Accuracy of Machine Learning to Predict Cardiac Arrest

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Introduction

The incidence of in-hospital cardiac arrest (IHCA) in the U.S. is estimated at 209,000 annually. IHCA is a medical emergency and is often fatal without swift action. The average survival rate of an IHCA is less than 26%. Additionally, 40% of those surviving an IHCA will have moderate to severe functional impairment at discharge. The chance for a meaningful recovery is low; for that reason, the best strategy is early recognition with proactive steps to halt their clinical decline.

Problem

The traditional hospital-based track and trigger systems, such as the modified early warning score (MEWS), have failed to produce consistent and reliable predictions of IHCA. Recent advancements in other industries have shown the benefits of harnessing artificial intelligence to interpret complex datasets with remarkable accuracy.

Purpose

To assess the state of research to determine if machine learning models more accurately predict IHCA when compared to the modified early warning score (MEWS).

Search Strategy

A review of the literature was conducted in January 2019. Database searched included CINAHL, EBSCO, and PubMed. Inclusion criteria included machine learning principles applied to hospitalized adults experiencing IHCA, from peer-reviewed articles, within the last seven years. Five studies, one prospective and four retrospective, were included in this review.

Synthesis of Evidence

All five studies showed that the incidence of in-hospital cardiac arrest were more accurately predicted when machine learning models (AUROC 0.78-0.86) were utilized compared to the modified early warning score (MEWS) (AUROC 0.55-0.70). Major trends in the studies included the use of deep learning models for variable selection.

Implications

The success of a healthcare organization depends on its ability to accurately interpret and act on incoming data. Machine learning allows the healthcare team to harness the electronic health record and bridge the digital divide. This technology enables a proactive approach for the patients who stand to benefit the most.

While there is indication through this work that machine learning models should be available to all clinicians, there are notable gaps in the availability of this technology at the bedside. Further research is needed to ensure the translation of this novel technology to the clinical practice setting.

References


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