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Risk Assessment for Hospital Readmissions: Insights from Machine Learning Algorithms

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Abstract

Hospital readmissions have become a major concern for healthcare providers due to their impact on patient outcomes and healthcare costs. In recent years, there has been a growing interest in using machine learning algorithms to identify factors associated with hospital readmissions and improve risk assessment. This research presents the results of a study analyzing hospital readmissions using a dataset of 130 US hospitals for years 1999-2008. Three machine learning algorithms were used to identify factors associated with hospital readmissions: random forest, XGBoost, and decision tree. The results of the study showed that the most important factor across all three algorithms was the number of emergency room visits in the year before hospitalization. The second most important factor was the number of lab procedures performed during the hospital stay. The third most important factor varied among the three algorithms, with ChangeMedication (change in diabetes medication) being important in random forest and XGBoost, while MedPrescribed (diabetes medication prescribed) was important in decision tree. Interestingly, age was found to be the least important factor in all three algorithms. These findings suggest that changes in medication and the number of emergency room visits and lab procedures may be key factors in predicting hospital readmissions. Healthcare providers can use these findings to develop comprehensive risk assessments that take into account a wide range of factors, including medication changes, prior healthcare utilization, and current healthcare needs. By analyzing readmission to develop targeted interventions and care plans, healthcare providers can help reduce the risk of hospital readmissions and improve the overall quality of care for patients.

Keywords: Hospital readmissions, Machine learning algorithms, Healthcare costs, Emergency room visits, Medication changes, Risk assessment

Introduction

High rates of readmissions can be a sign of inadequate discharge planning, poor communication between healthcare providers, and a lack of follow-up care, all of which can result in negative patient outcomes. By reducing hospital readmissions, healthcare providers can improve patient outcomes, decrease healthcare costs, and improve overall healthcare quality.

Hospital readmissions refer to the instances when a patient is discharged from a hospital and subsequently admitted back into the hospital within a specified timeframe. The timeframe is typically set at 30 days or less, although it can be longer in certain cases.

Hospital readmissions have become a significant concern in the healthcare industry due to their potential consequences. When a patient is readmitted to the hospital shortly after being discharged, it can have various negative impacts on both the patient and the healthcare system. In this essay, we will explore the consequences of hospital readmissions in detail, including increased healthcare costs, negative impact on patient outcomes, lower quality of life for patients, and potential harm to patients.

Firstly, hospital readmissions can lead to increased healthcare costs. When patients are readmitted to the hospital, they require additional medical attention and resources, which increases healthcare costs. Furthermore, hospitals may also face financial penalties for excessive readmissions. Medicare and Medicaid, for instance, penalize hospitals that have high readmission rates by reducing their reimbursements. As a result, hospitals are incentivized to reduce their readmission rates to avoid financial penalties.

Secondly, hospital readmissions can have a negative impact on patient outcomes. When a patient is readmitted to the hospital, it often means that their initial treatment was not effective. This can result in a delay in receiving appropriate treatment, which can exacerbate their condition. Additionally, patients who are readmitted to the hospital are more likely to experience complications, such as infections and adverse drug reactions. This can lead to longer hospital stays and further health complications. Furthermore, readmitted patients may be at higher risk of mortality than patients who are not readmitted.

Thirdly, hospital readmissions can lead to lower quality of life for patients. When patients are readmitted to the hospital, they are often separated from their families and friends, which can result in feelings of loneliness and isolation. Additionally, readmitted patients may experience a decline in their physical and mental health, which can negatively impact their quality of life. Patients who are readmitted to the hospital may also experience financial difficulties, as they may be unable to work or provide for their families during their hospitalization.

Finally, hospital readmissions can potentially harm patients. Patients who are readmitted to the hospital may be at higher risk of developing healthcare-associated infections, such as MRSA and C. difficile. These infections can be difficult to treat and can lead to further health complications. Additionally, readmitted patients may be at higher risk of medication errors, which can lead to adverse drug reactions and other complications. Patients who are readmitted to the hospital may also experience psychological harm, such as anxiety and depression, which can further worsen their condition.

Machine learning algorithms have become increasingly important in the field of healthcare management. These algorithms enable healthcare providers to analyze vast amounts of data and extract meaningful insights, improving patient care and outcomes. One of the primary applications of machine learning in healthcare management is in the area of predictive analytics. By analyzing patient data, including medical history, symptoms, and genetic information, machine learning algorithms can predict the likelihood of disease onset or progression, allowing healthcare providers to take proactive measures to prevent or treat the disease. This is especially important for chronic diseases like diabetes, heart disease, and cancer, where early detection and treatment can significantly improve patient outcomes. Machine learning algorithms can also be used to identify patients who are at risk of readmission, enabling healthcare providers to take preventive measures and reduce hospital readmission rates.

