Leveraging Explainable Machine Learning to Forecast Healthcare Staying Duration

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ABSTRACT

Efficient bed management minimizes hospital costs and improves efficiency and patient outcomes. This study presents a predictive hospital-ICU length of stay (LOS) framework at admission, where it leverages hospital EHR. Our work utilizes supervised machine learning classification models to predict ICU patients' LOS in hospital clinical information systems (CIS). Our research marks the first known instance of utilizing explainable artificial intelligence (xAI) for the purpose of explainable machine learning applied to real data collected from hospital stays. We evaluated the predictive classification models using a range of performance metrics (Accuracy, AUC, Sensitivity, Specificity, F1- score, Precision, Recall and more) to predict short and long ICU lengths of stay upon hospital admission. XGBoost predicted short and long LOS with a 98%AUC. This study shows howhospitals and ICUs might use machine learning to forecast patients on admission. Our study extends clinical information systems for hospitals to provide robust and trustworthy LOS, predictive models by using xAI to explain predictive model outputs.

Keywords: XGBoost, hospital-ICU

I.INTRODUCTION

Efficiently predicting the length of stay (LOS) for patients admitted to the Intensive Care Unit (ICU) is critical for hospital resource planning, patient care optimization, and cost management. Traditional methods for LOS prediction often lack transparency, limiting their practical value in real-world clinical settings. This project proposes a novel explainable machine learning framework that predicts whether a patient's ICU stay will be short or long at the time of hospital admission. Using real-world hospital EHR data, the framework integrates supervised classification models and explainable artificial intelligence (xAI) techniques to provide interpretable and accurate predictions. Unlike existing studies that either focus on specific feature types (e.g., only vital signs) or omit key evaluation metrics, our model leverages a broad set of clinical features and explains its decisions, thus enhancing the transparency and trustworthiness of predictions in clinical information systems (CIS).

II. LITERATURE REVIEW

In the last few decades, there has been an uptick in enthusiasm for using methods such as data mining and machine learning for improved hospital operations. Specifically, hospitals aim to improve their ICU performance by cutting the amount people who fall die there. Identifying quantifiable outcomes, such as chances of complications, mortality, and how long it takes hospital stay.

Several variables influence the length of stay, so this is an essential metric for patients and healthcare providers alike. Specifically, characteristics unique to the highly intricate conditions found in the intensive care unit impact the time of stay in critical illness, which is critical for both a patient's comfort as the overall price for treatment. If other outcomes are difficult to monitor, such as icu or critical care facility mortality, the duration of stay is used as a stand-in. A further variable is the duration of stay, that demonstrated used to figure out the seriousness of ailments and the use of medical resource. Many kinds of period of stay and death forecast strategies for urgent medicine and the critical care unit are looked into in the present study. It also emphasizes fatality forecast and the length of stay evaluation methods. Additionally, this research gives an outline along with evaluation of the analytical techniques used to predict fatality and how long we stay connected to a collection of significant study results on the topic of evaluation of survival that have appeared between 1984 and 2016. The investigation moreover arguments available roughly of the area's blemishes and complications.

III. EXISTING SYSTEM

Alghatani et al. [28] experimented with six classifiers to predict LOS (short: <2 days, long: >2 days). Using the MIMIC-III (v1.4) database, six classifiers (LR, RF, SVM, XGBoost, linear discriminant analysis: LDA, KNN: k-nearest neighbor) were tested on eligible ICU admissions [29]. A total of 33 features were used to predict the short and long LOS. Using quantiles, RF and XGboost outperformed other models (AUC = 69.78%, 69.69%). However, their system was limited to benchmarking the classifiers only on vital signs. Further, they did not explain the prediction decisions of the quantiles approach in an AI explainable approach. Gentimis et al. [30] used the MIMIC III database to expect distance of break (short LOS: < 5 days, long LOS: > 5 days) using ANN. They extracted 25 features from MIMIC-III tables that contained 25 features (admissions, CPT events, ICU stays, services, procedures ICD, and diagnoses ICD). ANN predicted LOS with 80% accuracy, however, the study lacks important model performance metrics such as (AUC, sensitivity, and specificity. These metrics are important to differentiate the model's performance in terms of accuracy and how likely the model is to distinguish the decision boundaries to effectively predict LOS short or LOS long. LOS prediction was performed using seven predictive models by Steele and Thompson [31]. In their work, the Bayesian Network (BN) achieved the best result among other predictive models with (AUC = 90%). However, the study suffered from drawbacks. For example, it did not specify the nature of clinical, laboratory, and vital signs collected to assess further models performance on more admission features considered a viable picture of the patient's information to identify the short from the long LOS.

DISADVANTAGES

One of the main dares in action datasets through countless disappeared standards, nonvalues (NaN), or blanks is training machine learning models that can drastically impact the machine learning quality, performance, and predicted outcomes [36]. To address this challenge, data imputation was used to handle the missing values or values containing blanks in the four imported tables of the Al- Ain dataset [36]. The null function from the Pandas library in Python was used to replace any non-value with a zero value (0) since the input was not available or possible due to the nonapplicable option.

