Hybrid Artificial Intelligence Hospital Resource Management Using CATBOOST

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Abstract: **Efficient bed management is crucial for reducing hospital costs and improving patient outcomes. This study proposes a framework to predict ICU length of stay (LOS) at admission using electronic health records (EHR) and supervised machine learning models. It is the first to employ explainable AI (xAI) for interpreting machine learning predictions using real hospital data. The framework predicts short and long ICU stays, evaluated through metrics such as accuracy, AUC, sensitivity, and F1-score. XGBoost achieved a 98% AUC in predicting LOS. This approach enhances clinical information systems, offering hospitals reliable, explainable LOS predictions to optimize ICU resources and support patient care decisions at admission.**

Keywords: **Healthcare decision support systems, explainable artificial intelligence, machine learning, XGBOOST**

INTRODUCTION

Hospital length of stay (LOS) is a crucial indicator of healthcare efficiency, directly impacting resource management and costs. While shorter stays allow faster patient turnover, they can also compromise care quality, while extended stays increase the risk of complications. Prolonged hospitalization often results from coordination delays in transitioning patients to appropriate care services, such as aged care or rehabilitation. Effective ICU resource management is especially critical in high-pressure situations, such as pandemics, to minimize risks like infections and improve outcomes. Traditional LOS prediction methods, such as APACHE, SAPS, and SOFA scores, while useful, are not disease-specific and have limitations in accuracy. This highlights the need for more advanced, data-driven prediction systems. AI-powered models utilizing electronic health records (EHR) offer a more accurate approach, enabling hospitals to optimize ICU stays without compromising patient care and ensuring better resource utilization. These systems could transform ICU management and improve patient outcomes.

LITERATURE SURVEY

1. Ma et al. (2020)
    - Focused on predicting ICU length of stay using an individualized single classification algorithm.
    - Integrated extreme learning machines (ELM) with just-in-time learning (JITL) for tailored patient care.
    - The model demonstrated superior performance compared to one-class SVM but lacked interpretability
2. Su et al. (2021)
    - Developed a machine learning model for early prediction of ICU mortality, severity, and length of stay in sepsis patients.
    - Used sepsis 3.0 criteria to validate the model's effectiveness.
    - The study emphasized the importance of early prediction for resource allocation and patient care
3. Staziaki et al. (2021)
    - Combined clinical parameters and CT findings using machine learning to predict ICU admission and length of stay in torso trauma cases.
    - Demonstrated the integration of imaging data in predictive analytics for critical care management
4. Alghatani et al. (2021)
    - Proposed a model to predict ICU length of stay and mortality based on patient vital signs.
    - Machine learning techniques were used to validate predictions.
    - The study emphasized real-time monitoring for better decision-making in intensive care units
5. Gentimis et al. (2017)
    - Used neural networks on MIMIC III data to predict hospital length of stay.

   - Highlighted the potential of deep learning in medical record analysis for hospital planning and administration
6. Steele & Thompson (2019)
   - Focused on data mining for generalizable pre-admission prediction of elective length of stay.
   - Used large-scale hospital datasets to identify key predictors of extended stays
7. Yeh et al. (2020)
   - Investigated the Quick-SOFA score as a predictor of prolonged hospital stay in elderly influenza patients.
   - Used statistical and machine learning approaches to enhance prediction accuracy
8. Li et al. (2019)
   - Applied the least absolute shrinkage and selection operator (LASSO) regression technique for ICU length of stay prediction.
   - Optimized feature selection to improve model accuracy
9. Levesque et al. (2015)
   - Examined the impact of clinical information system implementation on shortening ICU length of stay.
   - Showcased how digital transformation in hospitals improves efficiency
10. Calloway et al. (2013)
    - Studied the effect of clinical decision support systems (CDSS) on reducing length of stay and improving cost-efficiency in hospitals.
    - Showed the role of AI-driven decision support in hospital management

PROBLEM STATEMENT

Hospitals face challenges in managing ICU resources due to unpredictable patient stays. An accurate, interpretable system is needed to predict ICU length of stay, minimizing inefficiencies and improving resource allocation.

PROPOSED METHOD

To manage ICU resources efficiently many existing algorithms were introduced such as SOFA, APACHE and many more but all those algorithms were trained on basic features not concentrating on patient's complete EHR (electronic health record) history. This patient's history may indicate correctly weather patients has to stay in ICU or not and may tell weather patient required LONG or SHORT stay of ICU. Based on LONG and SHORT stay hospitals can allocate and resources accurately.

Currently no proper tool exists which can analyse patients complete EHR to predict ICU short or long stay type. So author of this paper utilizing complete patient EHR history and then utilizing different machine learning classification algorithms such as Logistic Regression, Random Forest, MLP, Gradient Boosting and XGBOOST and then evaluate each algorithm performance in terms of AUC, accuracy, precision, recall and FSCORE. Among all algorithms XGBOOST is giving best performance.

