EDITORIAL

AI Revolution in Orthopedic Biomechanics: From Fracture Classification to Real-Time Simulations

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Introduction

Over the past decades, orthopedic biomechanics has progressed from classical mechanics-based models to sophisticated computational simulations. Innovations in modeling and material analysis, such as the finite element method (FEM), which has transformed the simulation of complex bone responses, and advanced imaging modalities like 3D CT and MRI, which provide detailed anatomical insights, have significantly expanded our understanding of bone behavior. Moreover, the integration of patient-specific data has facilitated personalized fracture analysis and treatment strategies, thereby enhancing the precision of orthopedic care.

Despite substantial advancements, orthopedic biomechanics continues to face challenges, particularly in achieving a comprehensive understanding of complex fracture patterns and in the practical application of real-time intraoperative solutions. This editorial discusses how artificial intelligence (AI)-driven innovations may help address these persistent challenges by enhancing diagnostic accuracy, supporting personalized treatment planning, and facilitating improved intraoperative decision-making from an engineering perspective.

Current Challenges in Orthopedic Biomechanics

**Limitations in Fracture Classification:*

Traditional classification systems, such as the widely adopted AO/OTA framework, categorize fractures based on location and type but often oversimplify their complex morphology. These systems usually overlook subtle variations in shape, structure, and pattern that are influenced by factors such as age, bone density, and the mechanism of injury, which can lead to diagnostic inconsistencies and mismatches in treatment strategies. Although the AO/OTA 2018 update improved interobserver reliability through refined categories and detailed modifiers, it still falls short of fully capturing subtle morphological differences.[1,2]

The lack of a refined fracture pattern classification system directly affects fixation outcomes, as suboptimal classification may lead to inappropriate surgical approaches, fixation techniques, and implant selection. In the absence of precise pattern recognition, fractures may be inadequately stabilized, thereby increasing the risk of complications such as malunion, nonunion, or fixation failure. Developing a more comprehensive classification framework could enhance treatment precision, inform the design of fixation devices, optimize surgical strategies, and ultimately improve patient outcomes.[3]

**Constraints in Real-Time Surgical Simulation:*

In real-time surgical applications, the challenges are even more pronounced because traditional biomechanical models, such as static load analyses, musculoskeletal models, and even advanced FEMs, depend on static data and generalized assumptions, which are insufficient for dynamically adapting to patient-specific conditions during surgery. Although recent FEM advancements have incorporated patient-specific data and dynamic loading scenarios, they still demand substantial computational resources and remain highly dependent on the quality of input data (e.g., imaging resolution and material properties). Furthermore, these models fail to provide the real-time feedback that surgeons require during procedures. The absence of immediate intraoperative feedback, particularly during implant placement or fracture reduction, compromises surgical accuracy and increases the risk of complications.[4]

Role of AI in Fracture Pattern Clustering

AI-based fracture clustering and classification methods enable more precise morphological analysis, surpassing the capabilities of traditional approaches. By integrating machine learning and deep learning techniques, these models enhance fracture characterization, thereby improving diagnostic accuracy, informing treatment planning, and supporting clinical decision-making.[5-7]

Recent advancements in convolutional neural network

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THE ONLINE VERSION OF THIS ARTICLE ABJS.MUMS.AC.IR

Arch Bone Jt Surg. 2025; 13(10):607-610 Doi: 10.22038/ABJS.2025.88346.4012 http://abjs.mums.ac.ir

(CNN) models for X-ray and CT-based fracture detection have significantly improved diagnostic accuracy, surpassing that of junior radiologists and approaching the expertise of experienced specialists. Notable contributions include the work of Wang et al., who used deep learning models to successfully detect lower extremity fractures with accuracy exceeding that of junior radiologists. Similarly, the integration of hierarchical CNNs within the AO/OTA classification system has demonstrated robust performance, achieving 86% accuracy for three-class and 81% for five-class proximal femur fractures.[8] In addition, CNN-based approaches have achieved 96% accuracy in detecting proximal humerus fractures, matching the diagnostic proficiency of specialized orthopedists in complex cases.[9]

