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A Preliminary Exploration of Predicting Length of Stay at a Certain Medical Center Using Machine Learning Methods

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INTRODUCTION

Efficient patient flow management, including bed and capacity optimization, is a critical aspect of healthcare operations. Accurate prediction of **patient length of stay (LOS)** facilitates proactive scheduling by clinical staff, preventing backlogs and denials for future appointments or admissions. Recent advancements in machine learning, such as Random Forest Regression and eXtreme Gradient Boosting (XGBoost) Regression, have found application in healthcare.

Established in 1982, a prominent medical center in Taiwan boasts 1,600 beds, 6,000 employees, and handles over 9,000 outpatient visits daily, along with over 6,000 inpatient visits monthly. This study aims to **employ machine learning techniques to forecast patient LOS**, contributing to the hospital's digital transformation and operational decision-making.

AIM

This study aims to evaluate and optimize predictive models for estimating LOS in a hospital setting using machine learning regression techniques.

The primary focus is on **comparing the performance of three regression models**—Random Forest, XGBoost, and Logistic Regression—across different LOS groups (≤14 days, ≤30 days, and ≤90 days).

Additionally, the study seeks to **determine the impact of hyperparameter tuning** on the predictive accuracy of these models, particularly in the dataset where LOS is ≤ 14 days, and to **identify the most important features** influencing the LOS predictions.

RESULTS

1.The **ANOVA** test results for the MAE among the 3 regression models and 3 LOS groups showed a significant difference, with an **F-value of 143.131 and p < 0.001**.

2.Among 3 regression models, analyzing the dataset where LOS ≤ 14 days yielded a smaller MAE, with a statistically significant difference compared to LOS ≤ 30 and LOS ≤ 90 days, in Scheffe post-hoc tests.

3.In **Scheffe post-hoc** tests, Random Forest and XGBoost Regression models, with a smaller MAE compared to the Logistic Regression model, reaching statistical significance. However, the difference between the Random Forest and XGBoost Regression models did not reach statistical significance. MAE statistics for LOS groups and regression models are shown in **Table 1**.

4.Applying the Random Forest Regression model to the dataset where LOS ≤ 14 days, we conducted hyperparameter tuning with n_estimators=200 and max_depth=30, resulting in a significant reduction in MAE compared to the default setting (t= -2.7191, p=0.0066).

5.Employing the XGBoost Regression model on the dataset where LOS ≤ 14 days, we adjusted the hyperparameters with n_estimators=200, max_depth=9, and learning_rate=0.2, leading to a decrease in MAE compared to the default setting, although it did not reach statistical significance (t= -0.0245, p=0.9804).

