Predicting the Unpredictable: A Data Driven Machine Learning Prediction Model for Waiting Room Census in the Emergency Department

Greg Davis, MHA, FACHE; Lindsey Asher, DHA; Brendan M Carr, MD; James E Colletti, MD; Jennifer Miller, MBA;
Corinna Nelson, MS; Laura E Walker, MD; Derick D Jones, MD

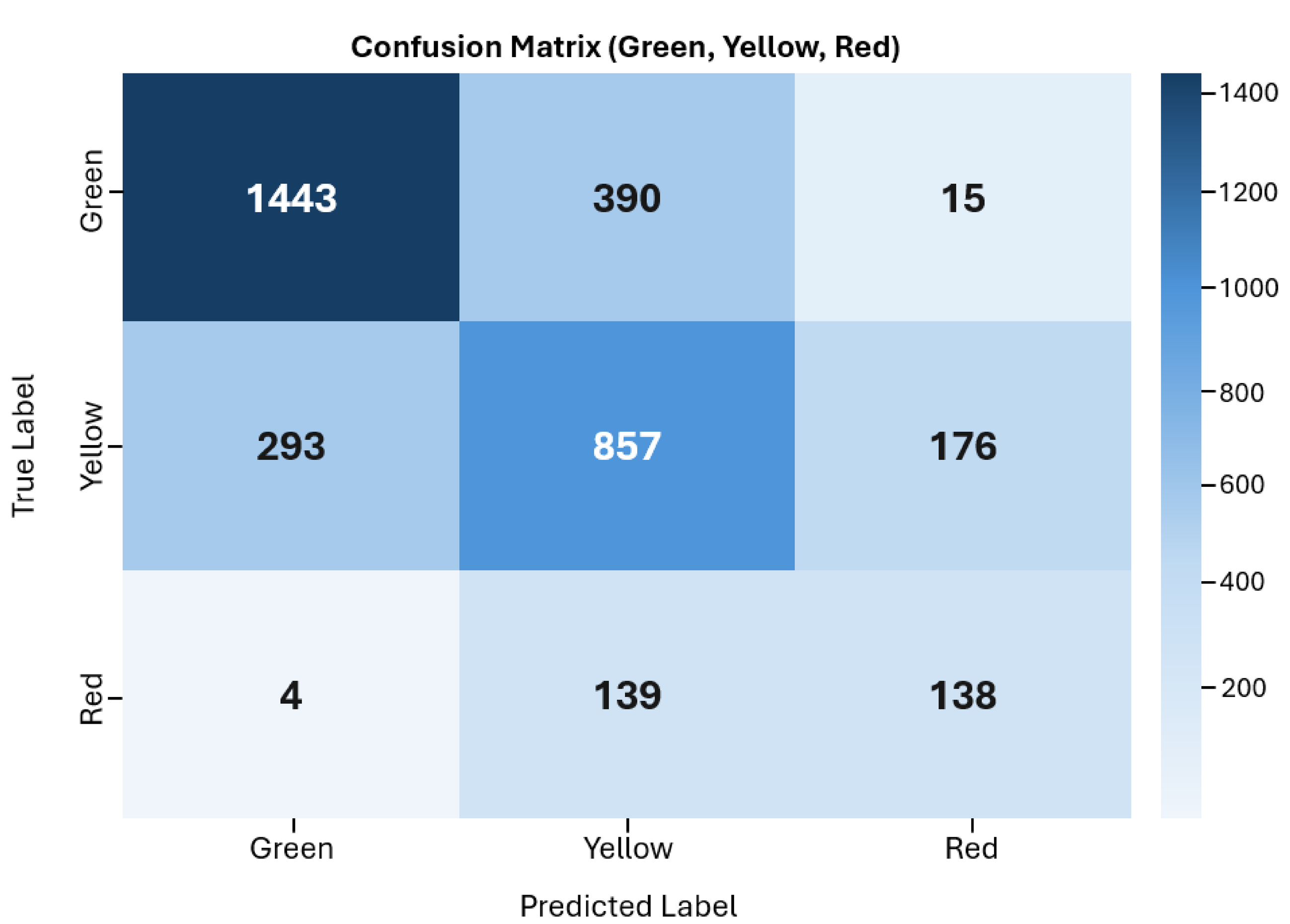
BACKGROUND

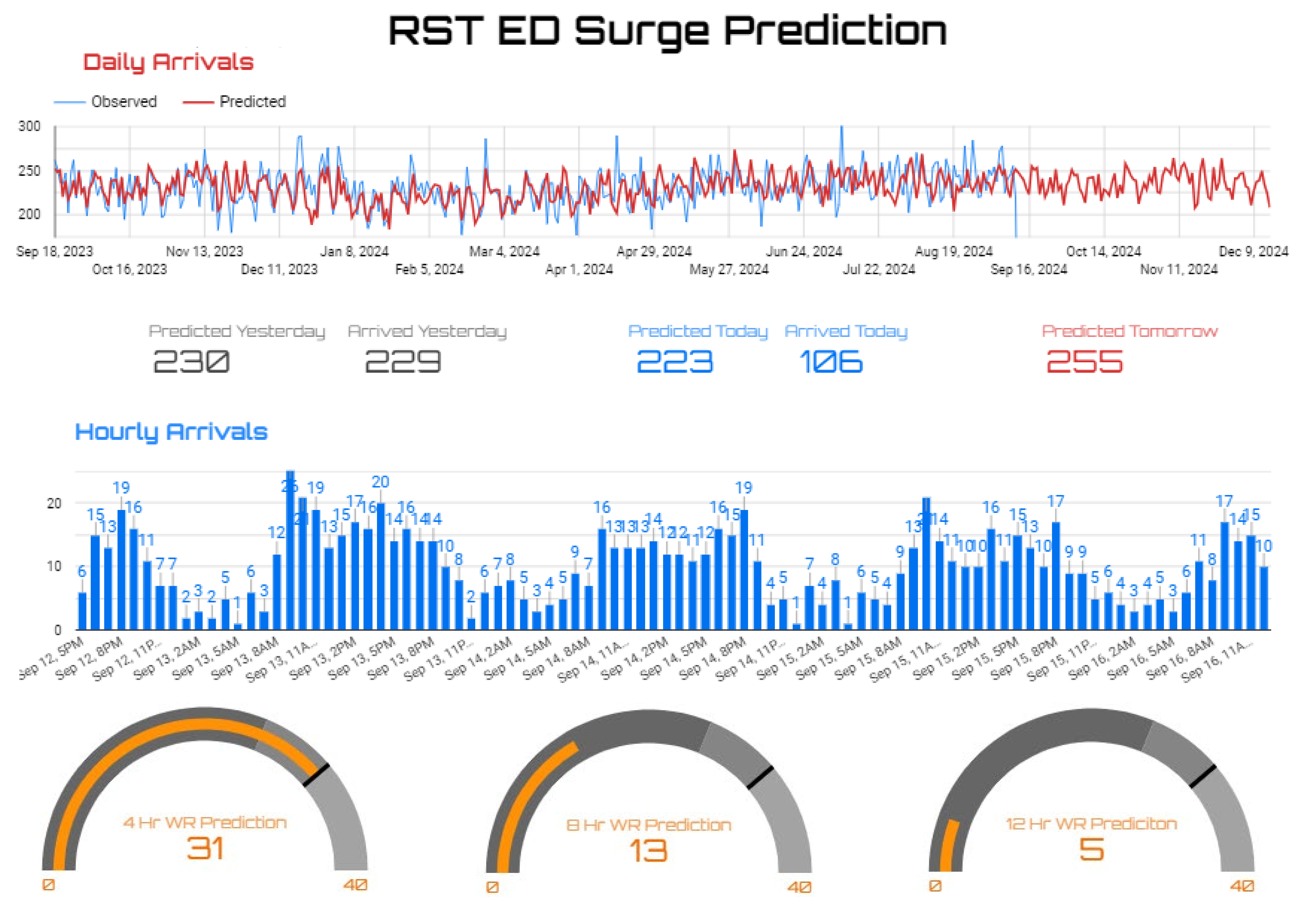
The Emergency Department (ED) is often the primary safety net for healthcare, handling unpredictable patient volumes in resource-limited settings. Increasing demand, exacerbated by constrained community health resources and the obligations under EMTALA (Emergency Medical Treatment and Active Labor Act), places immense pressure on EDs to meet a broad array of urgent needs. This dynamic creates unique operational challenges, including extended patient wait times, difficulty in resource allocation, and staff burnout, which collectively strain critical ED functions. While existing machine learning tools attempt to predict patient arrivals, they don't reflect more complex factors to accurately estimate waiting room census and are underutilized for process improvements and real-time operational adjustments. To address these gaps, Mayo Clinic sought to develop an advanced machine learning model tailored to forecast ED waiting room census and daily patient arrivals with greater precision.

