Stacked Ensemble Models for Multi-Department LOS Prediction in Geriatric Patients

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Purpose Efficient hospital management is increasingly important as aging populations increase demand for resources and service usage across departments. However the key metric for this service usage within departments, Length of Stay (LOS), varies widely even among patients with similar diagnoses due to comorbidities, treatment complexity, and departmental practices [1]. Existing LOS studies largely focus on single units such as ICU or surgical wards, providing limited generalizability across the full hospital stay [2]. Long and unpredictable LOS increases healthcare costs, reduces bed availability, and raises risks of complications [1]. These challenges are amplified for geriatric patients, who require multidisciplinary care and frequently move through multiple departments such as MICU and transplant units [2]. The absence of accurate, multi-department LOS prediction contributes to resource bottlenecks and delays in care for older adults [3]. Most current models ranging from Random Forests to deep learning architectures are built for isolated settings and do not capture the sequence of departmental transfers that strongly influence LOS [4]. The literature consistently reports poor cross-unit generalizability and significant departmental variability, resulting in fragmented models that fail to reflect real patient journeys [5]. This study addresses these gaps by developing multi-department LOS prediction models for geriatric patients using the MIMIC-IV v3.1 dataset. It aims to identify key care units, predict LOS for each department a patient enters, and provide actionable insights to support hospital planning, resource allocation, and care coordination. **Method** This study uses the MIMIC-IV Demo (v3.0) and Main (v3.1) datasets which contain hospital-wide and ICU-specific data for patients admitted to Beth Israel Deaconess Medical Center between 2008 and 2022 and adheres to HIPAA Safe Harbor de-identification standards [6]. Data are filtered to include geriatric patients aged ≥ 65, resulting in 143K patient profiles. Department-level LOS is computed by integrating admissions, diagnoses, and transfer tables for selected care units. Patient trajectories were constructed using subject_id, hadm_id, and stay_id, with missing timestamps, duplicates, and misaligned transfers cleaned. Machine learning methods employed for forecasting included Linear Regression, Ridge/Lasso, Random Forest, and Gradient Boosting. Individual application of each algorithm was contrasted with combining them into a stacked ensemble learner, which uses an additional meta-learner to dynamically adjust the weight of contribution of each forecast to a final aggregated result. **Results & Discussion** Table 1 lists the methods with the best results achieved after tailoring the approach for each department. R^2 results are reported on log-transformed service hours in order to convert long positive skews to a symmetric distribution. Emergency was the only department that lacked significant skewness, and had R^2 of 0.50 without this transformation. We are concurrently adapting this approach to work with interRAI data to forecast home care service usage by older adults in Canada.

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Table 1. Best Machine Learning Results by Department

Department	Best Method	Component Methods	MAE (hours)	R^2 (log hours)
Emergency	Stacked Learner	Random Forest, KNN, Ridge; Gradient Boosting (meta learner)	3.04	0.54
Hematology/Oncology	Gradient Boosting	N/A	75.69	0.61
Medicine	Weighted Voting	Gradient Boosting, Extra-Trees, Random Forest	49.14	0.64
Neurology	Extra-Trees	N/A	32.39*	0.62*

* - 95th percentile