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A Comparative Study of Machine Learning Algorithms for 30-Day ICU Readmission in Heart

Chuan-Mei Chu [1 +], Chen-Shug Wang [2], Hong-Yan Chen [1], Bo-Yi Li [3] and Te-Nien Chien [1]

[1] College of Management, National Taipei University of Technology, Taipei, Taiwan
[2] Department of Information and Finance Management, National Taipei University of Technology, Taiwan
[3] Department of Management Information Systems, National Chengchi University, Taiwan

Abstract. Early readmission of heart failure (HF) patients within 30 days following intensive care unit (ICU) discharge remains a significant clinical and economic challenge. Accurate prediction of this risk is crucial for improving patient management and optimizing resource utilization. This retrospective study analyzed data from 5,414 adult HF patients admitted to the ICU within the MIMIC-III database. To address class imbalance, advanced oversampling techniques were applied during training. Eight machine learning algorithms were implemented and evaluated for 30-day ICU readmission prediction. Model performance was assessed using accuracy and AUROC. Among the eight algorithms, LightGBM achieved the highest individual performance with an accuracy of 88.72% and an AUROC of 74.48% for predicting 30-day ICU readmission. The ensemble model, leveraging top-performing algorithms including LightGBM, demonstrated enhanced predictive capabilities. Key variables, such as vital signs and comorbidities, were identified as critical predictors. LightGBM demonstrates strong potential for accurately predicting 30-day ICU readmission in HF patients. The high performance of LightGBM and the benefits of ensemble methods suggest these tools can effectively identify high-risk patients, enabling targeted interventions to reduce readmissions and improve care. Future research should focus on external validation and clinical implementation.

Keywords: heart failure; intensive care units; machine learning; readmission prediction; electronic health records, readmission.

1. Introduction

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into healthcare, particularly through Electronic Health Records (EHR), has significantly advanced medical technology. These innovations enable the analysis of complex datasets, combining physiological indicators and patient demographics, thereby enhancing the accuracy of predicting patient outcomes, including hospital readmissions[1; 2]. Despite these advancements, readmissions continue to impose substantial financial burdens on healthcare systems, with studies indicating they can increase costs by up to 20% [3]. The Hospital Readmissions Reduction Program (HRRP), introduced under the Affordable Care Act (ACA), addresses this issue by penalizing hospitals with excessive readmissions. However, socio-economic disparities, disease complexity, and healthcare access inequities remain significant barriers [4]. Effective strategies, such as patient-centered discharge planning and improved care coordination, are needed—particularly for high-risk conditions like heart failure (HF) [5].

HF is a prevalent chronic condition, affecting approximately 64.3 million individuals globally and over 6 million in the United States [6]. It places a considerable strain on healthcare systems due to frequent hospitalizations and high mortality. ICU patients with HF are especially vulnerable, with mortality rates ranging from 20% to 60% within the first year after hospitalization. Thirty-day readmissions are common and exacerbate resource strain. Predicting which patients are at high risk for readmission is critical for enabling targeted interventions and improving outcomes. However, this task is complicated by the influence of comorbidities, clinical variability, and post-discharge factors.

+ Corresponding author. Tel.: + 886 932336323 fax: + NIL
E-mail address: sherchu66@gmail.com

AI and ML offer opportunities to address these challenges by enabling integration of diverse data sources for more proactive patient management. In ICU settings, these tools can support earlier risk identification, optimize care planning, and promote more equitable healthcare delivery. This aligns with Sustainable Development Goal 3 (Good Health and Well-being), which emphasizes leveraging innovation to improve healthcare access and outcomes [7; 8]. Recent studies demonstrate that AI- and ML-based predictive models can effectively reduce readmission rates by identifying high-risk patients before discharge[9].. This study addresses early ICU readmissions in heart failure patients by developing predictive models using advanced ML techniques. Drawing from diverse datasets—including physiological metrics, patient demographics, and comorbidities—the models generate actionable insights that support early interventions and personalized care planning. To improve model transparency and foster clinical trust, SHAP values were used to explain each variable's contribution to predictions[10]. This approach enhances the interpretability of complex algorithms, making them more applicable in real-world healthcare settings. Predictive models can also help optimize resource allocation, such as forecasting ICU bed demand and planning staff levels, which supports more efficient hospital operations and improves the care environment[11].

This research emphasizes the importance of cross-disciplinary collaboration among data scientists, clinicians, and policymakers to translate ML innovations into practical decision-support tools. The findings aim to reduce ICU readmissions, promote sustainable healthcare practices, and contribute to global health goals by demonstrating how AI can improve both outcomes and operational efficiency in critical care.

2. Materials and Methods

This study utilized data from ICU patients diagnosed with congestive HF, including vital signs, demographic information, and textual data from post-admission medical records. To ensure data quality, preprocessing steps such as data cleaning and handling of missing values were performed. Records with significant missing data were excluded, and imputation techniques were applied to preserve dataset integrity.

