Enhancing Patient Triage Efficiency and Capacity in Montanaro Hospital's Observation Unit

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Abstract

This paper investigates the operational inefficiencies within Montanaro Hospital's 23-bed Observation Unit (OU), specifically focusing on extended patient stays and the frequent transition of patients from observation to inpatient status (referred to as "flips"). Utilizing descriptive analytics and predictive modeling (Logistic Regression, Random Forest, Decision Tree), this study identifies key demographic and clinical factors contributing to patient flips. The findings indicate that factors such as normal temperature, prehypertension, and advanced age (81-90) are significant predictors of patient flips. Among the models tested, Random Forest demonstrated the highest accuracy (0.82) and sensitivity (0.88), making it the most suitable for predicting patient flips. This research proposes data-driven recommendations to optimize patient placement protocols, enhance OU utilization, and ultimately improve the efficiency and quality of care delivery at Montanaro Hospital.

1. Introduction

Observation Units (OUs) are critical components of modern healthcare systems, designed to provide short-term care, evaluation, and treatment for patients whose conditions are not severe enough to warrant immediate inpatient admission but require more monitoring than can be provided in an emergency department. The effective management of an OU is paramount to ensuring optimal patient flow, reducing healthcare costs, and improving patient outcomes. Montanaro Hospital's 23-bed Observation Unit, operational for just over a year, has encountered challenges related to extended patient stays and a high rate of patients transitioning from observation to inpatient status. Dr. Erin Kelly, the overseeing physician, has highlighted these issues as areas of concern, prompting a comprehensive review of existing protocols with the aim of enhancing patient placement procedures. This study seeks to address these challenges by leveraging data analytics to understand the contributing factors and develop a predictive model to identify patients at high risk of "flipping" to inpatient status, thereby optimizing OU efficiency and patient care.

2. Background and Problem Statement

The primary objective of an Observation Unit is to provide a cost-effective alternative to inpatient admissions for patients requiring a period of assessment and treatment, typically less than 24-48 hours. Successful OU operations depend on accurate patient triage and efficient management of length of stay (LOS). However, two significant challenges have been identified at Montanaro Hospital's OU:

1. **Extended Length of Stay:** Patients are staying longer than initially intended, leading to bed capacity issues and potential delays for new patients requiring observation care.
2. **Observation to Inpatient Movement ("Patient Flips"):** A substantial number of patients initially admitted to the OU are subsequently transitioned to inpatient status. This "flip" represents a misallocation of resources, as these patients could potentially have been admitted directly to inpatient units, streamlining their care pathway and freeing up OU beds.

These challenges collectively contribute to inefficient utilization of the Observation Unit, impacting patient flow, hospital capacity, and overall operational costs. Understanding the characteristics of patients who frequently "flip" is crucial for developing proactive strategies to improve initial patient placement decisions.

3. Objectives

The objectives of this study are:

- To conduct descriptive analytics to understand the demographic and clinical characteristics of patients admitted to Montanaro Hospital's Observation Unit.
- To identify the key variables that differentiate patients who stay in the OU from those who "flip" to inpatient status.
- To develop and evaluate predictive models capable of identifying patients at high risk of flipping from observation to inpatient status.
- To provide data-driven recommendations to Montanaro Hospital for optimizing patient triage protocols and enhancing the efficient utilization of its Observation Unit.

4. Methodology

4.1. Data Description

The dataset comprises 1111 observations with 17 variables relevant to patient demographics, clinical measurements, and outcomes from Montanaro Hospital's Observation Unit. The key variables include:

- **Age:** Age of Patient, in Years.
- **Gender:** Patient Gender (Male/Female).
- **Flipped:** Binary Variable (1 – Patient Flipped to Inpatient, 0 – Patient stayed in OU). This is the primary outcome variable.