AI-driven 3D mapping is advancing fracture clustering by enabling precise segmentation of complex injuries. Yao et al. utilized 3D mapping to analyze the distribution and frequency of fracture lines in tibial plateau fractures, producing detailed heat maps that revealed concentrated fracture zones, thereby improving classification accuracy and informing surgical strategies.[10] Similarly, McGonagle et al. demonstrated that fracture mapping enhances the understanding of tibial plateau injury patterns, thereby optimizing fixation techniques and improving stability of alignment.[11]

Advanced clustering approaches, such as DBSCAN algorithms applied to metatarsal fractures and K-means methods used for intertrochanteric fractures, have enhanced morphological classification by enabling more precise grouping of fracture lines.[12] However, standardizing clustering methodologies remains a significant challenge.

Real-Time Simulations with AI

AI is revolutionizing orthopedic biomechanics by enhancing surgical precision and patient safety through the use of real-time simulations. By integrating patient-specific data, AI can refine implant positioning, predict mechanical failures, and minimize risks such as implant instability or excessive bone resection before surgery.[13]

Recent advancements underscore the expanding role of AI in biomechanics. Zhang et al. developed a physics-informed deep learning model using sEMG data to predict muscle forces and joint kinematics.[14] Their approach improved the accuracy of real-time movement analysis and neuromuscular interaction, demonstrating considerable potential for adaptive musculoskeletal simulations in rehabilitation and orthopedic research, even though it was not directly intended for surgical applications. In 2025, Zha et al. introduced an AI-driven, biplane X-ray–guided method for reducing distal radius fractures, utilizing a UNet-based feature extraction approach and robotic-assisted repositioning to enhance alignment accuracy and minimize procedural errors.[15]

Beyond simulations, AI is transforming surgical execution through wearable sensors, robotic-assisted tools, and augmented reality (AR). AR overlays provide interactive anatomical models that guide surgeons in fracture orientation and fixation pathways during complex procedures such as joint reconstructions. Wearable systems, including inertial measurement units (IMUs) and EMG sensors, deliver immediate joint feedback. At the same time, AI-driven robotic platforms automatically adapt surgical interventions using patient-specific data, thereby enhancing both efficiency and accuracy.[16-19]

Computational advancements, such as 5G-driven biomechanics and smart sensing technologies, have been shown to improve real-time diagnostics and rehabilitation strategies. In 2025, Zhang et al. highlighted the synergy between 5G and AI in enhancing real-time analysis of biomechanical data, including gait patterns and joint mobility.[20] Monge et al. investigated smart sensing technologies, such as SensFloor smart carpets, for personalized rehabilitation strategies.[21] Furthermore, AI-driven deep CNN models are revolutionizing fracture detection.[22] For example, Ukai et al. demonstrated that by reconstructing multi-oriented slab images from 3D CT scans and integrating multiple real-time object detection models, higher precision in pelvic fracture identification can be achieved.[23]

As AI-based simulations continue to advance, they are establishing new standards in orthopedic biomechanics by enabling more accurate, efficient, and patient-centered treatments across both surgical and rehabilitation domains.

AI in Orthopedic Biomechanics: Benefits and Future Directions

AI is transforming orthopedic biomechanics, making diagnoses more precise, surgeries more accurate, and treatments more personalized.

Advanced algorithms, such as convolutional neural networks (CNNs), analyze imaging data to detect subtle variations in fractures, thereby enabling tailored interventions. These AI-driven techniques provide previously unattainable insights, while real-time simulations help surgeons minimize risks and refine their procedures.[24] Moreover, AI's capacity to detect hidden patterns is driving new advancements in fracture mechanics, implant design, and surgical techniques. Wearable sensors, augmented reality, and robotics enhance real-time surgical feedback, allowing for smarter and faster intraoperative adjustments. With breakthroughs such as 5G connectivity, AI-powered tools will continue to refine orthopedic procedures, establishing new standards for accuracy and efficiency.