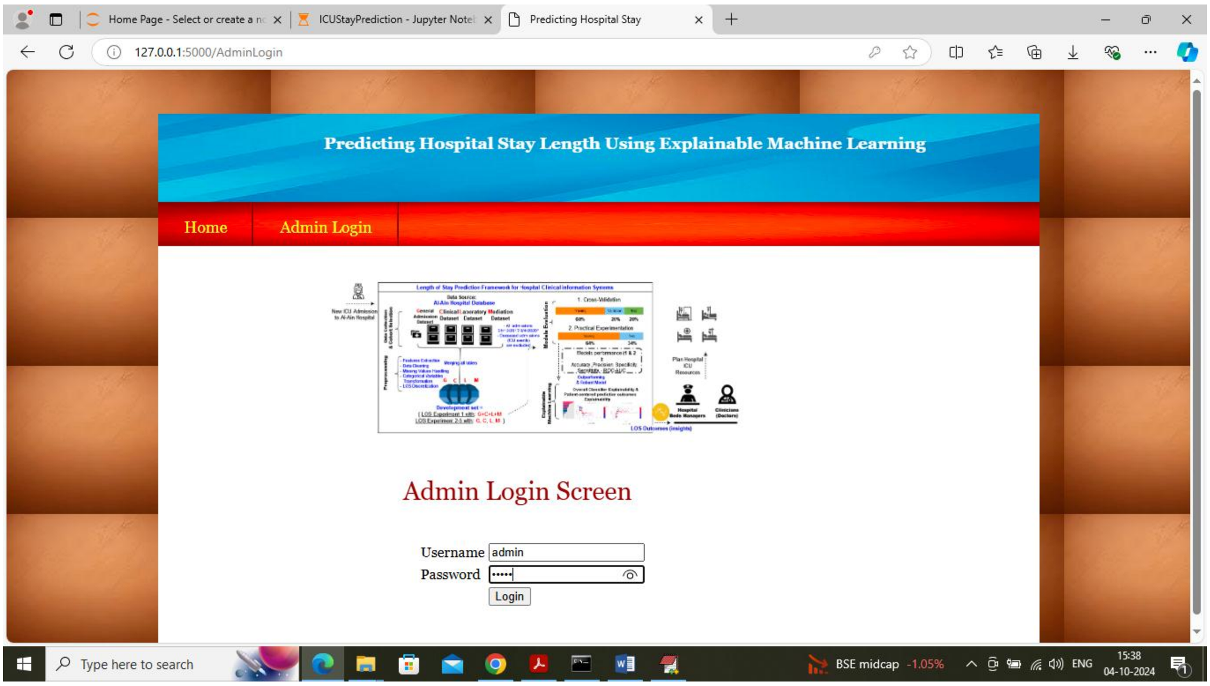
To tune algorithm performance author has employed hyper parameters tuning which can tune algorithms by using different parameters and then choose parameter with highest accuracy.
Author also experimented with Explainable AI algorithms to identify features which are contributing most to help algorithm in predicting class label.

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. Propose work utilizes supervised machine learning classification models to predict ICU patients' LOS in hospital clinical information systems (CIS). Propose paper marks the first known instance used method for finding the similarity between data points [26].

METHODOLOGY

A framework to predict the length of stay (LOS) for patients during their hospital admission, specifically their admittance into the ICU and discharge. This study use machine learning methods to predict the length of stay (LOS) of hospital inpatients using a real-world hospital dataset. Hence, this procedure is essential for assessing and validating prediction models using actual hospitalizations data. In this part, every step involved in the predictive framework (Fig 1) is addressed in detail. Therefore, the subsequent section describes each stage of the framework in detail. A. DATA DESCRIPTION AND FEATURES EXTRACTION Our retrospective study utilized electronic health record (EHR) data from Al-Ain hospital, encompassing all ICU admissions between December 31, 2017 and April 3, 2020 [58]. The deidentified nature of the EHR removed all patient details and identifiers in compliance with data protection regulations in the UAE and Australia. Our study population comprised 1045 distinct patients admitted to Al-Ain Hospital during the aforementioned period. Ethics approval was granted by the Al-Ain hospital and UAE University Ethics Committee (AAHEC-09-20-027), as well as preexisting amended ethics approval by Western Sydney University (WSU) with the ethics number (H13511). This research employed a comprehensive inclusion proto col that covered all ICU hospitalizations at Al-Ain Hospital. Exclusion criteria involved expired hospitalizations and hos pitalizations with significant missing data (Fig. 1). The International Classification of Diseases code ICD-10 [32] was used to classify diseases.

RESULTS



CONCLUSION

This study developed a predictive ICU framework using real hospital data to predict patients' length of stay at ICU admission. This practical framework offers significant implications for ICU bed management and resource utilization, achieving desired predictive results through its three-stage LOS predictive process. Among the various models tested, the XGBoost model emerged as the best performer due to its ability to provide explainable results to non-AI professionals. Notably, this study is the first to present an AI-explainable framework for predicting ICU patients' length of stay using a data-driven approach. The proposed framework is versatile, applicable across various diseases and health conditions, making it valuable for clinical research and electronic health records. It also has the potential to improve predictive tasks such as identifying patients at risk of mortality. Future research will focus on integrating user-centered clinical predictive systems into daily hospital workflows and thoroughly investigating the use of explainable AI in hospital, emergency department, and ICU settings. This will help establish genuine ML-xAI implementation and standardize their use in electronic health records and healthcare systems.

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