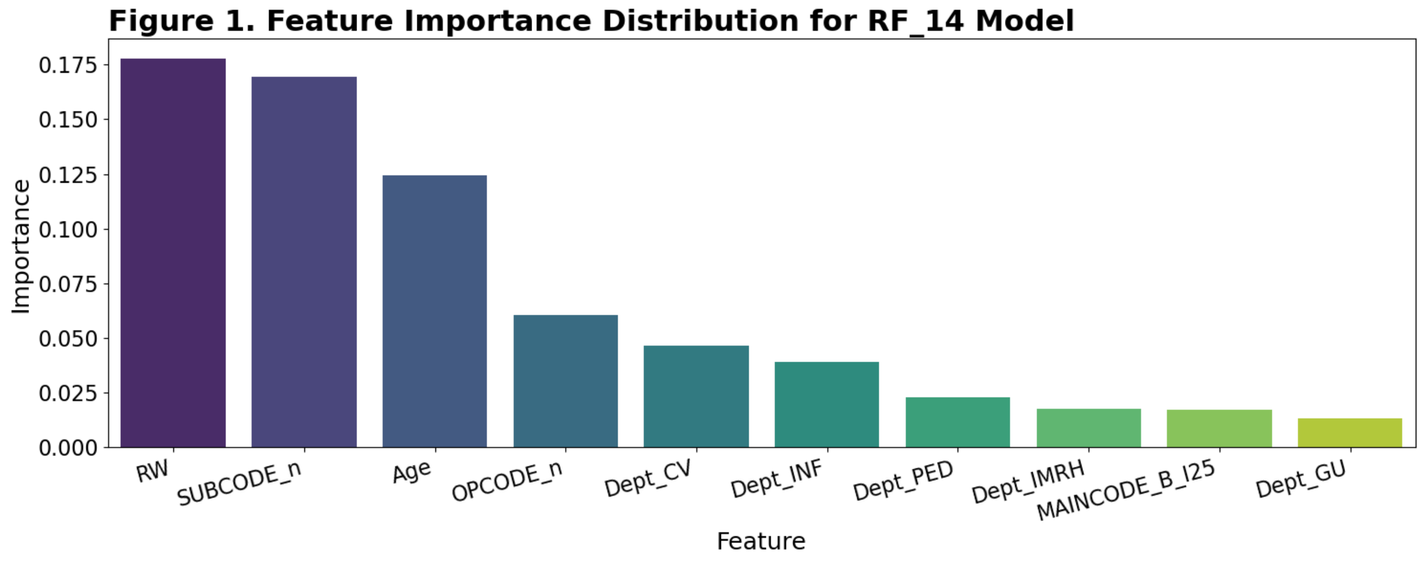
6.Consequently, we employed the dataset with **LOS ≤ 14 days**, using the **Random Forest Regression** model with **hyperparameters n_estimators=200** and **max_depth=30**, achieving the **minimization of MAE**.

7.The feature importance of this model, as shown in **Figure 1**, lists the top 5 features as follows: **RW** (0.1778), **number of secondary diagnoses** (0.1693), **age** (0.1244), **number of procedure codes** (0.0604), and **Department of Cardiology** (0.0467).

Table 1. MAE Statistics for LOS Groups and Regression Models

Group	n	Mean	Std	Model	MAE	Model	MAE	Model	MAE
LOS ≤ 14	19,487	3.9485	3.1261	LogReg_14	1.9918	RF_14	1.4524	XGB_14	1.4706
LOS ≤ 30	20,858	5.0271	5.2002	LogReg_30	3.2176	RF_30	2.2235	XGB_30	2.1852
LOS ≤ 90	21,308	5.8446	7.8044	LogReg_90	3.6718	RF_90	2.5924	XGB_90	2.5780

Figure 1. Feature Importance Distribution for RF_14 Model



METHOD

The data for this study were sourced from medical records of patients discharged from **January to July 2023**, totaling **21,308 cases** with Diagnostic Related Groups (DRG) code in the medical center. The variables included in the analysis comprised patient LOS, gender, age, department, relative weight (RW) of DRG code, principal diagnosis, secondary diagnoses, and procedure codes. The study compared patient LOS predictions by selecting the best model and tuning its hyperparameters to **minimize the Mean Absolute Error** (MAE). **Logistic Regression** (as a reference method), **Random Forest Regression**, and **XGBoost** (eXtreme Gradient Boosting) **Regression** models were employed.

Under each regression model, the datasets were further divided into 3 groups for comparison: **LOS ≤ 14 days** (consistent with the definition for quality indicators of patient readmission), **LOS ≤ 30 days**, and **LOS ≤ 90 days** (two definitions of overstay). The predictive performance, measured by MAE, was assessed using **ANOVA** tests and **Scheffe post-hoc** tests. Graphical representation and statistical analysis were conducted using Visual Studio Code (version 1.85) to write **Python** codes.

CONCLUSIONS

In contrast to traditional studies that typically focus on specific departments or diseases, our research employs advanced machine learning techniques for a **hospital-wide patient LOS forecast**, driven by advancements in AI and digital transformation.

Our approach, based on digital health data, offers potential for automation and can be used more widely. The medical center envisions integrating this technology into daily management practices, streamlining bed allocations, enhancing efficiency of patient flow, and ensuring optimal care for patients in the future.

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