Materials and Methods

The dataset represents a period of 10 years, specifically from 1999 to 2008, and comprises clinical data from 130 hospitals and integrated delivery networks in the United States. The dataset contains over 50 features, each of which represents different patient and hospital outcomes. The data was extracted from the database, with specific criteria being applied to ensure the relevance of the information. The encounters included in the dataset had to meet several criteria: (1) they had to be inpatient encounters, which means hospital admissions; (2) the patient had to have received a diabetes diagnosis of some kind during the admission; (3) the length of stay had to be between one and 14 days; (4) laboratory tests had to be performed during the encounter; and (5) medications had to be administered during the encounter. The dataset includes numerous attributes, such as patient number, race, gender, age, admission type, time spent in the hospital, medical specialty of the admitting physician, the number of lab tests performed, HbA1c test results, diagnosis, the number of medications administered, diabetic medications, and the number of outpatient, inpatient, and emergency visits in the year prior to hospitalization.

Table 1. Features

Feature	Notation	Impact on readmission
Age bracket	Age of the admitted	Older patients may have higher readmission rates.
Time in hospital	Time	Longer stays may increase readmission rates.
Number of procedures performed during the hospital stay	NumProcs	Higher number of procedures may increase readmission rates.
Number of lab procedures performed during the hospital stay	NumLabProcs	Higher number of lab procedures may indicate more severe illness, increasing readmission rates.
Number of medications administered during the hospital stay	NumMeds	Higher number of medications may indicate more complex conditions, increasing readmission rates.
Number of outpatient visits visits in the year before the hospital stay	NumOutpatient	Higher number of visits may indicate a higher risk of readmission.
Number of inpatient visits visits in the year before the hospital stay	NumInpatient	Higher number of visits may indicate a higher risk of readmission.
Number of ER visits in the year before the hospital stay	NumER	Higher number of visits may indicate a higher risk of readmission.
Specialty of admitting physician	AdmittingSpecialty	Physician specialty may affect treatment decisions and readmission rates.
Primary diagnosis	PrimaryDiagnosis	Certain diagnoses may have higher readmission rates.

Secondary diagnosis	SecondaryDiagnosis	Multiple diagnoses may indicate more complex conditions, increasing readmission rates.
Additional secondary diagnosis	AdditionalSecondaryDiagnosis	Additional diagnoses may indicate more severe illness, increasing readmission rates.
Glucose serum level	GlucoseSerum	High glucose levels may indicate uncontrolled diabetes and increase readmission rates.
A1C level	A1C	High A1C levels may indicate uncontrolled diabetes and increase readmission rates.
Change in diabetes medication	ChangeMedication	Changes in medication may indicate uncontrolled diabetes and increase readmission rates.
Diabetes medication prescribed	MedPrescribed	Prescribing medication may reduce the risk of readmission.

In our data preprocessing stage, we first examined the skewness of the data to ensure that the distribution was roughly symmetrical. To unskew the data and make it more normally distributed, a log transformation was performed. We also addressed missing values in the data by replacing them with the mean. This helped to ensure that we were not introducing bias into our analysis due to missing data. Additionally, to facilitate the analysis of the data, we standardized the features by removing the mean and scaling to unit variance. This ensured that each feature was given equal importance in the analysis. Finally, we created a pipeline that assembled several steps to be cross-validated together. By setting different parameters, we were able to optimize our analysis and improve the accuracy of our results.

This study applied 3 machine learning techniques, namely, Decision Tree, Random Forest, and XGBoost. Decision tree is a popular and simple machine learning algorithm that is used for both regression and classification problems. The algorithm works by creating a tree-like model of decisions and their possible consequences, where each node represents a decision based on a feature, and each branch represents the outcome of the decision. Decision trees are easy to understand and interpret, making them popular among data scientists and machine learning practitioners.

One of the key features of the decision tree algorithm is its ability to handle both categorical and continuous data. The algorithm can handle categorical data by splitting the data based on the values of the categorical variable, and can handle continuous data by choosing a split point that maximizes the information gain or reduces the impurity of the data. The algorithm can also handle missing data by either imputing the missing values or ignoring the missing values in the split.

Another important feature of the decision tree algorithm is its interpretability. Decision trees can be visualized as a tree-like structure, where each node represents a decision based on a feature and each branch represents the outcome of the decision. This makes it easy to understand and interpret the model, and can help in identifying the most important features in a given problem.

