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Challenges And Limitations Of Artificial Intelligence And Machine Learning In Life Sciences: A Review

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Abstract

Artificial Intelligence (AI) and Machine Learning (ML) play a significant role in the life sciences progress , supporting breakthroughs in diagnostics, drug discovery, genomics, agriculture and personalized healthcare.Implementing Artificial Intelligence and Machine Learning practically faces many hindrances such as regulatory compliance, reproducibility, trust, data quality issues , model interpretability and constraints in computational infrastructure in spite of their significant transformative potential. This review offers a synthesized analysis of findings from recent literature (2023–2025) to study these challenges in detail and proposes strategies to mitigate these challenges. To ensure that AI/ML systems are ethically responsible, robust and suitable for real-world biological and clinical applications, understanding and resolving these challenges is important

Keywords: Artificial intelligence, Machine learning, Life sciences, reproducibility, trustworthiness, bias, interpretability, regulation

Introduction

AI and ML have gained significant prominence in life-science research and application domains, covering a broad range of high-throughput omics workflows, imaging such as in radiology, pathology , clinical prediction, and drug sensitivity modeling. These advanced tools aid in faster discovery, cost savings, and a lot more precision based interventions. Nevertheless, there is increasing recognition in the scientific community that significant hindrances must be overcome before AI can realize its full potential in real-world biological research environments . This analytical study emphasizes challenges and constraints based on the latest research.

Bias, Data Quality, and Representativeness

In Life sciences biggest barrier for ML is quality of data and heterogeneity. Biomedical datasets come from different sources like different labs, imaging protocols, patient populations and create biases and batch effects which often degrade model performance when applied broadly. For example , in studying multi-omics, false positives are problematic , and meticulous validation is needed to confirm biological relevance. Training-data biases undermine equitable model behavior and significantly restrains generalization to diverse life-science domains. ML models lack reliability and interpretability, raising critical trust issues for clinical decision support in recent survey regarding cancer drug sensitivity prediction

Reproducibility and Robustness

Recent study revealed that reproducibility is a major problem and a crisis in Machine Learning for medicine and it has gaps in standard reporting and methodological rigor . Significant factors like reproducibility, model non-determinism, data preprocessing variability, stochastic training procedures and hardware differences . To address these issues few researchers suggested some standards in reporting such as The REFORMS checklist, which provides 32 guiding questions for improving transparency and reproducibility in ML-based science.

Interpretability, Explainability, and Trust

In Life sciences Authentic and Trustworthy AI is important , specifically when decisions impact the health of a patient .Nevertheless ,many superior -performing ML models, especially deep learning systems, function as “black boxes.” . This opacity worries clinicians and biologists as they need to understand why a model made a prediction. To ensure the safe and responsible implementation in healthcare, Reviewers has recently put forward a “Clinician-AI-Collaboration” framework that reinforces interpretability at all stages such as data preprocessing, model development and post-hoc interpretation.

In Interpretable Machine Learning, statistical researchers have identified open key challenges, such as the lack of validated methods for uncertainty quantification in discovery scenarios and the tension between model complexity and human-understandable reasoning .

Ethical, Fairness, and Societal Implications

If proper management is not there AI models in life sciences can extend or even escalate current health disparities. Recent reports on bias in healthcare AI describes how unrepresentative training data can lead to unjustified outcomes, and also suggested strategies like transparent reporting and fairness-aware algorithms .Moreover , without pertinent checks, AI systems may emphasize systemic biases in clinical care, research prioritization, and in allocating resources.

Regulatory and Legal Challenges

The regulation of AI and ML in life sciences is trailing with technological innovation. As current frameworks were not designed for adaptive learning systems, life sciences companies face obscurity regarding aligning with AI models having regulatory standards like Good Practice guidelines and device regulation as per the analytical studies of IntuitionLabs. Specifically in situations where patient safety is utmost important, regulatory uncertainty convolutes innovation and obstructs adoption.

Workforce Limitations, Education and Infrastructure

Computational infrastructure like GPUs, secure cloud environments and inter -disciplinary expertise lacking in many life science institutions which are needed to build, deploy, and maintain AI/ML systems. To understand the capabilities and adverse outcomes of these AI and ML tools training is necessary . Currently there is a mounting necessity for AI literacy among biologists, clinicians, and lab scientists. Without proper training there is always a risk of misuse or overreliance on ML outputs. Improper integration, misapplication and poor adoption of AI into research workflows can lead to dangerous outcomes .

Over-Reliance and Illusion of Understanding: Emerging Risks

Beyond technical problems , there are intense cognitive risks. As per some people's opinions in scientific research , AI may create an illusion of understanding . System outputs seem persuasive, but they capture misleading correlations instead of true underlying mechanisms. Excessive dependence on AI-generated results without analytical evaluation often lead to scientific monocultures, where human researchers overly depend on algorithmic reasoning without questioning or evaluating the interpretations.

Recommendations and Strategies of mitigation : Based on review of recent research analysis

Adopt Reporting Standards such as usage of guidelines like REFORMS for transparency, reproducibility, and rigor in ML-based research. For ensuring Data Diversity and Quality, organize representative and clearly explained datasets, reduce batch effects and biases and in need use federated data approaches .Regarding Prioritizing interpretable Models, use inherently interpretable models wherever possible and involve domain experts like clinicians, biologists in design and evaluation.Construct robust validation tool by assessing multiple centers models , hardware settings, and cohorts, stress test for distribution shifts and by non-determinism .

As a part of regulatory Engagement, work with regulators prior , ensure compliance with safety and quality standards. contribute to development of adaptive regulatory frameworks. Interdisciplinary training,Investing in infrastructure, and shared platforms for AI life-science research play an important role in capacity building .Establishing oversight involving ethicists, patient representatives, and domain scientists; adopting fairness oriented design practices and reviewing societal impact are part of Governance and ethics

Conclusion

Artificial Intelligence and Machine Learning offer substantial potential to reshape research and innovation in the area of Life Sciences . But there are several concerns like interpretability of models , data quality and availability, algorithmic bias, and integration with existing healthcare systems. Moreover ethical, regulatory, and privacy concerns also are the significant hurdles to pervasive adoption.

Recent study accentuates the pressing need to address interpretability, reproducibility, regulation, bias, and infrastructure difficulties . The scientific community can more safely and equitably translate AI and ML's promise into practice and maximize their benefits for research, diagnostics by promoting trustworthy and transparent models, adopting rigorous standards,interdisciplinary collaborations and by engaging proactively with regulatory and ethical concerns.

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