OBJECTIVES

PROCEDURAL FACTORS

Utilize an applied machine learning model to accurately predict ED waiting room census and proactively identify surge conditions. This approach aims to provide real-time, actionable insights that enable ED teams to anticipate patient volumes, adjust workflows, and allocate resources effectively, ensuring timely patient care. By continuously refining the model with real-time data, the system adapts to dynamic conditions, equipping ED teams with up-to-date insights to mitigate bottlenecks and improve the overall patient experience.





METHODS

PLANNING/RESEARCH METHODS

Data Collection: The team utilized the electronic medical record to analyze all the emergency department encounters between July 01, 2022, and June 30, 2024, at a tertiary academic emergency department in the Midwest. Over a two-year period, 17,271 consecutive department hours were analyzed, encompassing 165,285 patient encounters. Waiting room census and hourly arrivals for each hour in the time frame were calculated

Feature Engineering: To capture temporal relationships in ED arrivals, numerous variables were considered reflecting the fluctuation of ED arrivals throughout the day and year, adding lagged arrivals in the 1 to 72 hours prior to each hour.

Target Definition: The team defined the target metric as waiting room census levels representing surge conditions with maximum thresholds that apply with all the ED rooms open: Green Status: < 15, Yellow Status: >= 15 and < 31, Red Status: >= 31.

IMPLEMENTATION METHODS

Modeling Approach: The team developed and tested machine learning models to predict hospital surge conditions 4, 8, and 12 hours in advance. Two distinct approaches were used: Gradient Boosted Decision Trees (XGBoost) and Deep Neural Networks (DNN). Both models were trained on 80% of historical arrival data, with the remaining 20% reserved for testing.

Evaluation Metrics: Performance metrics used to evaluate the models include precision, recall, accuracy, class specific area under the receiver operator curve and confusion matrices to assess performances in capturing surge peaks. Standards for machine learning indicate a target area under the receiver operating curve (AUC) ranges between .7 and 1.0, and the goal for model accuracy is greater than 70%.

DISCUSSION

This project demonstrated that using applied machine learning is a feasible approach to accurately predict waiting room census in the ED. However, challenges such as data quality, complex feature engineering, and real-time data integration were encountered. Ongoing efforts must continue to improve the overall accuracy of the model – including consideration of additional influencers of waiting room census. The ability to accurately predict waiting room census has transformational potential for the operational management of EDs to alleviate clinical burden, improve patient experience, and drive appropriate and timely care. ED practice leaders can use models like this to allocate resources effectively, proactively manage staffing levels, and anticipate patient flow within the ED and ancillary support services to ensure optimal operational efficiency. Predictive capabilities will support proactive activation to mitigate potential issues before they arise. The utility of this will be invaluable for emergency department and hospital leaders who are facing similar resource constraints and community demand for services.

RESULTS

The analysis revealed 50% of the time was spent at green surge status, 38.3% at yellow surge condition, and 11.7% at red surge condition. Findings indicate that while both models can effectively predict surge conditions, the XGBoost outperformed the DNN. Results for the AUC for each surge level were excellent for Green and Yellow Surge levels, acceptable for Red, and the overall accuracy of the model was acceptable for machine learning standards.

FIGURE 1