One of the limitations of decision trees is their tendency to overfit the data. Overfitting occurs when the model is too complex and fits the training data too closely, resulting in poor generalization performance on new data. To address this problem, various methods such as pruning and regularization have been developed to reduce the complexity of the model and improve its generalization performance.

Random Forest is a type of ensemble learning algorithm that combines multiple decision trees to make predictions. The algorithm works by building multiple decision trees using random subsets of the training data and features. The random selection of data and features reduces overfitting and improves the accuracy of the model. The predictions of the individual decision trees are then combined to produce a final prediction. The Random Forest algorithm is known for its high accuracy, robustness, and scalability.

One of the key features of the Random Forest algorithm is the concept of bagging. Bagging is short for bootstrap aggregating and involves creating multiple subsets of the training data by resampling with replacement. Each subset is used to train a decision tree, and the final prediction is the average prediction of all the decision trees. This technique helps to reduce the variance of the model and improve its accuracy. In addition, Random Forest also incorporates the concept of feature bagging, which involves selecting a random subset of features for each decision tree. This technique helps to reduce the correlation between the trees and improve the diversity of the model.

Random Forest is also known for its interpretability and feature importance analysis. The algorithm can provide information on which features are most important in making predictions. This can be useful in identifying the most relevant variables in a given problem and understanding the underlying relationships between the features and the outcome variable. In addition, Random Forest can handle both categorical and continuous data, making it a versatile algorithm for a wide range of problems. The algorithm can also be used for regression and classification problems, making it a popular choice for many data scientists and machine learning practitioners.

XGBoost, short for Extreme Gradient Boosting, is a powerful and highly popular machine learning algorithm that is used for both regression and classification problems. It is an ensemble learning algorithm that combines multiple weak learners to form a stronger learner. The algorithm works by building a series of decision trees, where each subsequent tree tries to correct the errors made by the previous trees. The key to XGBoost's success lies in its ability to handle complex and highly correlated data, and its robustness to noisy and missing data.

One of the main features of XGBoost is its optimization function, which uses a gradient descent algorithm to minimize the loss function and improve the accuracy of the model. The gradient descent algorithm calculates the gradients of the loss function with respect to each parameter, and updates the parameters in the direction of steepest descent. This optimization function, coupled with the use of decision trees, helps to reduce bias and variance and improve the accuracy of the model. In addition, XGBoost uses a regularization term that penalizes complex models, preventing overfitting and improving the generalization performance of the model.

Results

The study compared the performance of three machine learning algorithms - random forest, XGBoost, and decision tree - in predicting hospital readmission. The analysis was conducted on a dataset with 25,000 observations. The results reported in table 1 showed that the random forest algorithm performed the best with an R-squared value of 0.978 and an RMSE of 0.074. These metrics suggest that the model has a high level of accuracy in predicting hospital readmission.

The XGBoost algorithm also performed well in predicting hospital readmission, with an R-squared value of 0.975 and an RMSE of 0.079. However, its performance was slightly lower than that of the random forest algorithm. Nonetheless, these results indicate that XGBoost can be an effective tool in predicting hospital readmission.

In contrast, the decision tree algorithm had a lower R-squared value of 0.777 and a higher RMSE of 0.236. These metrics suggest that the model may not be as accurate in predicting hospital readmission compared to the other two algorithms.

