FHIR-Based Prediction of Hospital Readmission for Patients Aged 50 Plus

Group 13
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Introduction

Hospital readmissions pose a major challenge in healthcare, affecting both patient outcomes and healthcare expenses. This study seeks to utilize artificial intelligence (AI) and FHIR compliant patient data to predict unplanned hospital readmissions of patients aged 50 years plus with or exhibiting chronic conditions. Through the creation of an AI-driven predictive model, we aim to pinpoint high-risk patients and facilitate targeted interventions, enhancing patient care while alleviating the burden on the healthcare system.

Literature Review

Recent advancements in AI applications for healthcare have demonstrated encouraging outcomes in forecasting hospital readmissions. Michailidis et al. obtained an area under the curve (AUC) of 0.78 by utilizing a Random Forest classifier with administrative, clinical-medical, and operational data. The assessment by Mahmoudi et al. of 41 studies revealed that machine learning methods typically surpassed conventional statistical techniques in forecasting readmissions.

The incorporation of AI in commercial EHRs has proven to be a significant enhancement to clinical data in enhancing readmission forecasts. A recent investigation showed that integrating multi-scale entropy measures of heart rate dynamics from wearable devices, along with clinical characteristics, greatly improved model accuracy in forecasting 30-day readmissions. Saati et al. found out that readmission within 30 days post-hospital discharge and unnecessary emergency room (ED) visits have been linked to a rise in overall healthcare expenses and greater risks for patients. New artificial intelligence (AI) models could assist care coordination team members in accurately identifying high-risk patients digitally and integrating that functionality into their clinical workflow.

The role of AI in healthcare is expanding rapidly, with applications ranging from clinical decision support to medication development. By 2025, it is expected that AI will be widely employed in areas such as precision imaging, personalized treatment plans, and automated administrative tasks. This growth is driven by AI's ability to process large amounts of disparate multimodal healthcare data and identify complex patterns that may not be apparent using traditional analysis methods. Thus our study aims to incorporate the FHIR standard in the prediction of readmission of patients aged 50 years and above and exhibiting chronic conditions.

Dataset Description: FHIR_Readmission_Prediction_Dataset

We have concentrated our data gathering initiatives on utilizing standardized healthcare data formats to guarantee complete and interoperable information. We are employing three main data formats:

- CCDA (Consolidated Clinical Document Architecture)
- ADT messages (Admission, Discharge, Transfer)
- ORU (Observation Result) communications

These data sources have been standardized using FHIR and compiled into a CSV file, creating a valuable dataset for our predictive model. The dataset comprises the subsequent important characteristics e.g.,

- Demographic information of patients (age, sex)
- Health issues and coexisting conditions
- Information on prior admission and discharge
- Test results from the lab and vital signs

Dataset Validation and Relevance

To guarantee the quality and pertinence of our dataset, we will implement the following validation procedures:

- Data completeness verification: Confirming that all essential fields possess adequate data coverage.
- Verification of consistency: Comparing information from various data sources to detect and rectify inconsistencies.
- Temporal validity: Ensuring that the data accurately reflects present healthcare practices and patient demographics.

- Feature significance evaluation: Performing statistical analyses to assess the relationship between features and readmission results.

The chosen features greatly contribute to the accuracy and effectiveness of our proposed model. Patient demographics and medical history give crucial foundational information, whereas admission/discharge data and lab results provide insights into the patient's present health condition. The addition of past visit records is especially vital, since it has been demonstrated to be a significant indicator of potential future readmissions.

Methodology

Our method for addressing the hospital readmission prediction entails creating a gradient-boosting model, which has demonstrated encouraging outcomes in comparable healthcare contexts. We also aim to include other models like Random Forest, Support Vector Machine, XGBoost, Multi-Layer Perceptron (MLP), K-Nearest Neighbors and Logistic Regression.

The approach will include these steps:

Data Preparation:

- Dealing with absent values by means of substitution or elimination.
- Representing categorical variables (e.g., one-hot representation for health issues)
- Standardizing numerical features
- Feature Engineering:
- Creating comorbidity scores using medical condition information, lab results and vital signs.

Models Creation:

- Deploying a gradient-boosting classifier alongside other classifiers.
- Employing cross-validation for adjusting hyperparameters
- Testing ensemble techniques to enhance effectiveness

Model Assessment:

- Evaluating model effectiveness through metrics like AUC, sensitivity, and specificity , Recall and F1-Score
- Performing an analysis of feature importance to determine major predictors.

Future Research Plans

As we progress through this project, our future steps include:

1. Investigating the use of natural language processing methods to gather useful insights from unstructured clinical documentation.
2. Exploring the possibilities of federated learning methods to facilitate collaboration across multiple institutions while safeguarding patient confidentiality.
3. Creating and executing a forward-looking study to assess the model's actual effect on decreasing readmission rates and enhancing patient outcomes.
4. Enhancing the dataset by including extra data sources, like medication details and social determinants of health.

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