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AI-driven Models with Effective Feature Selection Accurately Predict ICU Admission after Laparoscopic Cholecystectomy

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Bachelor of Engineering

Zhejiang Wanli University 2023

Thesis Committee Chair: Rameshbabu Manyam, PhD

An abstract of
A thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University in partial fulfillment of the requirements for
the degree of Master of Public Health in Department of Biostatistics and Bioinformatics

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Abstract

AI-driven Models with Effective Feature Selection Accurately Predict ICU Admission after Laparoscopic Cholecystectomy

By Pengfei Lou

Laparoscopic cholecystectomy (LC) is widely recognized for its advantages over open cholecystectomy, including shorter hospital stays, reduced postoperative pain, and lower mortality. However, despite its favorable safety profile, some patients still experience complications that require intensive care unit (ICU) admission. This study aims to develop interpretable, AI-driven models to predict ICU admission following LC and to identify key patient-specific risk factors.We retrospectively analyzed data from 1,411 patients who underwent LC at Irvine Medical Center between 2017 and 2022. The primary outcome was ICU admission after surgery. A total of 51 variables were collected, including demographics, comorbidities, medications, laboratory results, and postoperative complications. Recursive feature elimination with cross-validation (RFECV) was applied to select the most predictive features.Five machine learning models were developed: Random Forest, Decision Tree, Support Vector Machine, Neural Network, and Logistic Regression. Model performance was assessed using area under the receiver operating characteristic curve (AUROC), recall, accuracy, F1 score, and Matthews Correlation Coefficient (MCC). Among all models, the Random Forest showed the highest performance, with an AUROC of 0.83.To enhance interpretability, SHapley Additive exPlanations (SHAP) were used to evaluate the contribution of each feature to model predictions. SHAP force plots provided individualized explanations, highlighting how specific features influenced ICU risk on a per-patient basis. Top predictors included prolonged length of stay, extended anesthesia duration, and non-routine discharge disposition.This study is the first to integrate interpretable AI models with SHAP visualizations for predicting ICU admission following LC. Our findings suggest that machine learning models can effectively identify high-risk patients and provide transparent, clinically relevant insights to guide decision-making.Future work should focus on external validation and real-time integration of these models into clinical decision support systems to improve risk stratification and optimize resource utilization in postoperative care.

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CHAPTER 1: INTRODUCTION

Laparoscopic Cholecystectomy (LC), a minimally invasive and relatively safe operative procedure, is one of the most commonly performed surgeries in the treatment of gallbladder disease due to its outstanding advantages such as minimal postoperative length of stay, pain, and mortality compared to open cholecystectomy[1]. Although the rate of mortality after LC remains low, the risk of postoperative complications at the patient level is unknown, and sometimes, a simple complication after LC may lead to catastrophic consequences[2]. Most postoperative complications appear because some cases cannot be completed laparoscopically. Still, surgeons decide to continue instead of switching to open cholecystectomy, which, at times, compels the hospital to compress Intensive Care Unit (ICU) resources, posing great challenges to hospital resources management, especially when the laparoscopic cholecystectomy has been regarded as a safe procedure[3]. Therefore, it is important to explore risk factors for ICU admission after LC. In prior studies, several preoperative risk factors for ICU admission after LC have been proven to relate to older age, male gender, and obesity[4].

Furthermore, postoperative death has been the third greatest contributor to all deaths around the world[5]. Although the rate of surgical mortality has declined during the past decade, the number of patients who need intensive care monitoring has been on the rise. Thus, the optimum use of ICU resources is of utmost importance to hospitals and healthcare providers. In this context, the emergence of electronic health record (EHR) data provides a promising platform to manage patient medical data efficiently, thus helping hospitals and surgeons focus more on patient care and decision-making in ICUs. The effective analysis of EHRs could increase the possibility of survival, especially for those patients who are at high risk and need intensive monitoring[6]. In addition, the COVID-19 pandemic, in several ways, has exposed the inefficiency of current healthcare resource management (especially ICU allocation) and the limitations of data-driven decision-making that can cause unforeseen disasters[7]. To tackle such problems effectively, cutting-edge decision-support frameworks utilizing machine learning (ML) methods should be useful and potentially make healthcare processes more efficient and help clinicians make better decisions.