Table 2. Performances

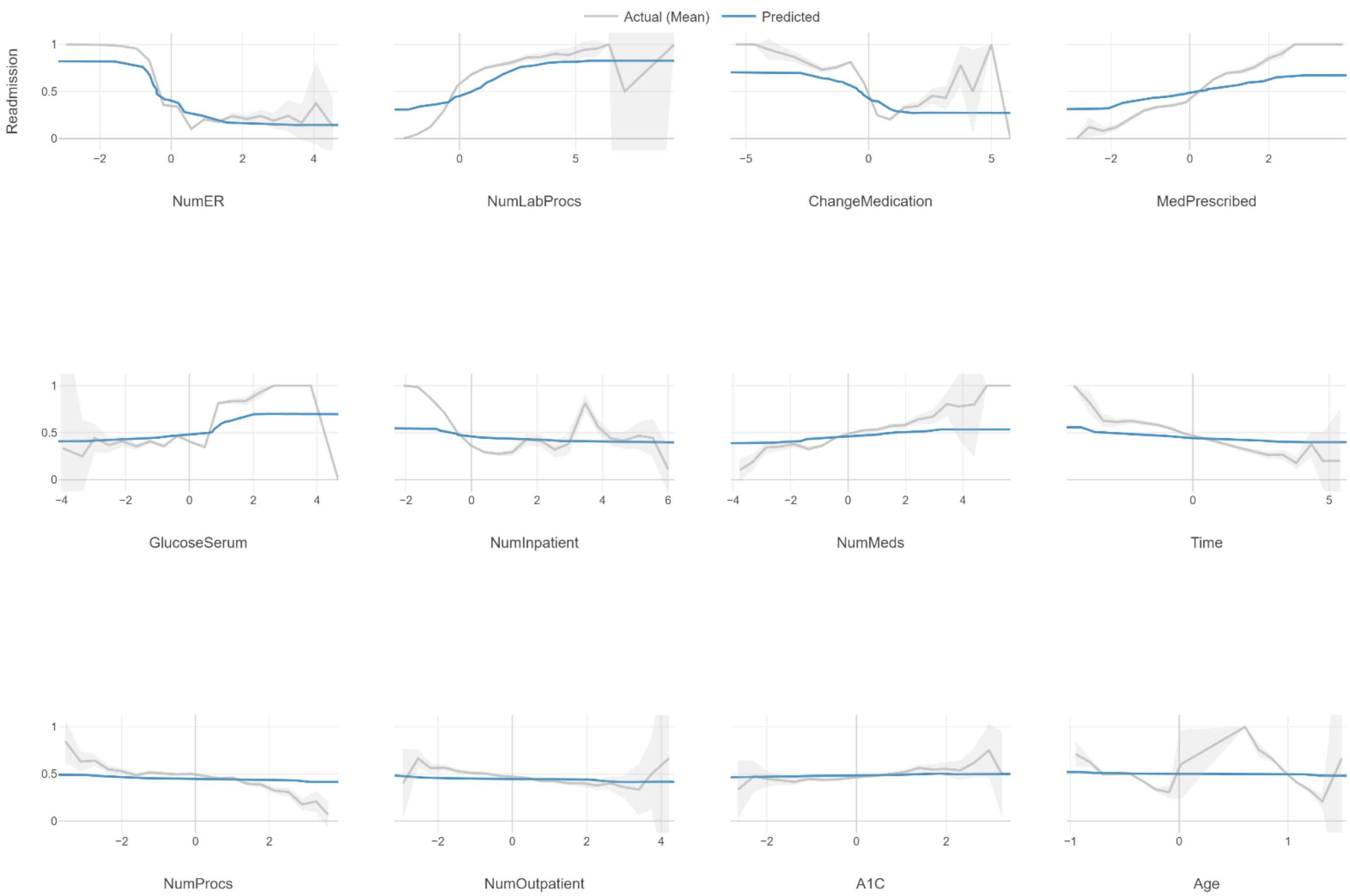
Model	R Squared	RMSE	Number of Rows
Random Forest	0.978019	0.073998	25000
XGBoost	0.974752	0.079307	25000
Decision Tree	0.777205	0.235585	25000

The results of this study highlight the importance of the feature NumER (Number of Emergency room visits in the year before the hospital stay) in predicting hospital readmission. Interestingly, this feature was found to be the most important in all three machine learning algorithms - random forest, XGBoost, and decision tree. This suggests that the number of emergency room visits in the year before hospitalization is a strong predictor of future hospital readmissions. This finding is particularly important for healthcare providers, as it suggests that patients with a high number of emergency room visits may require additional monitoring and care to prevent future hospital readmissions.

One possible explanation for the importance of the NumER feature is that it may be indicative of underlying chronic conditions or health issues that require ongoing management. Patients with chronic conditions may be more likely to require emergency room visits, and may also be at higher risk of hospital readmission. By identifying patients with a high number of emergency room visits, healthcare providers can take proactive steps to manage their conditions and prevent future hospitalizations.

The finding that NumER was the most important feature in all three machine learning algorithms also suggests that this feature is robust and reliable. Different machine learning algorithms may have varying levels of complexity and predictive power, but the fact that they all identified NumER as the most important feature suggests that it is a strong predictor of hospital readmission across different modeling techniques. This adds to the growing body of evidence supporting the use of emergency room visit data as a tool for predicting hospital readmissions, and highlights the potential value of this data for healthcare providers seeking to improve patient outcomes and reduce healthcare costs.

