learning models (DLM) offer an efficient alternative, approximating the MSM forces with acceptable accuracy and reduced computation time (Eghbali et al. 2024).

The objective of this study was to develop a DLM to predict the clavicular, acromial, and spinal deltoid forces after rTSA.

## 2. Methods

### 2.1 Data

The dataset comprises 998 virtual patients reconstructed from CT-scan-derived data from 495 real patients

collected at the Centre Hospitalier Universitaire de Vaud (CHUV), Switzerland. The virtual patients were generated using a Metropolis Markov Chain Monte Carlo (MCMC) algorithm, sampling patient-specific parameters from Bayesian distributions fitted to the real patient (Velikova et al. 2024). The parameters include sex, height, weight, physiological cross-sectional area (PCSA) of the four rotator cuff muscles, and glenoid positional factors (lateralization, anteriorization, distalization). Male and female data distributions were analyzed separately to ensure anatomically consistent virtual data.

### 2.2 MSM

Muscle forces were estimated with a MSM (Sarshari et al. 2021). Each virtual patient performed one of three simulated activities: scapular-plane abduction, scapular-plane abduction with a 2 kg load, or frontal-plane abduction with a 2 kg load. Each activity was performed with an angular velocity around  $20^\circ s^{-1}$ . MSM outputs include muscle forces dependent on the shoulder abduction angle produced by each patient, from which the clavicular, acromial, and spinal deltoid force amplitudes were extracted at  $60^\circ$  of abduction and used as DLM targets.

### 2.2 DLM Optimization

A fully connected DLM was trained to map patient-specific inputs to MSM-predicted deltoid forces at  $60^\circ$  of abduction. Bayesian optimization was conducted

over 100 iterations, tuning the number of hidden layers (3–10), neurons per layer (16–128), activation functions (ReLU, ELU), dropout rates (0.1–0.3), and optimizers (Adam, Nadam). Learning rates of  $10^{-4}$  and  $10^{-3}$  and loss weights for each deltoid part were explored.

The dataset was split into 85% training and 15% testing, with 15% of the training data used for validation. Model performance was evaluated using the coefficient of determination ( $R^2$ ) and mean absolute error (MAE).

### 3. Results and discussion

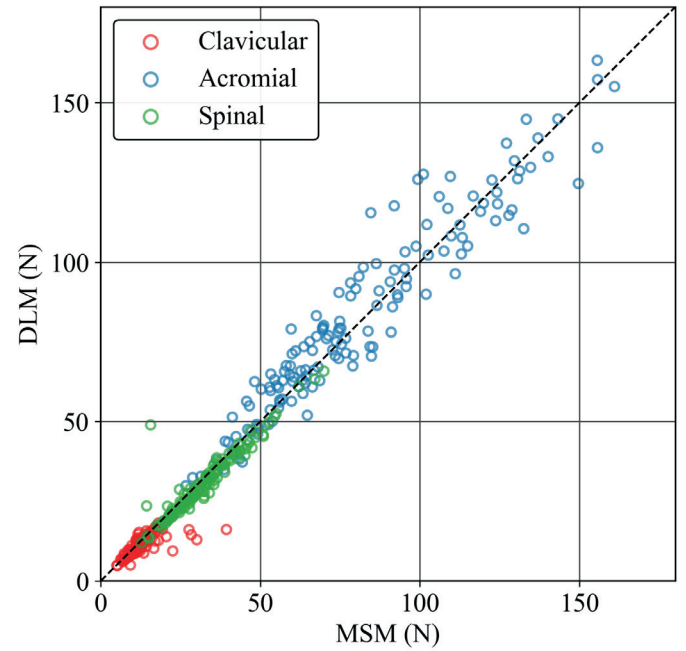
The optimized DLM consists of 5 fully connected hidden layers with 128, 112, 48, 80, and 128 neurons, respectively, each followed by Batch Normalization and using ELU activation. The Adam optimizer selected has a learning rate of . Regularization is achieved exclusively through Batch Normalization. Additionally, the best loss weights are 2.2, 4.8, and 9.6 for the clavicular, acromial, and spinal deltoid forces.

There is a strong agreement between MSM and DLM forces for the acromial and spinal deltoids, while the clavicular deltoid shows weaker performance due to its lower force contribution (Fig. 1 and Table 1). The MAE represent approximately 3.4%, 2.6%, and 3.3% of the MSM-derived force amplitudes at  $60^\circ$  of abduction for the clavicular (49N), acromial (265N), and spinal (71N) deltoids, respectively.

**Table 1.** Performance of DLM with coefficient of determination ( $R^2$ ) and mean absolute error (MAE).

Deltoid part	$R^2$	MAE (N)
Clavicular	0.419	1.669
Acromial	0.911	6.969
Spinal	0.867	2.339

Overall, DLM predictions fall within the uncertainty bounds of MSM estimates and exhibit a low risk of overfitting, while achieving substantial gains in computational efficiency, reducing runtime from approximately 30 minutes to less than 1 second. Notably, while the clavicular deltoid shows reduced predictive accuracy, the dominant force contribution is captured effectively despite moderate  $R^2$  values, and its influence on total deltoid force calculations remains minimal due to the balanced weighting scheme. This enables straightforward integration into clinical and research workflows and scalable prediction of additional muscle forces.



**Figure 1.** DLM vs. MSM predictions of clavicular, acromial, and spinal deltoid forces after rTSA for the test dataset.

This study is limited by the restricted set of simulated movements and the exclusive use of virtual patients generated. The lack of real patient data limits generalizability and motivates future experimental and clinical validation.

### 4. Conclusions

This study demonstrates the efficacy of DLM for patient-specific prediction of the clavicular, acromial, and spinal deltoid muscle forces. The proposed DLM achieves acceptable accuracy with dramatically reduced computation time, supporting its integration into an automated workflow of finite element modeling for the statistical analysis of fracture risk assessment.

#### Contributor Roles

**LP:** Conceptualization, Methodology, Analysis, Writing original draft; **DPP:** Supervision, Writing – review & editing; **AT:** Conceptualization, Methodology, Resources, Project administration, Funding acquisition, Data curation, Supervision, Writing – review & editing.

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