In recent times, Artificial intelligence (AI) and ML algorithms have been extensively explored for their potential utility in clinical settings[8],[9],[10]. For example, Lan Lan et al.[11] built an accurate model to predict ICU admission after non-cardiac surgery in a study conducted in China. They found that the gradient-boosting ML model produced the best performance with an AUROC of 0.90. In another study by Stefanie Jauk et al[12]., the Random Forest model excelled over other models with an AUC of 0.91 in the test set, showing an excellent ability to distinguish between patients who need admission to the ICU and those who do not. The model also achieved a sensitivity of 0.73 and a specificity of 0.80. Furthermore, Anthony Gebran et al[13] used a novel, interpretable artificial intelligence technology called optimal classification trees to predict the need for postoperative intensive care unit admission. Their model demonstrated excellent discrimination for predicting the need for intensive care unit admission with C-statistics of 0.89 in the training set and 0.88 in the test dataset. These studies highlight the utility of AI-driven models in helping hospitals manage ICU resources efficiently. ICU misclassification after Laparoscopic cholecystectomy-related surgeries is of utmost concern for hospitals because patients come from different backgrounds, and normally, they are in large amounts. This necessitates a highly accurate clinical decision tool for patient-specific preoperative prediction of ICU admission after LC.

Therefore, the aims of this study are 1) to develop and test five AI-driven models for predicting ICU admission after LC and 2) to identify, visualize, and interpret the relevant risk factors for ICU admission after LC.

CHAPTER 2: METHODS

2.1 Data Source and Study Population

The study population included EMR data from patients who underwent LC between 2017 and 2022 at Irvine Medical Center in Orange County, California. Data were extracted from an open-source database, the Medical Informatics Operations Room Vitals and Events repository (MOVER)[14]. The study cohort comprised EMR data of patient demographics, previous medical history and hospital visits, medications, patient LDA (lines, drains, and airway devices), laboratory measurements, procedure events, and postoperative complications. The final analysis of the study cohort included 1411 patients.

2.2 Study Variables and Primary Outcome

Based on an extensive literature review on the subject[15],[16],[17],[18],[19],[20],[21], 51 features comprising patient demographics, patient health history, medication usage, laboratory measurements, and postoperative complications were included in this study. The main outcome of the study was whether a patient was transferred to the ICU after LC.

2.3 Data Preprocessing and Missing Data Handling

Data were integrated and processed using open-source software tools such as Structured Query Language, MySQL, and Python[22],[23]. The study population was divided into training and testing sets using a stratified split in an 80:20 ratio. The handling of missing data included two steps. First, if the proportion of missing data for each variable was greater than 0.1, the feature was excluded from the dataset. 17 variables (i.e., encounter type code, encounter type, ordering date, order class, medication id, medication display name, medication name, medication start date, medication end date, medication order status, medication record type, medication administration action, medication action time, dose unit, medication route, and administration signature) were deleted due to high percentage of missing data. In the remaining 34 variables, there were still 18 variables with less than 0.1 of missing values. Missing values in categorical variables (of those 18 variables) were imputed with the most frequent value in each categorical variable. For continuous variables and datetime variables, missing values were imputed with median values and mean values calculated from the non-missing values, respectively.

The Synthetic Minority Oversampling Technique (SMOTE) and Tomek Link methods were applied to address the class imbalance in ICU admission events[24]. After variable consolidation and transformation, 13 variables were chosen for the final analysis. Then, one-hot encoding was used to transform the unique value of each category variable (Lab category, Abnormal flag, Discharge disposition, ASA physical status classification, sex, Anesthesia type, Postoperative complications, Patient class) into individual variables to avoid being treated as numerical values.

Then, these values were transformed into Boolean values (i.e., True / False) for the machine to better understand[25]. Subsequently, some duplicate variables were deleted.

2.4 Model Development and Performance Evaluation

The proposed risk prediction framework employs the technique of Random Forest methods, i.e., combining the decisions from multiple models to increase prediction accuracy (Figure 1)[26]. The first component, 'Feature Engineering' in Figure 1 . A, forms the foundation as it handles raw data extraction, data cleaning, transformation, and study cohort preparation, as described in the preceding section. The second component processes the 'feature selection' strategy, and this role is handled by an automatic feature selection algorithm, 'Recursive Feature Elimination with Cross Validation (RFECV, Figure 1.B)[27].

