AI for Emergency Department Predictions

Surya Teja Gowd Ayinavilli
School of Enterprise Computing and Digital Transformation
Technological University Dublin
Dublin, Ireland
suryatgowd@gmail.com

Dipesh Badal
School of Enterprise Computing and Digital Transformation
Technological University Dublin
Dublin, Ireland
x00229547@mytudublin.ie

John Staunton
School of Enterprise Computing and Digital Transformation
Technological University Dublin
Dublin, Ireland
X00229681@mytudublin.ie

Olohigbe Ohiwerei
School of Enterprise Computing and Digital Transformation
Technological University Dublin
Dublin, Ireland
X00229601@mytudublin.ie

Rajesh Jaiswal
School of Enterprise Computing and Digital Transformation
Technological University Dublin
Dublin, Ireland
Rajesh.Jaiswal@tudublin.ie

Keith Quille
School of Enterprise Computing and Digital Transformation
Technological University Dublin
Dublin, Ireland
keith.quille@TUDublin.ie

Abstract

Emergency departments face constant pressure from overcrowding, making early prediction of patient admission a valuable support for clinicians. In this study, we used the MIMIC-IV-ED v2.2 dataset, containing about 296,000 visits and 38 triage-level features, to develop and compare multiple machine learning models for admission prediction. Across five approaches—Logistic Regression, Decision Tree, Random Forest, XGBoost, and a Deep Neural Network—performance ranged from moderate to strong, achieving AUROC values up to 0.84 and balanced accuracy around 77%. Despite these results, recall for admitted patients remained around 60%, indicating that many potential admissions were not detected. Explainable AI methods (SHAP and LIME) identified triage acuity, patient age, arrival transport, and medication counts as key drivers of model decisions. Fairness analysis revealed demographic disparities, with younger patients predicted more accurately than older adults, and elderly women particularly disadvantaged. Compression experiments further showed that quantisation and pruning reduced model size and latency with minimal performance loss. The study highlights the potential of predictive triage systems while underscoring the importance of fairness monitoring, calibration, and regulatory compliance before deployment.

Keywords

ED, Admission Prediction, XAI Fairness, EU AI Act

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1 Context

Emergency departments (EDs) face ongoing challenges with overcrowding, long wait times, and limited resources, creating pressure for more efficient triage decisions. Predictive modelling offers a potential solution by identifying, at the point of arrival, which patients are likely to be admitted. Building on recent large-scale datasets such as MIMIC-IV [2], machine learning has emerged as a promising tool for clinical decision support. Prior work has benchmarked ED prediction tasks, showing that models can achieve strong accuracy but often struggle with generalisability and fairness [3]. In this study, we evaluated five models on the MIMIC-IV-ED dataset: Logistic Regression, Decision Tree, Random Forest, XGBoost, and a Deep Neural Network. XGBoost and the neural model achieved the highest performance, reaching AUROC scores of 0.84 with balanced accuracy around 77%. Among traditional models, Logistic Regression performed moderately (AUROC around 0.78, balanced accuracy around 72%), while the Decision Tree model performed the weakest overall, showing lower recall for admitted patients. Explainable AI was central to our approach. SHAP and LIME consistently highlighted triage acuity, age, arrival transport, and medication counts as influential features.

Beyond model interpretability, we examined fairness by analysing demographic subgroups. Accuracy and recall were higher for younger patients but lower for older adults, particularly women aged 75 and above, aligning with concerns raised by intersectional fairness research [1]. We also explored model compression to evaluate deployability in real-world ED settings. Post-training quantization and Random Forest pruning reduced model size and inference time by more than half while maintaining accuracy, demonstrating the practical value of lightweight models. Our findings underscore the trade-off between predictive performance, fairness, and usability. While predictive triage support is feasible, adoption in healthcare requires threshold calibration, subgroup monitoring, and strong governance. Future work will explore integrating clinical text features and aligning evaluation with regulatory frameworks to ensure safe and human-centred deployment.

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