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# Bridging Machine Learning and Physics: Advancements in Continuum Mechanics and Transport Phenomena

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## ABSTRACT

Machine Learning has demonstrated transformative potential in diverse scientific fields, with deep learning standing out for its exceptional performance [1]. However, the *black-box* nature of these deep learning models has raised concerns about their lack of physical interpretability.

In an endeavor to bridge this interpretability gap, sophisticated methodologies such as Physics-Informed Neural Networks (PINNs) [2], DeepONet [3], symbolic regression [4], Scientific Machine Learning (Sci-ML) [5], and differentiable programming [6] are an attempt to solve this issue. This symposium seeks to bring together experts for an in-depth discussion on approaches that integrate domain-specific physical laws and principles directly into machine learning algorithms, thereby fostering a more interpretable and reliable modeling framework.

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