- **OU_LOS_hrs:** Length of stay in OU in Hours.
- **DRG01:** Initial Diagnosis-Related Group.
- **BloodPressureLower (Diastolic) & BloodPressureUpper (Systolic):** Blood pressure measurements in mmHg.
- **BloodPressureDiff:** Difference between systolic and diastolic blood pressure.
- **Pulse:** Patient Pulse.
- **Pulse Oximetry:** Measure of level of Oxygen in patient blood.
- **Respirations:** Number of breaths patient takes per minute.
- **Temperature:** Temperature in Fahrenheit.
- **Temperature Category:** Categorization of temperature: <97 (Below Normal), ≥97 & ≤100 (Normal), >100 (Fever).
- **BP Category:** Categorization of blood pressure based on AHA/ACC guidelines:
    - Normal: sys < 120 & dia < 80
    - Elevated: sys ≥120 & sys ≤129 & dia < 80
    - Hypertension Stage 1: sys ≥130 & sys ≤139 & dia ≥80 & dia ≤89
    - Hypertension Stage 2: sys ≥140 & dia ≥90
    - Hypertensive Crisis: sys > 180 | dia > 120

4.2. Descriptive Analytics

Descriptive analytics were performed to summarize the dataset and identify initial patterns related to patient flips. This involved:

- Calculating the percentage of patients flipping from observation to inpatient status.
- Analyzing the distribution of flips across different categories for variables such as Temperature, Primary Diagnosis Group (DRG01), Age, and Blood Pressure.
- Summarizing the top categories contributing to patient flips.

4.3. Predictive Modeling

To predict patient flips, three machine learning models were developed and compared:

1. **Logistic Regression:** A linear model used for binary classification, suitable for predicting the probability of an event (patient flip) occurring.
2. **Random Forest:** An ensemble learning method that constructs a multitude of decision trees at training time and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. This method is robust to overfitting and can capture complex non-linear relationships.
3. **Decision Tree:** A non-parametric supervised learning method used for classification and regression. It partitions the data into subsets based on feature

values, creating a tree-like structure of decisions.

The models were evaluated based on the following performance metrics:

- **Baseline Accuracy:** The accuracy achieved by simply predicting the majority class (patients who did not flip). In this dataset, 53% of patients flipped to inpatient status, meaning the baseline accuracy for predicting "not flipped" would be 47%, and for "flipped" would be 53%. (Note: The provided baseline accuracy is 53%, indicating that 53% of patients *flipped*. Therefore, a baseline model that always predicts "flip" would have 53% accuracy).
- **Accuracy:** The proportion of correctly classified instances.
- **AUC (Area Under the Receiver Operating Characteristic Curve):** A measure of the model's ability to distinguish between classes. A higher AUC indicates better discriminatory power.
- **Sensitivity (Recall):** The proportion of actual positive cases (flipped patients) that were correctly identified.
- **Specificity:** The proportion of actual negative cases (patients who stayed in OU) that were correctly identified.
- **RMSE (Root Mean Squared Error) & MAE (Mean Absolute Error):** Error metrics typically used for regression, but sometimes adapted for classification error analysis, though generally, accuracy, AUC, sensitivity, and specificity are more directly applicable for binary classification.

5. Results

5.1. Overall Flip Rate

The analysis revealed that 46.1% of patients stayed in the OU (Flipped Status = 0), while **53.9% of patients flipped from observation to inpatient status** (Flipped Status = 1). This high flip rate underscores the need for improved triage protocols.

5.2. Analysis of Patient Flips by Category

Temperature Category:
Patients with "Normal Temperature" constituted the largest group among flipped patients, with 449 patients flipping (87.70% of all flips). This suggests that a normal temperature alone is not a strong indicator that a patient will remain in the OU.
Primary Diagnosis Group (DRG01):
"Syncope" emerged as the primary diagnosis group with the highest number of flips, followed by "Dehydration" and "Chest Pain". This highlights specific medical conditions that frequently lead to inpatient admissions from the OU.
Blood Pressure Category:
"Prehypertension" (referred to as "Elevated" in the BP Category definition) accounted for 250 flipped patients (48.83% of all flips). This group also showed a significant proportion of flips,

indicating that patients in this category might require closer scrutiny during initial triage.
Age Category:
The "Age 81-90" category showed the highest number of flips (205 patients, 40.04% of all flips), suggesting that older patients are more prone to requiring inpatient care after an initial OU admission. As age increases, the number of flipped patients also appears to increase, with the "90+" category having a relatively high proportion of flips despite a smaller overall count.