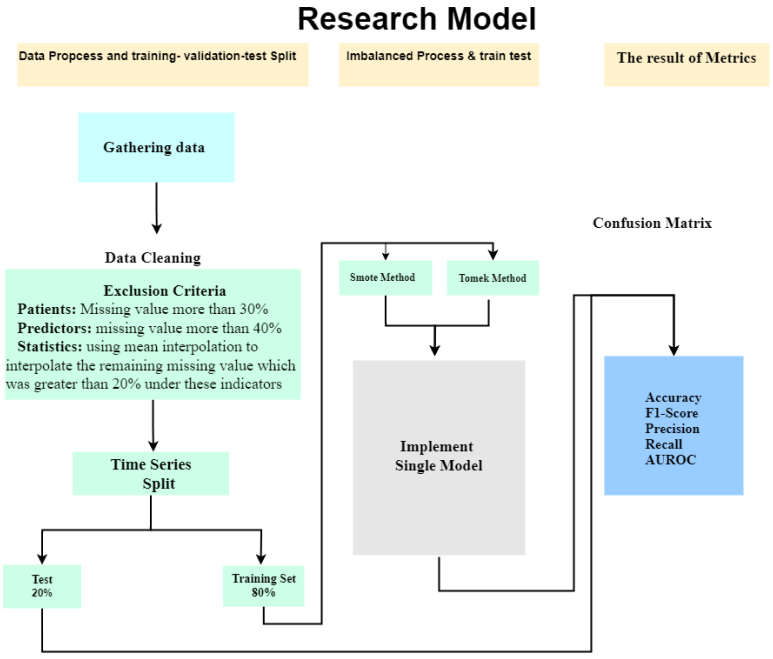

Fig. 1: The detailed process of data extraction.

This study utilized the MIMIC-III critical care database, a publicly available, de-identified dataset from Beth Israel Deaconess Medical Center. The dataset includes clinical variables such as vital signs recorded within 24 hours before ICU discharge—heart rate (HR), blood pressure (BP), oxygen saturation (OS), respiratory rate (RR)—as well as laboratory results and textual data from discharge summaries and clinical notes. These variables are crucial in identifying HF patients at high risk for readmission [12]. Access to the dataset was granted upon completion of the NIH course and the Human Research Participant Protection examination (Certificate No. 35628530). To ensure data quality, a three-stage preprocessing strategy was

used: records with over 30% missing values were excluded; variables with over 40% missing data were removed; and mean imputation was applied for variables with 20%–40% messiness [13]. The final dataset consisted of 37 variables, including important comorbidities such as ischemic heart disease and diabetes.

To predict 30-day ICU readmissions, the dataset was split into a training set (80%) and a test set (20%). SMOTE and Tomek Links techniques were applied during training to address class imbalance, ensuring better detection of minority-class cases. Eight machine learning algorithms were employed: LightGBM, CatBoost, Gradient Boosting, AdaBoost, DNN, Logistic Regression, LSTM, and KNN. LightGBM is optimized for large datasets and supports fast computation [14], while CatBoost is efficient in handling categorical data [15]. Gradient Boosting and AdaBoost are ensemble methods that iteratively improve model performance [16]. DNN captures complex patterns in data [17], and Logistic Regression serves as a baseline linear model [18]. LSTM models are suitable for sequential data [19], and KNN classifies based on proximity to known cases [20]. Model performance was evaluated using accuracy, precision, recall, F1-score, and AUROC [21]. To enhance interpretability, SHAP values were used to quantify the contribution of each feature to the model's predictions [22] allowing clinicians to better understand key risk factors and support more personalized decision-making for HF patients.

3. Results

The study utilized data from the MIMIC-III critical care database to evaluate the predictive capability of a single machine learning model, Random Forest, for 30-day ICU readmissions in HF patients. The final dataset included 5,414 anonymized patient records, with 12.5% (678 patients) readmitted to the ICU within 30 days of discharge, and 87.5% (4,736 patients) who were not readmitted. Random Forest was trained on the data and evaluated based on several performance metrics: accuracy, precision, recall, F1-score, and AUROC (Area Under Receiver Operating Characteristic). The LightGBM model achieved an accuracy of 88.72%, a precision of 87.01%, and an AUROC of 74.48%, which were the highest performance scores among the models evaluated. The results are summarized in Table 1 and Figure 2.

