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Emergency Department Patient Journey Prediction with Machine Learning

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Abstract

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Original Manuscript

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Dear Editor,

We were pleased to read the article by Patel et al. “Traditional Machine Learning, Deep Learning, and BERT (Large Language Model) Approaches for Predicting Hospitalizations from Nurse Triage

Notes"(1) published in the Journal of Medical Internet Research (JMIR). The study compared machine learning (ML) models, including Bio-Clinical-BERT and TF-IDF, to predict hospitalisations based on nurse triage notes. We commend the authors for their valuable contribution to the field of ML predictive analytics. Their findings align with our recent work aimed at enhancing patient flow through emergency departments (ED) using ML models. We wish to highlight our study to further contribute to this growing body of research.

Our study aimed to evaluate the performance of various ML models in predicting three key outcomes in ED patient's journeys: prolonged ED length of stay (LOS ≥8 hours), chest X-ray (CXR) utilisation and inpatient admissions. We analysed data from 50,000 ED visits at two major public metropolitan hospitals in South Australia. The models tested included XGBoost, random forest and logistic regression. Our primary objective was to assess the accuracy of these models in predicting the outcomes to support clinical decision-making and enhance operational efficiency.

The patient cohort had a mean age of 52.5 (SD 22.1) and 50.4% were female (n = 25,211). Additionally, 78.6% (n = 39,300) of patients reported English as their primary language. The median ED LOS was 4 hours 31 minutes (IQR of 2 hours 50 minutes to 7 hours 8 minutes). CXRs were ordered for 27.2% (n = 13,578) of patients, and 26.7% (n = 13,343) were admitted as inpatients.

Among the models evaluated, XGBoost demonstrated the strongest performance across all predictive tasks, achieving AUROC values of 0.79 for predicting prolonged ED LOS, 0.88 for CXR utilization, and 0.85 for inpatient admissions. The random forest model also performed well, with AUROC scores of 0.78 for prolonged LOS, 0.87 for CXR prediction, and 0.84 for inpatient admissions. Although the logistic regression model was less accurate overall, it still provided AUROC values of 0.70, 0.79, and 0.74 for the same outcomes, respectively. These findings suggest that ML models offer reliable predictive insights, particularly for frequently ordered investigations like CXR, and hold promise for enhancing clinical workflows.

Our findings closely resemble those of Patel et al.(1), especially regarding the effective use of traditional and advanced ML techniques as clinical predictors in the ED. Both studies demonstrate the potential benefits of integrating ML into ED workflows. Additionally, our research contributes further insights by acknowledging the impact of systemic factors, such as inpatient bed occupancy on LOS predictions. We believe that integration of systemic factors, we could improve the predictive accuracy of ML models and further boost their clinical utility.

Both studies, highlight the need for ongoing research into ML application in healthcare. Future studies should explore the role of systemic factors and real-time data integration to further enhance the clinical utility of ML models in ED settings, ultimately improving patient outcomes and operational efficiency.

Sincerely,

Joshua G. Kovoor.

References

1. Patel D, Timsina P, Gorenstein L, Glicksberg BS, Raut G, Cheetirala SN, et al. Traditional Machine Learning, Deep Learning, and BERT (Large Language Model) Approaches for Predicting Hospitalizations From Nurse Triage Notes: Comparative Evaluation of Resource Management. JMIR AI. 2024;3:e52190.