EMERGENCY DEPARTMENT SURGE FORECASTING USING MACHINE LEARNING METHODS

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DESCRIPTION

Matching Emergency Department (ED) supply with demand is an immense challenge that, when unmet, leads to patients not receiving care in appropriate time frames. The capacity to predict such 'surge' scenarios would have invaluable impact on patients and staff. This work focuses on using Electronic Health Record (EHR) data to create a proof-of-concept machine learning (ML) model for anticipating surge events in the ED. The model relies on a composite of zone-specific patient arrival forecasting models that predict arrivals 3 hours in advance, and an individualized patient wait time prediction model that predicts patient wait times at triage. Patient arrival counts and waiting time inputs are combined into one thresholding system that enables early detection and proactive mitigation strategies for ED surge events (Figure 1).

OBJECTIVE

Predict surge events in the ED to help mitigate long waiting times.

ACTIONS TAKEN

A retrospective comparative analysis of ML models was conducted to select optimal predictors and model architectures for both the patient arrival forecasting and patient waiting time prediction models. This included a rigorous training and validation period, followed by out of sample testing to evaluate the model performance on 'unseen' data. The target prediction inputs, dependent variable selection and model performance benchmarking were discussed and validated with key ED management stakeholders. A retrospective analysis of physician on-call days was investigated as a proxy for surge events to determine adequate target thresholds for alerts.

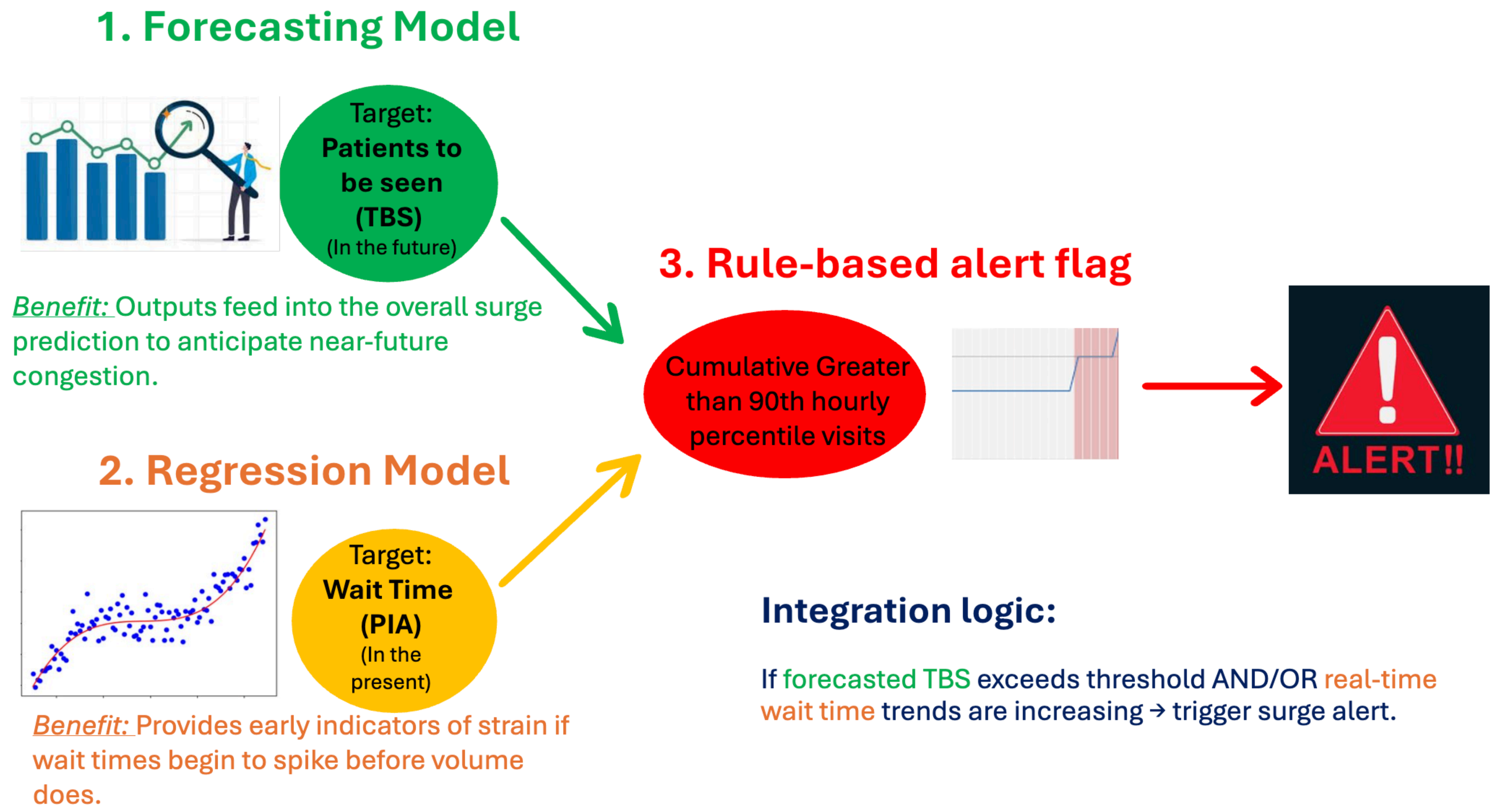

Figure 1. Diagrammatic representation of an integrated surge alert system relying on patient arrivals and wait times.

