

HANOI UNIVERSITY OF SCIENCE AND TECHNOLOGY

GRADUATION THESIS

Prediction of In-hospital Mortality in Mechanically Ventilated Patients with Congestive Heart Failure

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Specialization: Global ICT

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HANOI, 12/2024

ACKNOWLEDGMENT

During the time I worked on this project, I have learned so much and gained valuable experience. These achievements would not have been possible without the support and help of many people.

First and foremost, I would like to express my deepest gratitude to my advisor, Dr. Nguyễn Hồng Quang, for his guidance, support, and encouragement. From my third year, he has given me numerous opportunities to participate in various projects, helping me realize the value of my hard work and feel that I am growing and improving every day. His careful, patient, and gentle mentoring has been invaluable to me. I consider myself incredibly fortunate to have had the opportunity to learn from him.

I would also like to extend my heartfelt thanks to my family, especially my parents and my sister. Thank you for always being my source of motivation, for encouraging me to strive and work harder, and for allowing me to pursue what I love while believing in my abilities. Your unwavering trust and support mean the world to me.

Additionally, I am deeply thankful to my beloved partner for his care, love, and support throughout the journey of completing my thesis. I couldn't have achieved this without you by my side, being my comfort zone. Thank you for always being there for me.

Finally, I would like to thank my friends for all the precious moments we shared during our time together, the unforgettable memories in class, and for always being willing to help each other so that we can all grow and succeed.

Thank you all for being a part of this journey and for making it meaningful and fulfilling.

PLEDGE

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ABSTRACT

In-hospital mortality among mechanically ventilated congestive heart failure CHF patients is a pressing concern, requiring accurate risk prediction to enhance clinical care. This study aimed to develop and validate a predictive model for mortality using advanced machine learning techniques and feature selection strategies.

Patient data from the MIMIC-IV database were analyzed, starting with 90 features narrowed to 60 using backward elimination. Seven machine learning models, including GATE, were evaluated through nested k-fold cross-validation. To improve performance, three GATE models trained on first, last, and mean value data were combined into an ensemble. SHAP analysis was employed to identify 20 key features, and a compact model was developed and optimized based on this streamlined feature set. Performance metrics, including AUROC, were used to evaluate model accuracy.

Data from 8,517 patient stays were analyzed. The GATE model outperformed the other six models, with the ensemble demonstrating enhanced generalizability. SHAP analysis identified critical features such as age, MV duration, SAPSII and LODS scores, lactate levels, and markers of organ dysfunction. The compact GATE model, built on 20 essential features, achieved an AUROC of 0.87, closely matching the full model's 0.88, while improving computational efficiency and interpretability.

The GATE-based prediction model provides robust and accurate identification of mortality risk in mechanically ventilated CHF patients. The compact model offers a practical balance between performance and efficiency, making it a valuable tool for clinical decision-making and resource allocation.

TABLE OF CONTENTS

LIST OF ABBREVIATIONS.....	iii
CHAPTER 1. INTRODUCTION.....	1
1.1 Problem Statement.....	1
1.2 Background and Research Problems	2
1.3 Research Objectives and Conceptual Framework	5
1.3.1 Research Objectives	5
1.3.2 Conceptual Framework.....	7
1.4 Contributions	8
1.5 Organization of Thesis	8
CHAPTER 2. LITERATURE REVIEW	9
2.1 Scope of Research	9
2.2 Background.....	10
2.2.1 Foundation Knowledge of Clinical Background	10
2.2.2 Machine Learning and Predictive Models.....	12
2.3 Related Work	26
2.3.1 Relationship Between Long-term Survival and Prolonged Mechanical Ventilation	26
2.3.2 Applying ML Algorithms in Medicine to Predict MV Outcomes	27
CHAPTER 3. METHODOLOGY	32
3.1 Overview	32

3.2 Data description	33
3.3 Data collection	34
3.4 Feature selection and Data preprocessing	34
3.5 Statistical analysis.....	39
3.6 Model development and optimization	39
3.7 Features importance.....	40
3.8 Implementation	40
CHAPTER 4. RESULTS AND EVALUATION	41
4.1 Baseline Characteristics	41
4.2 Models Development and Evaluation.....	44
4.3 Features Importance.....	46
CHAPTER 5. DISCUSSION	51
CHAPTER 6. CONCLUSIONS	53
6.1 Summary	53
6.2 Suggestion for Future Works	54
REFERENCE	65
7. APPENDIX	66
7.1 ICD Codes of 72 types of CHF	66

