DEEP LEARNING APPLICATIONS IN COMPUTATIONAL MECHANICS

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ABSTRACT

The integration of deep learning into complex engineering and scientific problem-solving has attracted considerable attention across diverse disciplines, especially within the computational mechanics community. Deep learning has been crucial in modelling physical phenomena and solving inverse material characteristic challenges. Utilizing Physics-Informed Neural Networks (PINNs) and their variants offers a groundbreaking approach to addressing multiphysics and inverse problems, presenting a compelling alternative to traditional Reduced Order Models (ROM).

Recent advancements have led to the development of various physics-informed deep learning methodologies tailored for computational mechanics. These methodologies excel in areas such as fracture mechanics, inelastic materials, and multiphase poroelasticity. Additionally, uncertainty quantification, another pivotal area, effectively merges with machine learning techniques, especially in scenarios lacking sufficient or reliable data. Traditional methods like the Bayesian framework or Gaussian Processes have been integrated with deterministic deep learning to enhance optimization and incorporate stochastic elements. Examples include Bayesian Physics-Informed Neural Networks (B-PINNs) and Deep Kernel Learning (DKL), both proficient in addressing forward and inverse nonlinear problems.

In this Mini Symposium, we invite contributions that delve into deep learning for physics modelling, Bayesian and Gaussian processes, and their applications to solid mechanics problems. Our goal is to cultivate a multidisciplinary dialogue among experts from computational mechanics and related fields. We anticipate a dynamic exchange of ideas and innovations that will advance our understanding and capabilities in these essential areas.