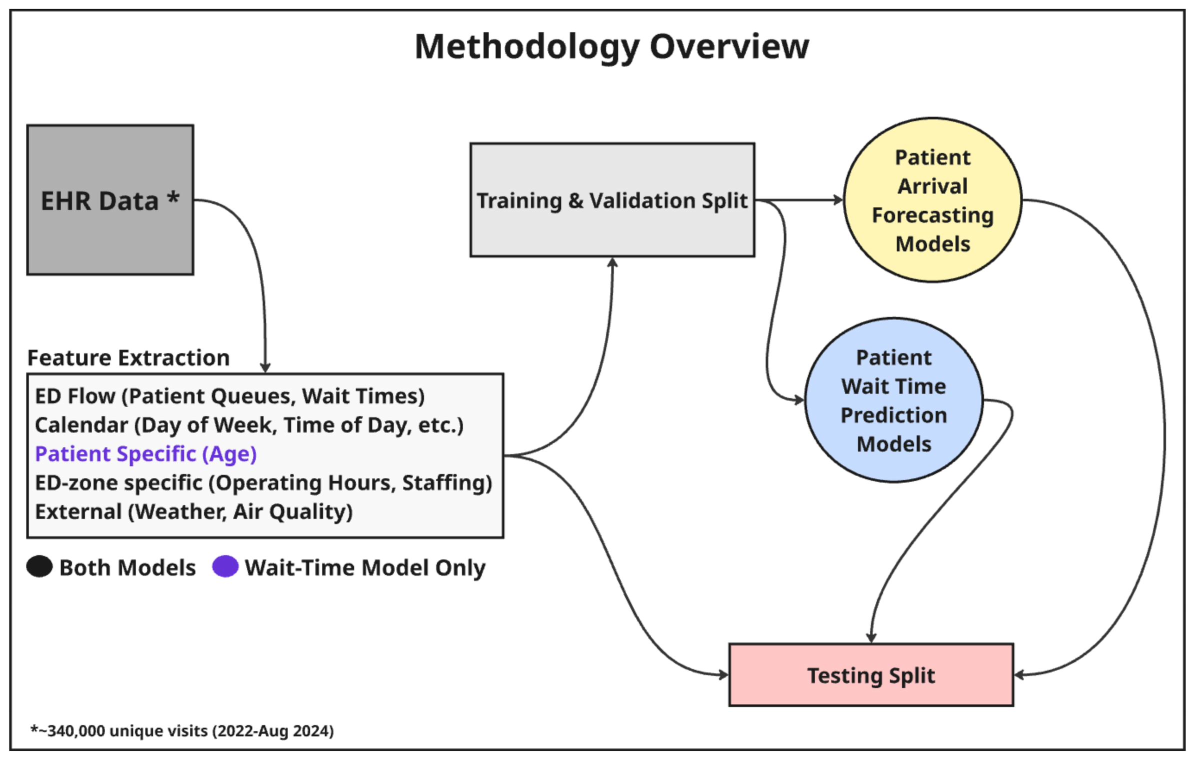

Figure 2. Overview of dataset characteristics, features used, and dataset partitioning.

Zone	Forecast Horizon (hours)	Model	Average MAE *	90th Percentile MAE *
FastTrack	1	SARIMA	2.40	3.55
	2	LSTM	2.80	4.64
	3	LSTM	3.60	6.25
OZone	1	SARIMA	2.94	3.63
	2	LSTM	3.49	4.95
	3	LSTM	4.16	6.53
Sub-Acute / Acute	1	SARIMA	1.90	2.58
	2	LSTM	2.23	3.36
	3	LSTM	2.84	4.37

Table 1. Patient arrival forecasting performance across an out-of-sample test set of 12 months. MAE = Mean Absolute Error; SARIMA = Seasonal Autoregressive Integrated Moving Average; LSTM = Long-Short Term Memory Neural network. * Averaged across 12 unique sliding window test set samples.

Zone	Model	Average MAE
FastTrack	Random Forest	36 minutes
OZone	XGBoost	42 minutes
Sub-Acute	Random Forest	63 minutes

Table 2. Individualized patient waiting time prediction results per zone; Acute zone is not applicable. MAE = Mean Absolute Error; XGBoost = eXtreme Gradient Boosting.

SUMMARY OF RESULTS

The average mean absolute error (MAE) for each of the patient arrival forecasting models was within a ±5 patients performance cut-off (Table 1). A large amount of variance was explained by historical values, with little explained via external variables (i.e. weather, air quality).

Patient waiting time is much more stochastic and difficult to predict, although aggregating predictions into a trend can be a useful indicator of system strain. MAE ranged from an average of 36 minutes in Fastrack, to 63 minutes in Sub-Acute (Table 2).

LESSONS LEARNED

ED arrivals and wait times can be predicted with reasonable accuracy using EHR data. Future work will prospectively investigate the utility of the chosen thresholds.

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