LIST OF FIGURES

Figure 3.1	Schematic overview of the system in this work. Starting from collected data, preprocessing is then presented with data cleaning, data transformation, feature selection and a nested loop of data partitioning with stratified K-fold cross-validation [35] with $K = 5$. Next, we have training, validation and testing. Finally, evaluation and explanation with SHAP [43] are demonstrated.	32
Figure 3.2	Flow diagram of the selection process of patients	35
Figure 3.3	Flow diagram of data selection process	37
Figure 3.4	Demonstration of the changes in number of features over the selection progress.	38
Figure 4.1	Process of splitting data using Nested k-Fold Cross-Validation	41
Figure 4.2	The AUROC curves of the seven models for the test set: Logistic Regression, XGBoost, CatBoost, TabNet, NODE, FT-Transformer and GATE	45
Figure 4.3	The AUROC curves of four models when testing with first value dataset	47
Figure 4.4	The AUROC curves of four models when testing with mean value dataset	47
Figure 4.5	The AUROC curves of four models when testing with last value dataset	48
Figure 4.6	Distribution of the impacts important features had on the output of the model estimated using the SHAP values	48
Figure 4.7	Comparison of the full and compact GATE models: The full model was built utilizing all available features, whereas the compact model was constructed using 20 key features identified through the SHAP algorithm. Both models underwent hyperparameter optimization to ensure their best possible performance.	49

LIST OF TABLES

Table 2.1	Confusion Matrix	16
Table 3.1	The variables included in the study, categorized into six groups: demographics, blood gas parameters, vital signs, laboratory results, comorbidities, and clinical scores. Each category highlights specific features relevant to assessing patient characteristics, physiological status, and disease severity during ICU admission. . .	36
Table 4.1	Baseline characteristics of the training set and test set	43
Table 4.2	Evaluated seven different models: Logistic Regression, XGBoost, CatBoost, TabNet, NODE, FT-Transformer and GATE. The evaluation metrics included AUROC, AUROC 95% CI, and the accuracy score.	45
Table 4.3	Comparison of AUROC Performance with State-of-the-Art Models	46
Table 7.1	ICD Codes for Congestive Heart Failure	68

LIST OF ABBREVIATIONS

Abbreviation	Definition
AUROC	Area Under the Receiver Operating Characteristic
CHF	Congestive Heart Failure
DL	Deep learning
GATE	Gated Additive Tree Ensemble
HF	Heart Failure
ICU	Intensive care unit
kNN	k-Nearest Neighbors
LODS	Logistic Organ Dysfunction System
MIMIC-IV	Medical Information Mart for Intensive Care IV
ML	Machine learning
MV	Mechanical ventilation
NODE	Neural Oblivious Decision Ensembles
OASIS	Oxford Acute Severity of Illness Score
SAPS II	Simplified Acute Physiology Score II
SHAP	SHapley Additive Explanations
SOFA	Sequential Organ Failure Assessment
XGBoost	Extreme Gradient Boosting

CHAPTER 1. INTRODUCTION

1.1 Problem Statement

Heart failure (HF) is a clinical syndrome resulting from structural or functional cardiac abnormalities, leading to symptoms such as shortness of breath, fatigue, and fluid retention. In 2021, HF was universally defined as a condition characterized by elevated levels of natriuretic peptides or evidence of pulmonary or systemic congestion [1]. Congestive heart failure (CHF), a more specific and advanced stage of HF, is characterized by significant fluid buildup and congestion. Due to its severity and complexity, CHF often requires intensive care unit (ICU) admission for management [2].

Mechanical ventilation, a critical life-support intervention, is frequently used in the ICU to manage CHF patients experiencing respiratory failure. Although life-saving, this intervention carries substantial risks, including hemodynamic instability, alveolar inflammation, and complications caused by altered intrathoracic pressures [3]. These challenges highlight the urgent need for advanced predictive tools to assess patient outcomes, aiding more effective clinical decision-making and improving management for this high-risk group.

Predictive modeling is an indispensable tool in healthcare, offering the ability to forecast patient outcomes based on clinical data, thereby enhancing decision-making. For mechanically ventilated CHF patients, predictive models assist in identifying individuals who might benefit from early interventions, intensive monitoring, or alternative therapeutic strategies. However, predicting early mortality in this population remains challenging due to the intricate interplay of systemic organ dysfunction, comorbidities, and rapidly changing clinical conditions.

Traditional scoring systems, such as SOFA, APACHE-II, LODS, MODS, and SAPS-II, are significantly associated with mortality in critically ill patients and have demonstrated utility in mortality prediction [4]. While the SOFA and GWTG-HF risk scores provide valuable insights, they have notable limitations. The SOFA score, for example, evaluates organ failure but lacks specificity for heart failure, whereas the GWTG-HF score captures HF-specific risks but insufficiently addresses systemic dysfunction. Additionally, these tools face challenges such as incomplete clinical data, including missing arterial blood gas measurements, and their static nature, which does not accommodate the dynamic changes in a patient's condition [5]. Population variability and the need for interpretable, actionable predictions