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Data-driven modeling in biomechanics: The synergy of artificial ıntelligence and numerical analysis

Abstract

Recent advances in biomechanics increasingly rely on the combination of computational modeling and artificial intelligence to understand and predict the behavior of biological tissues. Traditional methods, such as finite element analysis, often struggle with the inherent complexity, heterogeneity, and adaptability of living systems, requiring significant computational resources. By incorporating machine learning and deep learning techniques, researchers can create hybrid models that not only retain the interpretability of classical simulations but also offer rapid and accurate predictions. These data-driven approaches are capable of estimating mechanical responses, such as stress, deformation, and fracture risk, without performing exhaustive calculations for every scenario. Furthermore, integrating patient-specific imaging and anatomical data allows for customized simulations that improve the reliability of clinical assessments and implant designs. Case studies on orthopedic implants demonstrate that such AI-assisted frameworks can reveal subtle differences in material performance and structural stability while significantly reducing experimental effort. Despite challenges like the need for extensive datasets and transparent model reasoning, this emerging paradigm offers a powerful pathway toward more efficient, predictive, and personalized biomechanics, bridging the gap between computational science and practical medical applications.

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Short commentary

Biomechanics has undergone a profound transformation in recent years, primarily driven by advances in computational modeling and Artificial İntelligence (AI). Traditional biomechanical analyses, which relied heavily on empirical testing and deterministic numerical methods such as the Finite Element Method (FEM), are increasingly being complemented—or even replaced—by data-driven models capable of capturing complex biological behavior with enhanced efficiency and accuracy [1,2]. This convergence of AI and numerical analysis has opened new avenues for simulating, predicting, and optimizing biological systems across multiple scales, from cellular microstructures to whole-organ mechanics [3].

In conventional biomechanics, the finite element method has long been recognized as a powerful tool for understanding tissue-level mechanical responses under various physiological and pathological conditions [4]. However, biological tissues' nonlinear, heterogeneous, and adaptive nature poses challenges to purely physics-based models, often requiring extensive computational resources and detailed material characterization [5]. To address these limitations, researchers have increasingly integrated Machine Learning (ML) and Deep Learning (DL) techniques with FEM frameworks to build hybrid models that retain the interpretability of physics-based approaches while leveraging the predictive capacity of AI [6,7].

One of the most promising paradigms in this direction is data-driven modeling, which replaces or augments conventional constitutive equations with AI-based surrogate models trained on simulation or experimental datasets [8]. Such models can approximate stress–strain relationships, predict fracture initiation, or emulate tissue remodeling processes without explicitly solving governing equations at every iteration. For example, Hambli [2] proposed a multiscale modeling framework coupling finite element simulations with neural networks to simulate bone adaptation, significantly reducing computational time while maintaining high predictive fidelity. Similarly, Karniadakis et al. [9] introduced Physics-Informed Neural Networks (PINNs), which incorporate physical laws into deep learning architectures, ensuring that AI predictions remain consistent with fundamental biomechanical principles. Mutu [10] investigated the mechanical effects of different implant designs and biomaterials used in the treatment of oblique tibial fractures using Finite Element Analysis (FEA) and ML methods. Static structural simulations were performed in Ansys Workbench for seven implant configurations made of Ti–6Al–4V alloy and 316L stainless steel under axial loads ranging from 600 to 1000 N. From these analyses, a dataset of 1008 points containing maximum stress and total displacement values was generated and used to train three ML algorithms—Multilayer Perceptron (MLP), Support Vector Machine (SVM), and Decision Tree (DT)—in WEKA. The results showed that implants made of 316L stainless steel exhibited higher maximum stress but lower total displacement compared to Ti–6Al–4V implants, indicating better fixation stability. Among the ML models, SVM achieved the best predictive performance, with mean absolute errors of 0.24-0.41 for maximum stress and 0.0003-0.0015 for total displacement, outperforming MLP and DT. Overall, the study demonstrated that integrating artificial intelligence with numerical analysis enables accurate, low-cost, and efficient prediction of biomechanical responses, offering valuable insights for optimizing implant design and supporting data-driven decision-making in orthopedic biomechanics.

The integration of AI with numerical analysis also enhances personalization in biomechanical modeling. By utilizing patient-specific imaging data (e.g., CT or MRI), AI algorithms can automatically extract anatomical features, assign material properties, and optimize boundary conditions, leading to more accurate predictions of stress distributions, implant performance, and fracture risk [11,12]. This personalized, data-driven modeling approach is particularly valuable in orthopedics and cardiovascular biomechanics, where individualized assessments can significantly improve clinical outcomes.

Despite its promise, data-driven biomechanics faces ongoing challenges, including the need for large, high-quality datasets, explainable AI models, and robust validation frameworks [13]. The synergy between artificial intelligence and numerical analysis marks a paradigm shift toward more adaptive, predictive, and intelligent biomechanical simulations. As the boundary between physics-based and data-driven modeling continues to blur, this hybrid approach is poised to become the cornerstone of next-generation biomechanical research and clinical applications.

Conclusion

Machine learning algorithms have emerged as powerful tools for interpreting large and complex datasets, offering high-accuracy modeling and predictive capabilities that can transform biomechanical research. When integrated with FEA, these data-driven approaches enable comprehensive evaluation of structural behavior, material properties, and loading conditions in biological systems. Numerous studies have shown that factors such as implant geometry, biomaterial selection, and mesh characteristics play a critical role in determining stress distribution, strain localization, and overall deformation behavior in fracture fixation and other orthopedic applications. By coupling FEA with intelligent algorithms such as Support Vector SVM, Artificial Neural Networks (ANN), and DT, researchers can rapidly predict biomechanical responses without the need for extensive and costly experimental testing. This synergy not only accelerates the optimization of implant design and surgical strategies but also enhances the reliability and reproducibility of computational analyses. In the future, the integration of artificial intelligence, data science, and numerical modeling is expected to enable the creation of adaptive, personalized, and cost-efficient biomechanical solutions, supporting the evolution of precision medicine and intelligent clinical decision-making systems.

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