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Data-Driven and Physics-Inspired Modeling Approaches: Emerging Parallels Between Structural Materials Engineering and Cellular Mechanics

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Abstract

Recent advances in data-driven modeling and physics-inspired machine learning have significantly transformed predictive analysis across engineering and biomedical sciences. While these approaches are extensively applied in structural and material engineering, their conceptual parallels with cellular mechanics and biological material behavior are increasingly evident. This mini-review highlights emerging similarities between modeling strategies used in structural materials engineering and cell-scale biomechanical analysis, emphasizing the role of hybrid physics-data frameworks. The discussion underscores how methodologies developed for predicting complex material behavior can offer valuable insights for cellular and molecular biomechanics research.

Keywords: Data-driven modeling; Physics-informed learning; Cellular mechanics; Structural materials; Machine learning

Overview

Understanding complex nonlinear behavior is a central challenge shared by both structural materials engineering and cellular biomechanics. In recent years, Machine Learning (ML) and hybrid physics-data approaches have been increasingly employed to predict mechanical responses of materials subjected to complex loading and environmental conditions [1-8]. Similar challenges arise in cell science, where mechanical behavior at cellular and subcellular scales is governed by multiscale interactions and nonlinear responses.

Research in geotechnical engineering has demonstrated the effectiveness of ML-based regression, ensemble learning, and physics-guided models in predicting material strength, durability, and deformation behavior [2,3]. These approaches provide a transferable conceptual framework for modeling biomechanical phenomena in cellular systems.

Data-Driven Modeling in Structural Materials Engineering

Advanced ML techniques such as ensemble learning, boosting, and hybrid regression models have shown high predictive accuracy in estimating mechanical performance of construction materials, including concrete, fiber-reinforced composites, and geopolymer systems. Recent studies emphasize the superiority of combining data-driven learning with physical constraints to improve generalization and reliability of predictions [3-8].

Such approaches have been successfully applied to predict strength, ductility, and failure mechanisms in complex material systems, highlighting their robustness in handling uncertainty, heterogeneity, and nonlinear relationships [5,6]. As illustrated in (Figure 1), hybrid data-driven and physics-informed modeling approaches provide a unified framework for predicting complex nonlinear behavior in both structural materials and cellular systems, highlighting strong methodological parallels between engineering and biological sciences [9-14].

Parallels with Cellular and Molecular Mechanics

Cells and biological tissues exhibit mechanical behaviors analogous to engineered materials, including viscoelasticity, anisotropy, damage accumulation, and adaptive remodeling. Recent studies in cell science increasingly adopt ML-based and multiscale modeling techniques to capture these behaviors. The integration of Physics-Informed Machine Learning (PIML) offers a promising pathway to bridge experimental observations with theoretical models in cellular mechanics, similar to its successful application in structural engineering problems [12-15].

