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Biomechanical modeling of soft tissue multiphysics using hybrid machine learning and finite element analysis

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The numerical analysis of soft tissues may require the application of highly nonlinear differential equations coupled with multiphysics theories, which in the context of biomechanics are usually formulated by multiphasic models, see, e.g., [1,2]. These systems of equations are implemented by expensive numerical solvers, e.g., using nonlinear finite element methods, which may be completely inefficient in time-sensitive clinical decision-making process. A common remedy is to first generate a data set of the numerical results that are used for subsequent training a machine learning (ML) model, i.e., ML-based surrogates [3], with the numerical solver being replaced by this efficient data-driven model. However, they still need to be extensive in numerical data generation. Here, we propose a hybrid ML (HML) method with the basic idea of inserting a highly efficient low-fidelity (LF) model prior to an ML model so that the numerical part is able to model a rough estimation of bulk responses, without considering all the physics involved. In this way, the ML part can only focus on improving the LF results to the fidelity of the expensive multiphysics models, while the parameters that can complicate the ML part can now be managed numerically. Figure 1 illustrates the evaluation results for some examples of low- and large-scale simulations, demonstrating that the HML implementations can improve the performance, especially in small training data regimes, so that no further numerical data creation is required. We conclude that the proposed HML method, which is a completely different alternative to the models defined by physics-based loss functions and traditional model-order-reduction techniques, may efficiently increase the accuracy of the ML-based surrogate modeling, in which the multiphysics equations play an important role in the biomechanical analysis of soft tissues.

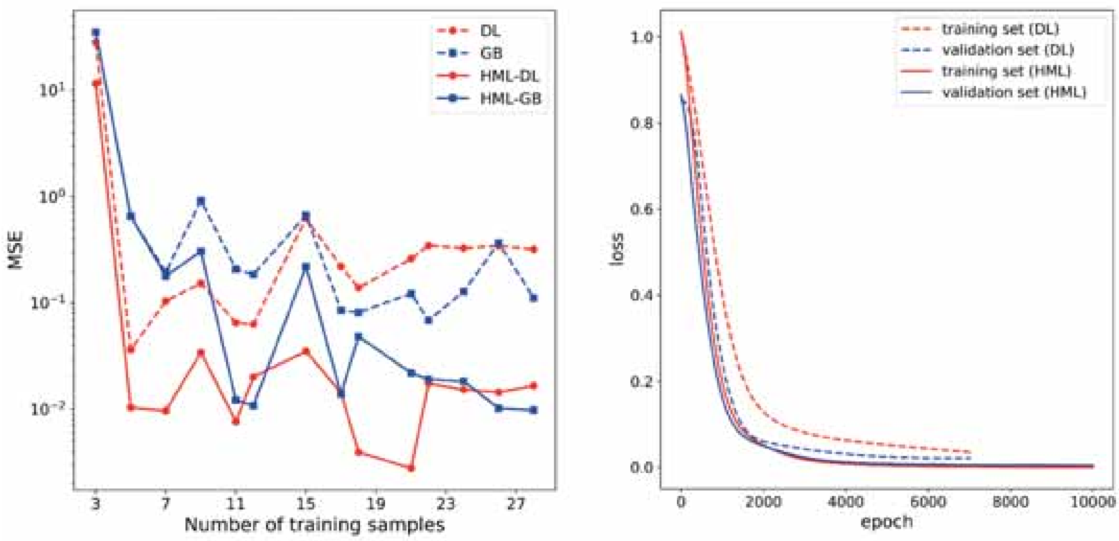

Figure 1: Comparison of hybrid and purely data-driven approaches: mean squared errors (MSEs) for each tuned model of a 2D axial problem (left), and recorded loss functions' values in each epoch for a 3D cartilage problem (right); Abbreviations: DL: deep learning, GB: gradient boosting, HML: hybrid machine learning.

References:

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