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Perspective

Redefining sepsis management: The comprehensive impact of artificial intelligence

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Introduction

Sepsis, a syndrome of life-threatening organ dysfunction caused by dysregulated host response to infection, continues to burden healthcare systems worldwide with high morbidity, mortality, and costs.[1] The early detection and diagnosis of sepsis are challenging due to the absence of definitive tests, overlapping symptoms with other conditions, and the need for rapid initiation of therapy to improve outcomes.[2]

With recent advances in computational power, artificial intelligence (AI) has shown promising results in healthcare applications and holds significant potential for revolutionizing sepsis management. Machine learning (ML), a subset of AI, encompasses techniques that learn and make predictions based on data. It operates on structured data, such as numerical values for vital signs and lab results, as well as unstructured data, including free-text clinical notes and patient histories.[3]

By integrating these AI tools into sepsis management, healthcare providers can leverage predictive analytics and decision support systems to improve sepsis management.

AI in Early Detection and Diagnosis of Sepsis

Already, advanced ML techniques such as deep learning and neural networks have been used to detect sepsis within narrow timeframes, as brief as a few hours, facilitating prompt medical interventions.[4] Early prediction models, such as the one formulated by Shashikumar et al.,[4] harness readily accessible structured data to detect sepsis with remarkable precision. Rapid detection can ensure timely administration of treatments such as fluids and antibiotics, of which delay is associated with increased mortality.[1]

AI systems can also rely on unstructured data, such as clinical notes, to improve early detection of sepsis.[5] A natural language processing-enabled algorithm developed by Goh et al.[5] can extract, analyze, and summarize physician clinical notes to help predict sepsis, ultimately increasing early detection of sepsis and reducing false positives. This highlights the potential of modern AI-powered systems to integrate both structured data and unstructured data, further enhancing the predictive acumen of AI for the early detection of sepsis.

Risk stratification plays a pivotal role in sepsis management, guiding clinicians in discerning patients more susceptible to detrimental outcomes; thereby informing treatment approaches and resource distribution.[6] Leveraging vast datasets, AI has already demonstrated enhanced risk stratification capabilities, with various models outperforming the Modified Early Warning Score in predicting intensive care unit (ICU) transfer or death.[7]

AI in Treatment Optimization for Sepsis

Deciding the optimal treatment for sepsis can be challenging due to the heterogeneous nature of the condition and the diverse responses of patients to treatments.[2,8] AI systems can support clinicians in this decision-making process. For instance, the AI clinician, a reinforcement learning model developed by Komorowski et al.,[8] learned optimal treatment strategies for sepsis in the ICU setting. By analyzing thousands of patient data, it recommended treatment plans that were shown to correlate

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with lower mortality rates in sepsis.[8] Such tools can be used as decision supports for clinicians in managing patients with sepsis.

Continuous monitoring is essential for tracking disease progression and response to treatment. AI systems can analyze real-time data from various sources, such as vital signs and laboratory results, to provide timely updates on patient status.[9] Markers that are difficult for bedside clinicians to interpret, such as heart rate variability, can be analyzed using computer algorithms and integrated with other clinical and laboratory measures to better predict deterioration in patients with sepsis.[10]

Implementation and Limitations

Although AI models may perform well within a dataset, external validation and real-world implementation may yield deferring results. For example, the Epic Sepsis Model, a proprietary model integrated within the electronic health record developed by Epis Systems (Verona, WI, USA), exhibited poor performance in predicting sepsis when externally validated in a US cohort study.[11] AI systems may also integrate biases, such as the underrepresentation of racialized demographic groups in training datasets, which can perpetuate healthcare inequities when implemented.[12] Addressing biases in AI models requires systematic inclusive data collection and consideration of intersectionality during model development and evaluation. Techniques such as disparate impact analysis, counterfactual fairness, and fairness through awareness are essential for identifying and mitigating biases, complemented by continuous evaluation, transparent communication, and adherence to regulations and policies to ensure equity and fairness in AI-generated outputs.[13] Diligent external validation and simulation in real-world environments are steps in ensuring models perform well when implemented. Ultimately, these efforts are crucial to ensure AI systems enhance rather than hinder clinical care when implemented.

The Future of Critical Care and Sepsis Management

As we envision the future of critical care and sepsis management, more emphasis will be placed on targeted therapies that can be tailored to the patient.[14] Recent advances have identified subgroups of patients with specific sepsis phenotypes that may benefit from tailored treatment beyond conventional treatments.[15] Advancements in precision medicine will require deep learning techniques to realize the potential of these data. In a world of increasingly personalized medicine, sepsis may be understood at a level of complexity that is beyond human interpretation. Treatments may be selected based on unique genetic markers, inflammatory signals, and microbial data. This approach, powered by an AI-centric infrastructure, has the potential to transform critical care and sepsis management, leading to more precise, effective, and personalized treatment strategies.

Conclusion

The application of AI in sepsis management has the potential to revolutionize care for this complex condition. From early detection and diagnosis to risk stratification, treatment optimization, and outcome prediction, AI can offer considerable advantages over traditional methods. However, it is crucial to address limitations in validation and potential biases to ensure equitable and effective implementation. With ongoing research and technological advancements, AI is poised to significantly impact sepsis management.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process[16]

In the development of this article, we used AI tools for article drafting.

The AI-produced content from structured and increasingly tailored input data underwent significant revisions by the author (Jamie Ghossein, Brett N. Hryciw) to ensure accuracy and reliability. We maintained constant human oversight throughout the process, including editing, revising, and validating the AI-generated content (Jamie Ghossein).

Generative Pre-Training Transformer (GPT)-4, a Large Language Model developed by OpenAI, was used through ChatGPT. This software has the primary function of generating human-like text based on input prompts, demonstrating an ability to understand and produce contextually relevant content.

We acknowledge potential ethical concerns using AI-generated content to generate recommendations regarding AI involvement in medical writing and therefore took care to re-evaluate and edit the output created.

We acknowledge potential inaccuracies or misinterpretations that may arise from AI-generated content and therefore took care to verify the output.

No conflicts of interest were present in the use of the AI model for this article.

CRediT Authorship Contribution Statement

Jamie Ghossein: Writing – review & editing, Writing – original draft, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Brett N. Hryciw:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Kwadwo Kyeremanteng:** Writing – review & editing, Supervision, Conceptualization.

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Ethics Statement

Not applicable.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data sets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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