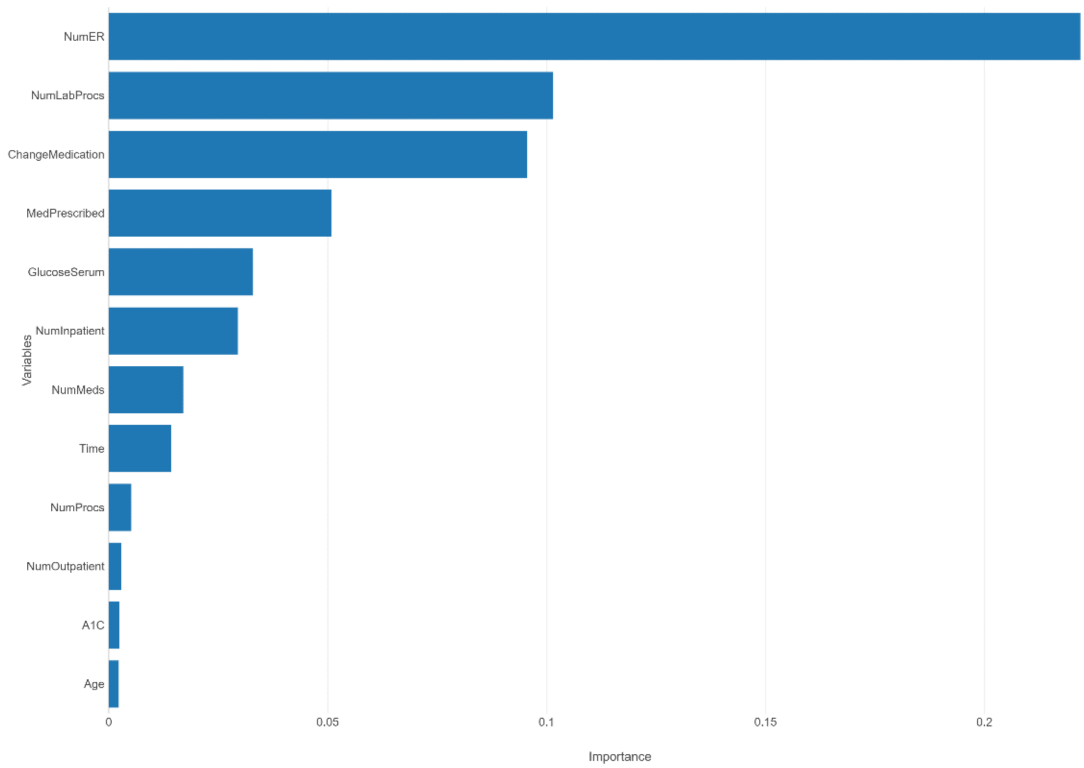
Figure 1. Random Forest prediction



The results of this study also identified NumLabProcs (Number of lab procedures performed during the hospital stay) as the second most important feature in all three machine learning algorithms - random forest, XGBoost, and decision tree. This finding suggests that the number of lab procedures performed during hospitalization may be an important predictor of future hospital readmissions. One possible explanation for this is that patients who require a high number of lab procedures may have more complex medical conditions or may require more intensive medical interventions. By identifying patients with a high number of lab procedures, healthcare providers can take proactive steps to manage their conditions and prevent future hospitalizations.

The finding that NumLabProcs was the second most important feature in all three machine learning algorithms highlights the robustness of this feature in predicting hospital readmissions. It suggests that the number of lab procedures may be an important factor to consider when assessing a patient's risk of future hospitalizations. Healthcare providers may want to prioritize patients who require a high number of lab procedures for closer monitoring and more intensive follow-up care after discharge.

Figure 2. Feature importance in Random Forest



The results of this study also revealed some differences in the importance of certain features among the three machine learning algorithms. Specifically, ChangeMedication (Change in diabetes medication) was the third most important feature in both random forest and XGBoost, while MedPrescribed (Diabetes medication prescribed) was the third most important feature in decision tree.

The finding that ChangeMedication was an important predictor of hospital readmissions in both random forest and XGBoost suggests that changes in medication may have a significant impact on patient outcomes. It is possible that patients who experience changes in their diabetes medication regimen may require additional monitoring or may be at higher risk of complications that could lead to hospital readmission. This highlights the importance of carefully managing medication changes for patients with diabetes and ensuring that patients receive appropriate follow-up care after changes are made.

The fact that MedPrescribed was the third most important feature in decision tree suggests that the specific type of diabetes medication prescribed may be an important predictor of hospital readmissions. Different types of diabetes medications may have varying levels of effectiveness and may be better suited for certain patients depending on their individual needs and health conditions. By identifying the specific medications that are associated with higher rates of hospital readmission, healthcare providers can develop targeted interventions and care plans to improve patient outcomes.

