ABSTRACT

Purpose and Aim: Prediction of clinical deterioration is a fascinating topic as well as a messy and complex problem. Vital signs are among the main features used, and many efforts to improve identification of risk patients have been made in this area, but there is no successful model integrated into the real world. There are some serious barriers not investigated yet. Therefore, in this research, we go beyond the common approach and look at the problem from new and different angles. Instead of looking at the vital signs' values, we get more precise insights about the deteriorating patients and their characteristics by utilizing continuous monitoring, time series analysis, and Machine Learning (ML) techniques.

Research Questions: We formulate our research questions as:

RQ1. Given the illness severity scores of patients, how can we predict their trajectories using an adaptive real-time system?

RQ2. What are the proper techniques for addressing data challenges such as missing values and data imbalance? And how these techniques affect the performance of predictive models? Is there an association between missing values and clinical deterioration?

RQ3. Considering temporal dependencies, what more information can we gain from patients' conditions during hospitalization?

RQ4. Considering temporal dependencies, what are the dangerous patterns happening in deteriorating patients' vital signs before an adverse event?

RQ5. Is there an association between clinical deterioration and Length of Stay as clinical outcomes?

Methods: Action Design Research (ADR) is used as a research methodology for this PhD project. ADR has four main stages and seven principles and based on these stages and principles, various tasks are determined at each stage. We adopt this methodology regarding our research questions, aims, roles and responsibilities in our work. These stages are (1)

Problem Formulation, (2) *Building, Intervention, and Evaluation,* (3) *Reflection and Learning*, and (4) *Formalization of Learning.*

Settings: This project is interdisciplinary research with collaboration of researchers from Center for Health Informatics and Technology of University of Southern Denmark and the Emergency Department of Odense University Hospital.

Results: Two datasets from two Danish hospitals are collected during the research, and six studies are designed for identifying deteriorating patients and their characteristics. In the first step, we conduct a comprehensive systematic literature review to identify the state-of-the-art studies and open areas in this field. Based on this review, we provide eight recommendations that can lead to developing robust predictive models in future. In the next step, time series analysis is used to introduce new features that can integrate into scoring systems and give a more accurate picture of patients' conditions. Following this step, we develop hybrid models consisting of ML and autoregressive models to predict near future status of each patient. In the next step, we evaluate the hypotheses of association between clinical outcomes and show how Length of Stay (LOS) data can be used to stratify patients at risk of clinical deterioration. In this step, we also demonstrate that how quality of data can impact the performance of ML models. Finally, in the last study, we develop an adaptive system with the capability of visualization and interpretability based on shapelets mining and ensemble learning that can analyze vital signs' trajectories and identify the local patterns that are highly associated with clinical deterioration.

Conclusions: Applicability, transparency, and interpretability are among our main goals in this research. These metrics help us get closer to the ultimate aim in this field of research: integrating ML-based models in clinical practice. We identify the research gaps and barriers that prevent researchers from achieving this goal in this research. Therefore, we pay attention to some criteria such as time complexity and optimization as well as visualization ability for models, which are important for clinicians. We also introduce new features based on patients' trajectories during hospitalization that can be used in scoring systems and give clinicians more accurate insight into the patients' conditions.