School of Business
OPIM 5604: Predictive Modeling
Evaluating Model Performance

Diabetes Care in U.S. Hospitals: Predicting Early Readmission for Better Outcomes

Executive Summary

Vinay Kiran Reddy Chinnakondu vinay_kiran_reddy.chinnakondu@uconn.edu

Problem Statement

Our large dataset, spanning a decade from 1999 to 2008 and including 130 U.S. hospitals, is dedicated to patients diagnosed with diabetes. Despite the proven benefits of preventative and therapeutic treatments, the dataset highlights inconsistent care across hospitals, resulting in suboptimal diabetes control. The consequence of such variability includes increased readmission costs, patient complications, and elevated morbidity or mortality rates.

Consisting of 101,766 rows and 50 columns, each representing hospitalized patient records, the dataset provides a comprehensive view of diabetes management. Patient details, admission information, physician specialty, lab tests, HbA1c results, diagnosis, medication history, and prior-year outpatient, inpatient, and emergency visits are included for patients who stayed up to 14 days. The primary objective is to evaluate early readmission within 30 days of discharge, serving as a key metric to identify potential issues in diabetes management. This analysis aims to contribute valuable insights into enhancing the quality and effectiveness of care for diabetic patients, ultimately improving outcomes, and reducing associated healthcare costs.

Observations

In our study, we prioritized key metrics critical for reducing false negatives and correctly predicting patient readmissions. Our main focus was on sensitivity and the accuracy of 1 to reliably identify patients likely to need readmission. We compared different models and found that the Neural Network was the most effective, although it was not the most accurate overall. It struck the best balance between cost-effectiveness and high sensitivity, excelling in identifying true positive cases. While the Logistic model was also cost-effective, it fell short in sensitivity by 15% compared to the Neural Network with a 45% cutoff. This difference was crucial in our decision to go with the Neural Network where it exhibited the best model cost thus far. The analysis also highlighted a notable pattern where patients aged 20 to 30 years, with blood glucose levels over 300 mg/dL, and a history of previous admissions were at a significantly higher risk of readmission.

Recommendations and Conclusions

Our findings demonstrate the model's utility for both healthcare providers and insurance companies. Healthcare providers can leverage the model to identify the top 20% of patients at the highest risk of readmission, allowing for better allocation of resources like staff time and follow-up care. For insurance companies, the model facilitates the categorization of patients into risk tiers, leading to more accurate premium pricing and the development of risk-adjusted policies. Furthermore, insurance companies can incentivize hospitals to lower readmission rates through the creation of reward-based policies.

Overall, the choice of the Neural Network model represents a strategic decision that balances diagnostic precision, potential health impact, and cost-effectiveness. This approach aligns with our aim of enhancing patient outcomes and resource management in healthcare, while also enabling insurance companies to formulate better policies based on nuanced risk assessments.