IV. PROPOSED SYSTEM

The proposed framework is specifically designed to be readily comprehended by AI non-experts. This versatility allows for more informed decision-making in both clinical and administrative settings. The objective of this framework is to enhance hospital workflow and resource utilisation by improving the transparency and interpretability of LOS predictions. In addition, it tackles a notable and previously unaddressed research issue in CIS, thus offering a valuable contribution to the progress of explainable AI in healthcare environments.

ADVANTAGES

- A proposed practical data-driven predictive framework for inpatient length of stay prediction in the ICU.

A proposed model benchmarking technique to enhance LOS prediction and hospital resource utilization.

A readily implementable framework for seamless integration into CIS prediction pipelines.

A new, explainable prediction strategy for comprehensible outcomes for healthcare practitioners.

System Architecture

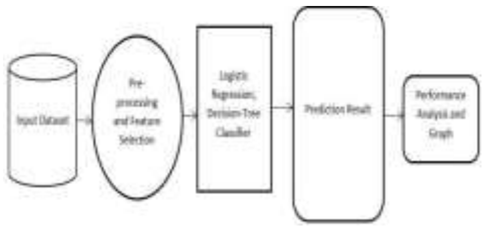


Fig1. System Architecture

V. MODULE DESCRIPTION

Server Login Module:This module provides secure access to the system for authorized users (such as administrators or hospital staff). Upon login, users can access the full functionalities of the system, including uploading datasets, viewing model results, and generating predictions.

Browse Datasets Module:This feature allows users to upload or browse hospital EHR datasets, which include patient admission details, vitals, and medical history. The uploaded data serves as input for model training and prediction.

Train and Test Dataset Module:Once the data is uploaded, this module handles the training and testing process. It splits the dataset into training and testing subsets, applies preprocessing (such as handling missing values), and trains the machine learning models (e.g., XGBoost). It then evaluates the model using the test data.

View Trained and Tested Accuracy in Bar Chart Module

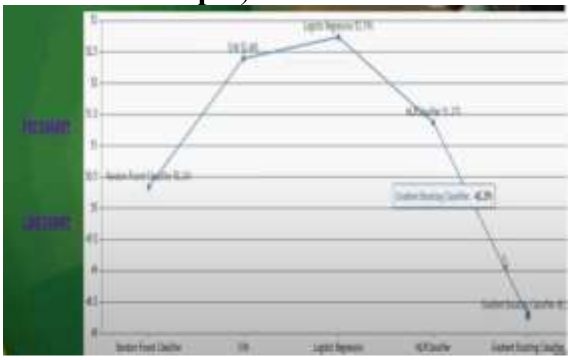
This visualization module displays the accuracy of trained and tested models using bar charts. It helps users compare and interpret model performance metrics such as accuracy, precision, recall, and F1-score in a visual and easy-to-understand format.

View Trained and Tested Accuracy Results Module

This module provides a detailed textual summary of the model evaluation results. It includes metrics like AUC, sensitivity, specificity, precision, and recall. These results help validate the effectiveness of the machine learning models used for LOS prediction.

View Prediction of Tweet Type Module (Note: This may be a naming or functional mismatch unless tweets are part of your data pipeline. Please clarify if tweet data is relevant. If not, it might be renamed as "**View Prediction of LOS Category**.") This module shows the predicted output of the model — whether the patient's ICU stay is expected to be **short** or **long** based on the input features.

View Tweet Type Graph Module (Again, assuming this is a placeholder name, this might be meant for **View LOS PredictionGraph**.)



This module provides a graphical representation of the prediction distribution. It may include pie charts or bar graphs showing the number of patients predicted to have short or long hospital stays.

VI. RESULT

The proposed explainable machine learning outline remained positively applied by means of real sanatorium EHR data to predict ICU patients' length of stay (LOS) at admission. The system was tested using classification models, with XGBoost achieving the highest performance. It accurately classified patients into short and long LOS categories with an Area Under the Curve (AUC) of 98%. The model also demonstrated strong results across various performance metrics, including high precision, sympathy, specificity, exactness, remember, and F1-score. These results confirm the model's ability to effectively distinguish between patients who require shorter ICU stays and those likely to need extended care, making it a valuable tool for hospital workflow and resource planning.

VII. CONCLUSION

In conclusion, this study presents a robust and explainable machine learning framework for predicting ICU length of stay (LOS) at the time of hospital admission. By integrating real EHR data with powerful classification algorithms and explainable AI (xAI) techniques, the system offers both high predictive accuracy and interpretability. The use of models like XGBoost, combined with clear performance metrics and effective data preprocessing, ensures the framework is reliable and practical for clinical application. Most importantly, the explainability of the model outputs empowers healthcare professionals to make informed decisions based on transparent predictions. This approach not only supports better hospital resource management but also enhances patient care by enabling timely interventions and planning. The framework represents a significant advancement in the application of AI in healthcare, making predictive tools more accessible, trustworthy, and impactful in real-world hospital settings.

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