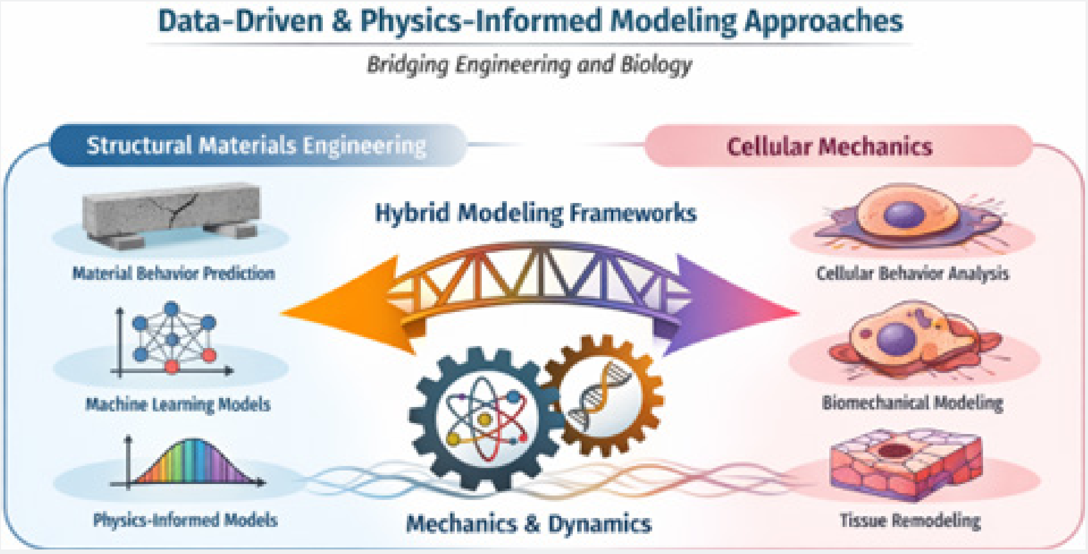

Figure 1: Integrating engineering principles and biomechanical insights for predictive analysis in boath materials and cells.

Future Perspectives

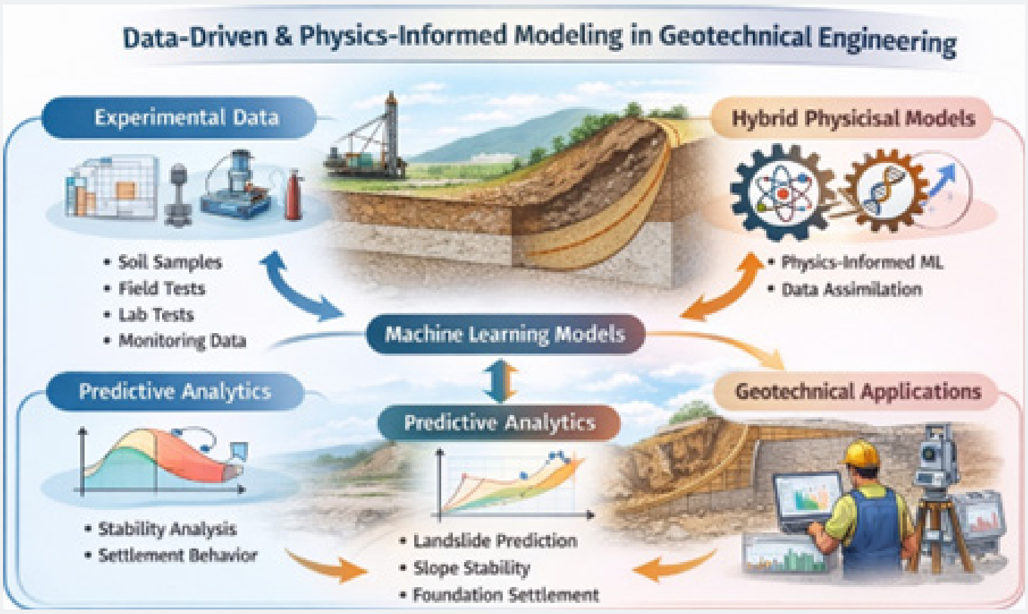

Figure 2: Schematic overview of data-driven and physics-informed modeling approaches in geotechnical engineering for predicting soil behavior, slope stability, landslide occurrence, and foundation settlement under complex environmental conditions.

Figure 2 demonstrates how data-driven and physics-informed modeling techniques, widely used in geotechnical engineering, can serve as transferable methodologies for predictive analysis in other complex systems, including biological and cellular environments.

The convergence of modeling strategies across engineering materials and cellular biomechanics suggests strong interdisciplinary potential. Techniques developed in structural materials research—particularly hybrid physics-data approaches—can accelerate predictive modeling in cell science, enabling improved

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understanding of mechanotransduction, tissue remodeling, and disease progression. Future research should focus on cross-disciplinary knowledge transfer, leveraging engineering-scale modeling frameworks to enhance predictive accuracy in biological systems [16-18].

Conclusion

This mini-review highlights conceptual and methodological parallels between structural materials engineering and cellular mechanics. Data-driven and physics-inspired modeling approaches provide a common language that can foster interdisciplinary innovation, benefiting both engineering and biomedical research communities.

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