PREDICTING PELVIC FLOOR STRESSES DURING VAGINAL DELIVERY: A MACHINE LEARNING APPROACH

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Introduction

The second stage of labor is associated with obstetric trauma, leading to long-term consequences such as incontinence or pelvic organ prolapse. These conditions greatly impact women's quality of life [1]. Although a widely discussed topic, childbirth trauma remains unpredictable. As a tool to analyze the biomechanics of labor, computational models and the finite element method (FEM) are commonly used in problems that cannot be addressed *in vivo*. However, since the FEM can be computationally expensive, researchers in the biomechanical field have been resorting to machine learning (ML) algorithms to reduce the cost of simulations. FEM-based simulations are still costly to generate, but a well-trained ML algorithm can reduce the time required to predict the desired outcomes [2]. This work aims to use ML models to predict the stresses on key regions of the pelvic floor muscles (PFM) during vaginal delivery, using different input material parameters to characterize these muscles.

Methods

A dataset was generated using data retrieved from FEM simulations. Childbirth simulations were conducted with different material properties of the Martins constitutive model [3], to characterize the PFM (Equation 1).

$$U = c\{e^{b(\bar{I}_1^C - 3)} - 1\} + A\{e^{a(\bar{\lambda}_f - 1)^2} - 1\} \qquad (1)$$

The *c*, *b* and *A* material constants varied between [0.01, 0.03], [1.0, 2.0] and [0.01, 0.05], respectively, whereas *a* was kept constant. A total of 2189 simulations were successfully completed. A dataset was created in which each node of the pelvic floor corresponds to an observation. A total of 46 nodes of the PFM near the urogenital hiatus were selected, resulting in a total of 100694 observations. Features such as node number and position, initial coordinates, and material parameters were used for training. Five models, namely Decision Trees (DT), Random Forest (RF), Extreme Gradient Boosting (XGBT), Support Vector Regression (SVR), and Neural Networks (NN), were chosen for the study [2]. A training and test set were created with a 90/10 split, recurring to the stratified shuffle split method, to guarantee the same feature distribution in both sets. Subsequently, hyperparameter optimization with cross-validation was performed. The models' performance was measured by the mean squared error (MSE) and the mean absolute error (MAE).

Results

In the FEM simulations, the stresses of the urogenital hiatus varied between 0 and 95 MPa, thus ML models must predict values within this range. Preliminary results of the tested algorithms are presented in Table 1. Performance assessment demonstrated that RF and NN algorithms provided the best results.

	DT	RF	XGBT	SVR	NN
MSE	0.435	0.418	0.513	5.013	**0.397**
MAE	0.353	**0.345**	0.387	1.033	0.372

Table 1: MSE and MAE for the ML algorithms used.

Since the MAE represents a mean of all predicted values, this error can also be analyzed per node. Thus, Figure 1 presents the MAE measured at each of the 46 selected nodes near the PFM for the RF model.

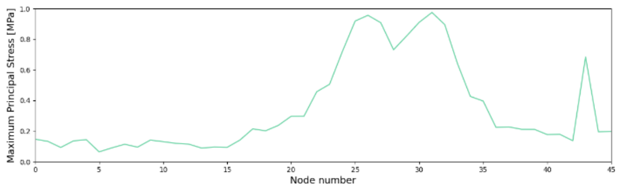

Figure 1: MAE per node for RF model.

Discussion

This work represents a preliminary approach to predict the outcome of childbirth simulations with ML techniques. The results obtained are promising and can be further optimized by gathering additional data and use of alternative methods to increase the models' performance. In a clinical setting, identifying stress levels or other relevant indicators in the pelvic floor can provide a patient-specific biomechanical analysis of potential delivery issues.

References

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