Emerging trends are poised to further transform the field. Generative AI is proving to be a game-changer in orthopedic literature review, statistical data processing, and medical data generation, helping to address challenges posed by limited clinical datasets and privacy concerns.[25] Simulating a broad spectrum of patient cases strengthens AI models and supports advanced virtual trials.[26] These trials play a pivotal role in optimizing implant placement and fracture reduction techniques, ultimately leading to better medical decision-making and improved procedural outcomes. Furthermore, recent breakthroughs underscore the growing impact of generative AI on orthopedic education and training, creating adaptive learning environments that enhance surgical skills and refine procedural planning.[27]

As AI continues to evolve, its integration with advanced computational methods is paving the way for more precise and personalized patient care. Beyond standardizing fracture classification, these innovations are reshaping the way orthopedic treatments are planned and executed. With ongoing technological progress and interdisciplinary collaboration, AI is poised to push the boundaries of orthopedic biomechanics, enhancing surgical precision and improving patient outcomes.

Challenges and Ethical Considerations

The integration of AI in orthopedic biomechanics faces both technical and ethical challenges. From a technical perspective, the success of AI-driven fracture clustering and real-time simulations depends heavily on high-quality imaging data; however, inconsistencies in imaging modalities, anatomical variations, and non-standardized data pipelines can undermine the reliability of AI algorithms.[28] Gao et al. introduced an AI-based classification system for distal radius fractures using fragment morphology, but issues related to data variability and algorithm adaptability remain unresolved.[29]

To improve model generalizability and ensure accurate fracture recognition, ongoing research is essential for refining classification frameworks that support patient-centered treatment. Despite advances in machine learning and segmentation techniques, establishing a standardized clustering methodology remains a significant challenge. For widespread clinical adoption, universal AI frameworks for fracture classification will be critical to achieving effective integration into orthopedic biomechanics.

Additionally, real-time surgical simulations require high-performance computing, parallel processing, and optimized algorithms to manage complex dynamic feedback systems.[30] These substantial computational demands complicate the practical deployment of AI in surgical settings.

On the ethical side, protecting patient privacy and ensuring data security are critical, as AI's reliance on large datasets increases the risk of breaches or misuse.[31] Furthermore, AI models trained on incomplete or biased datasets may unintentionally reinforce disparities in medical care. To promote fairness and reliability, rigorous validation protocols, algorithmic accountability, and bias-mitigation strategies are essential, along with well-defined ethical regulations that support the responsible implementation of AI.[32]

Accountability and informed consent further complicate the clinical integration of AI. Clinicians must balance AI-generated insights with their own expertise while ensuring that patients clearly understand how AI-driven technologies influence diagnosis and treatment.

Establishing robust regulatory frameworks is essential for defining liability and maintaining ethical standards. Ultimately, ongoing interdisciplinary collaboration among engineers, clinicians, and ethicists will be crucial for addressing these challenges as AI becomes increasingly integrated into medical practice.[33,34]

Conclusion

The integration of AI in orthopedic biomechanics represents a transformative milestone, enhancing diagnostic accuracy, treatment personalization, and surgical precision through advanced fracture clustering and real-time simulations. These technologies empower surgeons by delivering dynamic, patient-specific insights that optimize intraoperative decision-making and mitigate procedural risks.

Equally crucial is interdisciplinary collaboration among clinicians, engineers, and ethicists, which bridges technological innovation with ethical oversight while addressing challenges such as data variability, computational demands, and ethical concerns. With the advancement of generative AI and sophisticated simulations, personalized therapies are poised to drive the future of orthopedic care toward greater precision, efficiency, and patient-centeredness.

Acknowledgement

N/A

Authors Contribution: Authors who conceived and designed the analysis: Azadeh Ghouchani, Mohammad H. Ebrahimzadeh/ Authors who collected the data: Azadeh Ghouchani, Mohammad H. Ebrahimzadeh/Authors who contributed data or analysis tools: Azadeh Ghouchani/Authors who performed the analysis: Azadeh Ghouchani/Authors who wrote the paper: Azadeh Ghouchani, Mohammad H. Ebrahimzadeh

Declaration of Conflict of Interest: The authors do NOT have any potential conflicts of interest for this manuscript.

Declaration of Funding: The authors received NO financial support for the preparation, research, and authorship. The fourth author, G. Kassam received financial support for publication of this manuscript.

Declaration of Ethical Approval for Study: Ethical approval is not required for this study.

Declaration of Informed Consent: Informed consent is not required for this study.

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