Figure 3. XGBoost prediction

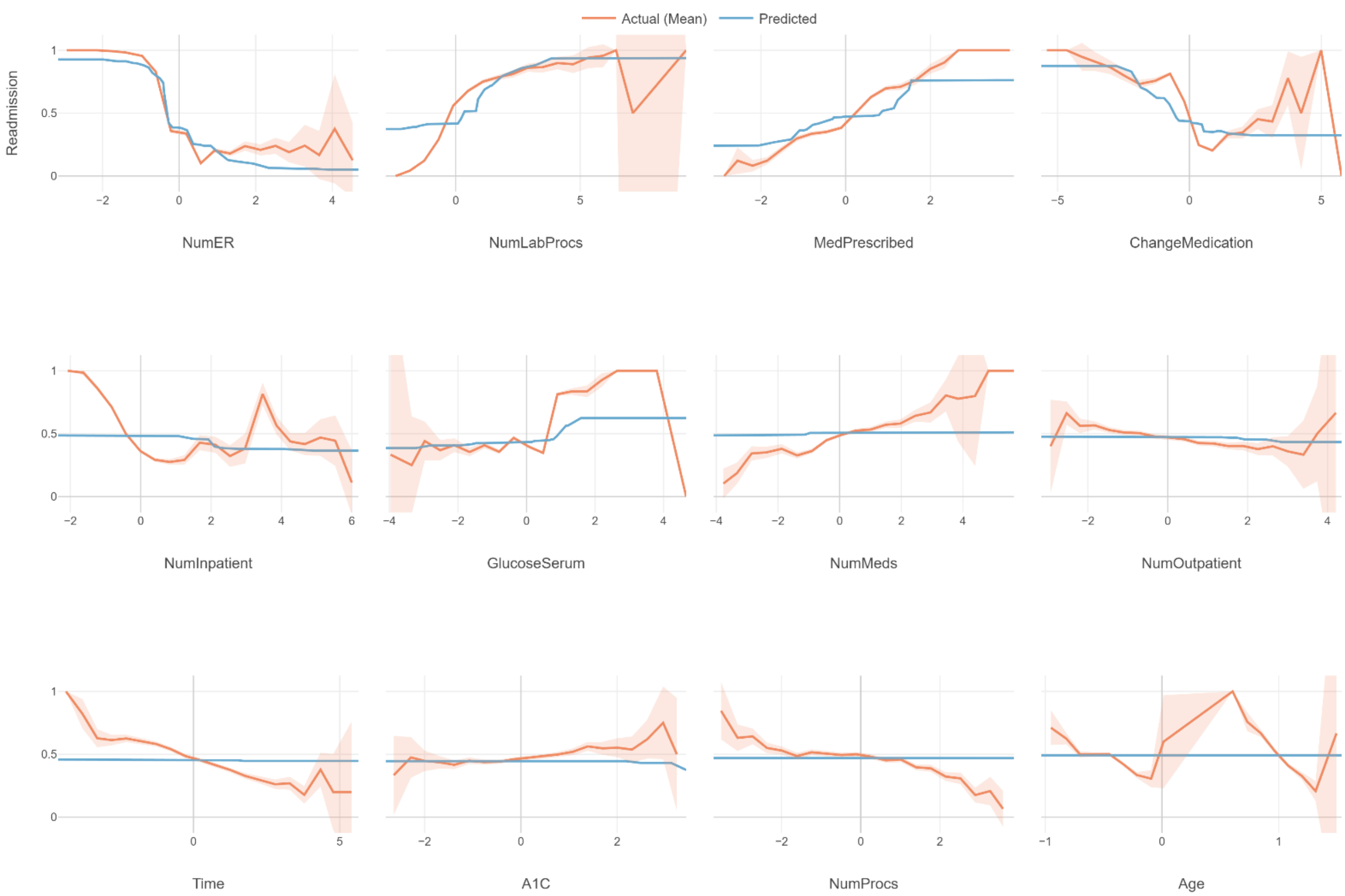
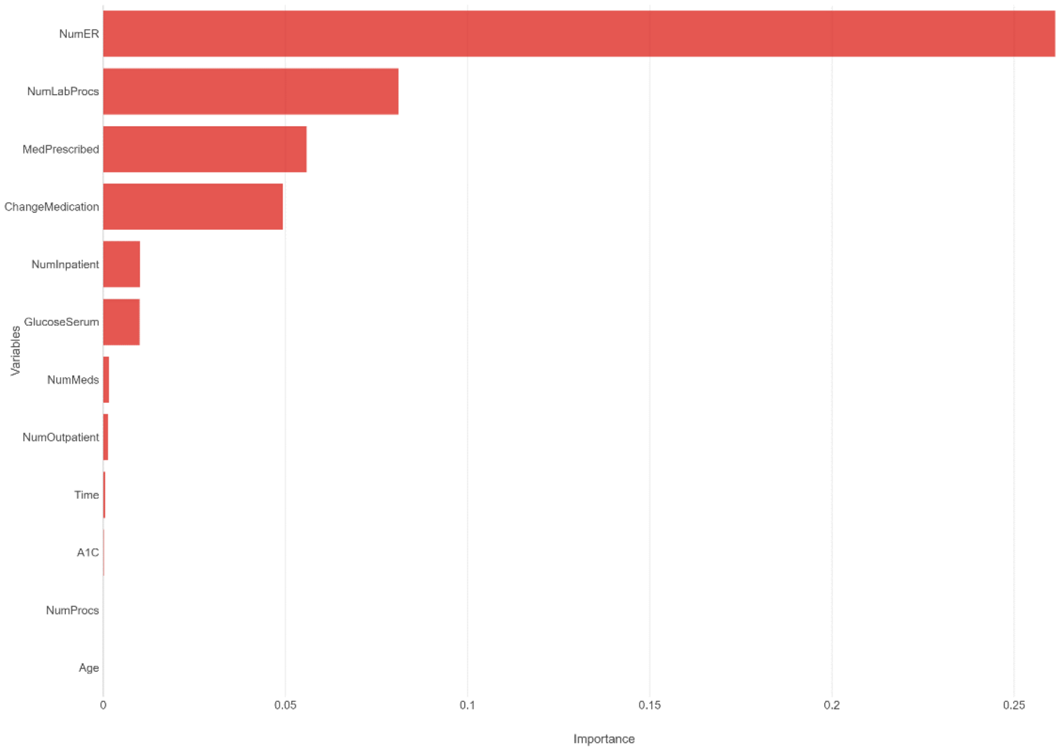