5.3. Flipped Patient Summary - Top 3 Categories

Category	No. Flipped	% Flipped (of total flips)
Normal Temperature	449	87.70%
Prehypertension	250	48.83%
Age 81-90	205	40.04%

5.4. Model Performance

The performance of the predictive models is summarized below:

Model	Baseline Accuracy	Accuracy	AUC	Sensitivity	Specificity	RMSE	MAE
Logistic Regression	53%	0.76	0.84	0.70	0.82	0.41	0.28
Random Forest	53%	0.82	0.76	0.88	0.82	0.42	0.18
Decision Tree	53%	0.77	0.73	0.82	0.78	0.49	0.23

Key Observations from Model Performance:

- **Accuracy:** Random Forest achieved the highest accuracy at 0.82, significantly outperforming the baseline accuracy of 0.53. Logistic Regression was next at 0.76, and Decision Tree at 0.77.
- **AUC:** Logistic Regression showed the highest AUC of 0.84, indicating its strong ability to discriminate between flipped and non-flipped patients. Random Forest had an AUC of 0.76, and Decision Tree 0.73.

- **Sensitivity:** Random Forest exhibited the highest sensitivity (0.88), meaning it was most effective at correctly identifying patients who would ultimately flip to inpatient status. This is crucial for proactive intervention.
- **Specificity:** Both Logistic Regression and Random Forest had high specificity (0.82), indicating their effectiveness in correctly identifying patients who would remain in the OU.
- **Error Metrics (RMSE, MAE):** Random Forest had the lowest MAE (0.18), indicating smaller average absolute errors in its predictions, even though RMSE for Random Forest (0.42) was slightly higher than Logistic Regression (0.41).

Considering the objective of identifying patients at risk of flipping to allow for proactive intervention, the high sensitivity of the **Random Forest model (0.88)** makes it the most suitable choice despite Logistic Regression having a slightly higher AUC. A high sensitivity ensures that a large proportion of actual flips are caught early, which is paramount for improving triage efficiency.

6. Discussion

The findings from this study provide valuable insights into the factors driving patient transitions from Montanaro Hospital's Observation Unit to inpatient status. The high flip rate of 53.9% highlights a significant opportunity for optimizing patient placement.

The descriptive analysis revealed several critical factors associated with patient flips:

- **Normal Temperature:** The observation that a large proportion of flipped patients had normal temperatures suggests that temperature alone is insufficient for ruling out the need for inpatient care. Other clinical indicators must be given more weight during triage for patients presenting with normal body temperature.
- **Prehypertension and Hypertension:** Patients categorized with prehypertension or hypertension stages showed a substantial propensity to flip. This indicates that even moderately elevated blood pressure readings might be an early warning sign for underlying conditions that could necessitate inpatient admission. Closer monitoring or a more conservative approach to OU admission for these patients might be warranted.
- **Advanced Age:** The increasing trend of flips with age, particularly in the 81-90 age bracket, underscores the vulnerability of elderly patients. Older individuals often present with multiple comorbidities and less clear-cut symptoms, making their initial assessment and observation challenging. This finding suggests that a more comprehensive geriatric assessment should be integrated into the triage process for older patients.
- **Specific Diagnoses:** Conditions like Syncope, Dehydration, and Chest Pain

frequently led to flips. This implies that while these conditions may initially appear suitable for observation, their underlying complexities often necessitate inpatient care. Developing specific protocols or more stringent admission criteria for these DRG groups could reduce unnecessary OU admissions.

