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Development and evaluation of a machine learning algorithm for predicting pressure injury risk during hospitalisation

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Background

Hospital-acquired pressure injuries (HAPIs) are a pervasive and costly complication in healthcare systems worldwide, significantly affecting patient morbidity, mortality, and length of hospital stay. Existing risk assessment tools, such as the Braden, Norton, and Waterlow scales, are widely used but demonstrate only moderate predictive validity. Their subjectivity and dependence on manual input by clinicians can lead to variability and missed assessments, particularly in busy acute care settings. As healthcare shifts towards digitalization and big data, machine learning (ML) presents an opportunity to enhance the accuracy and efficiency of pressure injury risk prediction using comprehensive electronic health record (EHR) data.

Objectives

This study aimed to:

1. Develop a predictive machine learning model using retrospective EHR data to identify hospitalized patients at risk of acquiring pressure injuries.
2. Evaluate the diagnostic accuracy of the ML algorithm by comparing its sensitivity and specificity with the standard Braden Scale scores documented in patient records.

Methodology

A retrospective, iterative study was conducted at Singapore's largest acute tertiary hospital, with approval from the institutional review board. Patient medical records from 2018 and 2020–2022 were extracted and de-identified, yielding data from 78,453 patients (120,887 encounters). Key clinical and demographic features, including age, gender, vital signs, urinary device use, nursing care notes, and laboratory results, were collated and engineered into analysable variables. HAPIs were defined as occurring ≥36 hours after admission.

Model development followed a multi-stage process:

- **Feature Engineering & Selection:** Thirty-one potential risk factors were initially identified and refined using feature importance rankings.
- **Model Training:** Multiple ML algorithms were evaluated in early iterations; LightGBM, a tree-based algorithm suited to large and sparse datasets, was selected for primary model development.
- **Iterative Testing:** Models were successively trained on increasing data sizes, validated and tested with stratified subsets (12,089 encounters each for validation and evaluation).
- **Comparison:** The performance of ML models using both comprehensive (31-feature) and reduced (six-feature) sets was compared to the Braden Scale using standard metrics: sensitivity, specificity, AUROC, and likelihood ratios.
- **Interpretability:** Shapley Additive Explanations (SHAP) were used for feature importance analysis.

Results

The final models demonstrated superior predictive performance relative to the Braden Scale. The six-feature ML model (**O**ne **R**ecord **PA**tient-6)—using mobility, age, heart rate, body temperature, body mass index, and skin moisture—outperformed the Braden Scale with a sensitivity of 0.83 and specificity of 0.80 (vs. Braden's 0.74 and 0.68, respectively). The 31-feature model (ORPA-31) yielded even higher specificity and AUROC but posed more significant deployment barriers in real-world clinical settings.

Feature analysis highlighted mobility as the strongest individual predictor, followed by age, heart rate, body temperature, skin moisture, and body mass index. Notably, age, an established risk factor in clinical practice, is not formally included in most traditional risk scales.

Discussion and Impact

This proof-of-concept demonstrates that machine learning algorithms, using routinely collected EHR data, can meaningfully improve the identification of patients at risk for HAPI compared to current manual methods. The proposed ML models provide a framework for real-time, automated risk stratification, reducing manual burden on nursing staff and supporting targeted, timely intervention. The compact six-feature model is especially promising for future clinical integration, as it balances performance with feasibility.

The study underscores the need for further validation, particularly across diverse healthcare settings and populations. Limitations include single-centre data, absence of certain social/ethnic variables, and the need for complete data input for predictions. Future work will include prospective "silent" trials to evaluate real-world impact, with the aim of embedding the model within EHR workflows to dynamically alert care teams and prevent adverse outcomes.

Conclusion

Machine learning offers a compelling alternative to traditional, manual risk assessment scales for hospital-acquired pressure injury prevention. This work demonstrates the feasibility and improved accuracy of an ML-based approach in a large tertiary hospital setting, paving the way for smarter, data-driven risk management and preventive care.

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