Figure 4. Feature importance in XGBoost



Interestingly, the results of this study also found that age was the least important factor in all three machine learning algorithms - random forest, XGBoost, and decision tree. This is a surprising finding, as age is often considered an important predictor of hospital readmissions in clinical practice.

One possible explanation for this finding is that other factors, such as the number of emergency room visits or the number of lab procedures, may be more closely related to patient outcomes than age. Alternatively, it is possible that age may not be as strong of a predictor of hospital readmissions as previously thought. Future research may be needed to better understand the relationship between age and hospital readmissions and to identify other factors that may be more important in predicting this outcome.

Despite the fact that age was found to be the least important factor in all three machine learning algorithms, it is important to note that age is still a relevant factor to consider when assessing a patient's overall health and risk of hospitalization. While it may not be as strong of a predictor of hospital readmissions as other factors, age may still be associated with other health risks and comorbidities that could impact patient outcomes. Healthcare providers should continue to consider age as part of a comprehensive risk assessment for hospital readmissions, but also be aware of the potential limitations of age as a predictor in isolation.

Figure 5. Decision Tree prediction

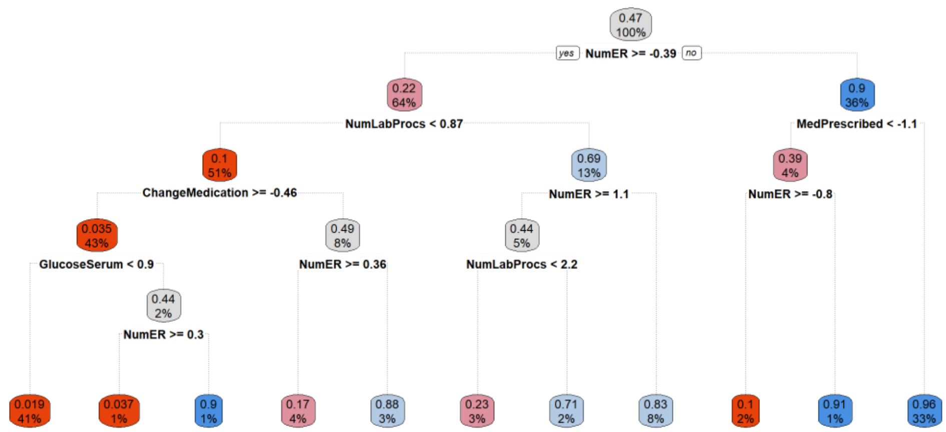
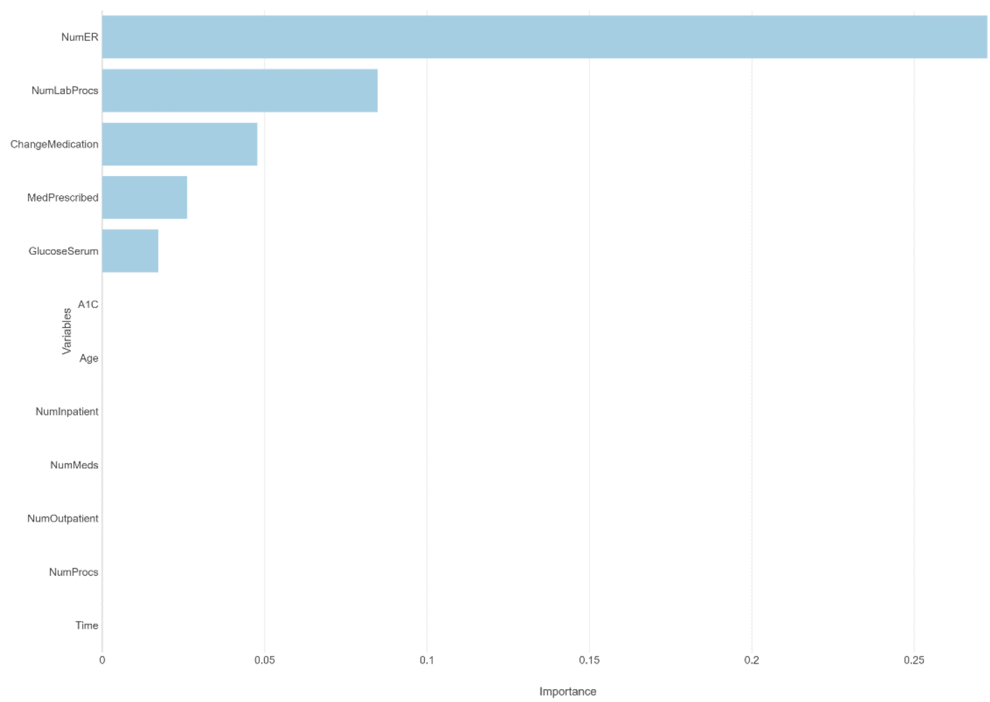


Figure 6. Feature importance in Random Forest



Conclusion

Hospital readmissions can have significant consequences for both patients and the healthcare system. The increased healthcare costs, negative impact on patient outcomes, lower quality of life for patients, and potential harm to patients are all serious issues that need to be addressed. This research highlights the use of machine learning algorithms in identifying factors associated with hospital readmissions. The findings emphasize the importance of the number of emergency room visits, lab procedures, and changes in medication in predicting hospital readmissions.