The performance of the predictive models further supports the utility of data-driven approaches in healthcare operations. The Random Forest model, with its superior sensitivity, offers a robust tool for early identification of at-risk patients. By predicting a high probability of flipping, Montanaro Hospital can adjust initial triage decisions, potentially admitting these patients directly to inpatient units, thereby reducing the burden on the OU and ensuring more appropriate care from the outset. This pre-emptive approach can lead to:

- **Improved OU Capacity:** By reducing unnecessary OU admissions for patients likely to flip, more beds become available for suitable observation cases.
- **Enhanced Patient Experience:** Patients who are directly admitted to inpatient units avoid the uncertainty and potential re-evaluations associated with "flipping" from the OU, leading to a smoother care journey.
- **Optimized Resource Allocation:** Direct inpatient admission for high-risk patients can streamline the use of hospital resources, including nursing staff, diagnostic services, and specialized care.

While the Random Forest model showed excellent sensitivity, the slightly lower AUC compared to Logistic Regression warrants consideration. This could be due to the nature of the data or the specific characteristics of the Random Forest algorithm in this context. However, for a scenario where minimizing false negatives (missing a flip) is critical, high sensitivity is often prioritized.

7. Recommendations

Based on the analysis, the following recommendations are proposed to enhance patient triage efficiency and capacity at Montanaro Hospital's Observation Unit:

1. **Implement a Predictive Analytics Tool:** Integrate the Random Forest model (or a similar high-performing predictive model) into the triage workflow. This tool should provide a real-time probability of a patient flipping to inpatient status based on their initial demographic and clinical data.
   - **Action:** Develop a user-friendly interface for the model, possibly as part of the Electronic Health Record (EHR) system, to assist emergency department physicians and OU staff in making informed admission decisions.
2. **Refine Triage Protocols for High-Risk Groups:**
   - **Temperature Category:** While normal temperature is common among flipped

patients, it should not be the sole determinant for OU admission. Triage protocols should emphasize other critical vital signs, comorbidities, and clinical presentation for patients with normal temperatures.
    - **Blood Pressure Categories:** Develop more stringent guidelines for OU admission or increased monitoring for patients presenting with "Elevated," "Hypertension Stage 1," or "Hypertension Stage 2" blood pressure readings.
    - **Age-Specific Protocols:** Implement enhanced geriatric assessment criteria for older patients (especially those 81-90 and above) being considered for OU admission, acknowledging their higher risk of requiring inpatient care.
    - **Diagnosis-Specific Pathways:** Create specialized pathways for patients presenting with high-flip DRG01 groups like Syncope, Dehydration, and Chest Pain. These pathways could involve more immediate consultation with inpatient specialists or direct admission criteria.
3. **Continuous Monitoring and Feedback Loop:**
    - **Regular Audits:** Conduct regular audits of patient flip rates and OU length of stay to assess the effectiveness of new protocols.
    - **Performance Metrics:** Continuously monitor the performance of the predictive model and retrain it periodically with new data to maintain its accuracy and relevance.
    - **Staff Training:** Provide ongoing training for clinical staff on the revised triage protocols and the effective utilization of the predictive analytics tool. Emphasize the importance of accurate data entry for model efficacy.
4. **Explore Alternative Care Models:** For patients identified as high risk for flipping but who may not immediately require acute inpatient care, investigate intermediate care options or expanded home healthcare services to reduce unnecessary inpatient admissions.

8. Conclusion

The analysis of Montanaro Hospital's Observation Unit data reveals significant opportunities for improving patient triage and unit capacity. The high rate of patient flips underscores the need for a more predictive approach to patient placement. By identifying key demographic and clinical risk factors and deploying a robust predictive model like Random Forest, the hospital can proactively identify patients likely to require inpatient care. Implementing the proposed data-driven recommendations will enable Montanaro Hospital to optimize its OU operations, enhance patient flow, reduce healthcare costs, and ultimately deliver more efficient and appropriate care to its patient population. This study demonstrates the power of integrating data analytics and machine learning into healthcare operations to drive tangible improvements in patient care delivery and resource utilization.

References

(Note: Specific references would be added here based on a comprehensive literature review for a full publication. For this generated paper, these are placeholders.)

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