Table 1: Performance metrics of classification models in ICU heart failure patients

Models	AUROC	Precision	Recall	F1	Accuracy
LightGBM	0.7448	0.8872	0.8744	0.8701	0.8872
CatBoost	0.7200	0.8826	0.8708	0.8656	0.8826
GradientBoosting	0.7254	0.8799	0.8710	0.8658	0.8799
AdaBoost	0.6896	0.866	0.8518	0.8436	0.866
DNN	0.5806	0.7893	0.7972	0.8058	0.7893
LogisticRegression	0.7072	0.7237	0.7645	0.8352	0.7237
LSTM	0.6654	0.753	0.7126	0.8155	0.7126
KNN	0.5598	0.6553	0.7096	0.797	0.6553

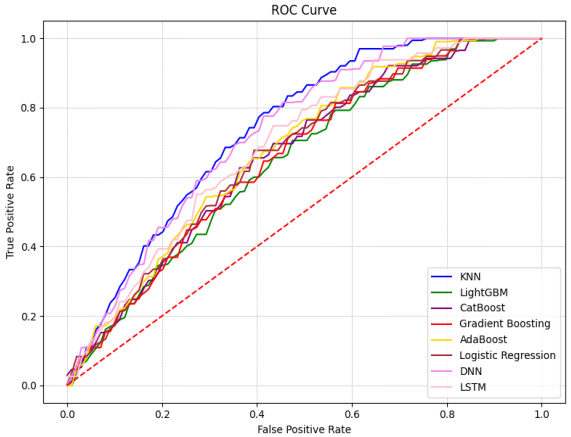

Fig. 2: ROC curves of various classifiers for predicting 30-Day readmission rates.

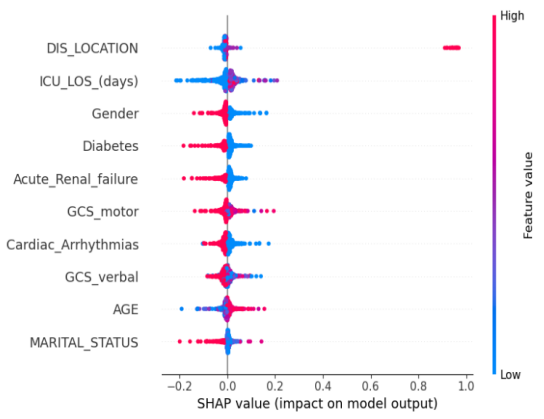

Fig. 3: SHAP Value Analysis of Key Features.

To enhance model interpretability, SHAP values were utilized to quantify the contribution of each feature to individual predictions. The summary plot indicates that DIS_LOCATION and ICU_LOS were the most influential variables in determining patient outcomes. Specifically, extended ICU stays were generally associated with higher predicted survival probabilities, whereas discharge to certain locations—such as hospice facilities or specialized institutions—correlated with increased mortality risk. Lower scores in GCS motor and verbal assessments also exhibited strong negative contributions, consistent with established clinical understanding of neurological impairment. While comorbidities such as diabetes, acute renal failure, and cardiac arrhythmias had a negative impact on predicted survival, their influence was comparatively moderate. Age demonstrated a mild inverse relationship with survival, whereas demographic variables such as marital status had minimal effect on the model's output. Figure 3 shows the SHAP value analysis for the top eight most important features.

4. Discussion and Conclusions

This study developed and evaluated multiple machine learning models to predict 30-day ICU readmission risk in heart failure patients using the MIMIC-III database. Among the models, LightGBM achieved the highest performance (AUROC = 0.7448), followed by Gradient Boosting and CatBoost. SHAP analysis revealed that discharge location and ICU length of stay were the most influential predictors, while lower GCS scores and comorbidities such as diabetes, acute renal failure, and cardiac arrhythmias were associated with higher readmission risk. These results align with established clinical knowledge, suggesting that the models effectively capture key risk factors. The integration of both structured and unstructured clinical data forms a robust machine learning framework that supports ICU readmission prediction. The use of SHAP values enhances model interpretability and builds clinician trust by revealing how specific variables influence predictions. Furthermore, the identification of high-impact predictors offers actionable insights that can inform targeted interventions and personalized care strategies, contributing to better patient outcomes and more efficient resource utilization. Nonetheless, the study has limitations. It relies on data from a single source (MIMIC-III), which may restrict generalizability. Some influential variables, such as discharge location, reflect post-hospital systems that are not easily modifiable. Additionally, important factors like socioeconomic status, medication adherence, and patient-reported outcomes were not included, which may limit prediction precision.

Future research should focus on validating these models in diverse healthcare settings and incorporating additional patient-specific factors, such as lifestyle and social determinants of health. Real-time implementation into ICU information systems and integration with clinical workflows will be essential to ensure practical utility. The continued development of explainable AI approaches, such as SHAP, will also be important for enhancing model transparency and clinical adoption. In summary, this study demonstrates the potential of machine learning to support early identification of HF patients at risk of ICU readmission. The proposed framework, combining predictive accuracy with explainability, highlights the role of AI in advancing decision-support tools and improving care quality in critical care environments.

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