The severity of illness and types of conditions that led to hospitalization are crucial factors that could impact readmission rates. Patients with severe illnesses or chronic conditions may be more likely to experience complications or require ongoing medical care after discharge, which could increase their risk of readmission. Similarly, patients with certain types of conditions, such as heart failure or chronic obstructive pulmonary disease (COPD), may have higher readmission rates due to the complex nature of their conditions and the need for ongoing management.

By not including data on the severity of illness or types of conditions that led to hospitalization, this study may have overlooked important factors that could impact readmission rates. For example, it is possible that patients with certain conditions or severity of illness may require more intensive post-discharge care or follow-up, which could impact their likelihood of readmission. Additionally, patients with certain conditions may require specialized interventions or care plans to manage their condition, which could also impact readmission rates.

Furthermore, the study did not analyze the impact of social determinants of health on readmission rates. Social determinants of health refer to the social, economic, and environmental factors that can impact an individual's health and healthcare access. Factors such as race, ethnicity, and socioeconomic status can impact a patient's access to healthcare, their ability to manage their conditions, and their overall health outcomes. As such, social determinants of health could be important factors that contribute to readmission rates. For example, patients from low-income backgrounds may face financial barriers to accessing healthcare, which could impact their ability to manage their conditions and prevent readmissions. Similarly, patients from marginalized communities may experience discrimination or lack of cultural competency in healthcare settings, which could impact their ability to receive appropriate care and prevent complications that could lead to readmissions.

By not including social determinants of health in the analysis, this study may have overlooked important factors that contribute to readmission rates. It is important for future studies to consider the impact of social determinants of health on readmissions and develop interventions that address these factors to reduce readmission rates and improve overall healthcare outcomes, as well as should aim to include more diverse populations and time periods.

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