RFECV, a popular greedy search feature selection algorithm, aims to identify the best possible feature subset that most impacts the desired outcome. It repeatedly creates models by keeping more representative features (i.e., variables or risk factors) aside while removing the irrelevant features at each iteration, thus facilitating reduced computational overhead, higher learning accuracy, and better prediction. It constructs the next model with the leftover features until all the features are exhausted and ranks the features according to the order of elimination. The optimal subset of features (i.e., the most relevant risk factors associated with ICU admission after LC) was deployed to the Random Forest model for further evaluation.

The third module (Figure 1.C) trains and validates the final model using 'Random Forest, ' a scalable decision tree ML algorithm. Random Forest creates multiple decision trees using different random subsets of the training data generated through bootstrapping. Each tree is trained on a different subset, and the final model's prediction is an aggregate of all the predictions of individual trees. Eventually, the final module generates performance evaluation metrics, such as AUROC curve, recall, accuracy, and false negative rate[28].

SHAP (SHapley Additive exPlanations) values were used to perform feature importance analysis by assigning each feature a relative importance value, representing its contribution to the model's prediction. Based on game theory, SHAP provides a unified and interpretable framework to explain individual predictions from machine learning models by quantifying how each feature increases or decreases the prediction relative to the base value[29]. To further illustrate the model's interpretability, SHAP force plots were generated for the top 3 high-risk and bottom 3 low-risk patients. These visualizations provide a clear breakdown of how specific features influenced each individual prediction.

In addition, the model was tuned to improve prediction accuracy using Bayesian optimization with 10-fold cross-validation to identify the best-performing set of hyperparameters[30]. The optimal hyperparameters were then used to train the final model.

In the training phase with the Random Forest algorithm, the model was trained using the labeled training data, and hyperparameter tuning was applied to optimize the parameters of the model for better performance. To obtain the optimal parameters, a 10-fold cross-validation (CV) was applied to the tunable parameters of the model. The optimal threshold for classification was determined by identifying the point closest to the top-left corner of the ROC curve and returning new results of performance metrics. The performance of the Random Forest classifier was further evaluated with a test dataset, including model interpretation through the SHAP value summary plots. Subsequently, four more algorithms (decision tree, support vector machine, neural network, and logistic regression) were constructed on the training data using a 10-fold CV and validated on the test data of patients. The relative importance of the risk factors, AUROC, recall, accuracy, and false negative rate, were used to assess and quantify the performance of the ML models.

CHAPTER 3: RESULTS

3.1 Baseline Characteristics

1411 patients were identified, and the proportion of ICU admissions after laparoscopic cholecystectomy-related surgeries was 0.32 (n=454) [TABLE 1]. Most of the patients transferred to the ICU were female (0.61, n = 276), and most were between 18 and 55 years old (0.53, n=240) with mild systemic disease (0.47, n=214) or severe systemic disease (0.46, n=207). About 0.55 of the patients who were admitted to ICU after LC (n=248) stayed at the hospital for 2 to 5 days, and they experienced 1.97 to 5.23 hours of anesthesia during surgeries. Approximately 0.9 (n = 409) of the patients transferred to the ICU were obese or overweight with a BMI greater than 35 lb/in^2. Laboratory tests showed that 0.3 of the patients (n = 134) transferred to the ICU were due to liver damage with abnormal values low (0.095, n = 43) or high (0.14, n = 62). The most common postoperative complication after LC was anesthesia-related postoperative complication (0.95, n=430).

3.2 Feature Selection

In this study, recursive feature elimination with 10-fold cross-validation was applied to identify the optimal number of features that can yield the highest AUROC score, which summarizes the performance of the classifier across all threshold values. The AUROC score is especially useful when the dataset is imbalanced. The Random Forest model demonstrated the highest predictive ability with a cross-validated AUROC score of 0.79 when the number of features (i.e., variables or risk factors) selected was 9 [Figure 2].

These 9 risk factors, in the order of significance, were the length of stay (days), anesthesia duration (hours), discharge disposition, American Society of Anesthesiologists (ASA) physical status, age, BMI, lab test, gender, and abnormal flag [Figure 3]. Each bar in Figure 3 indicates the global importance and relative magnitude based on SHAP value and represents the contribution of each feature to the final prediction of ICU admission.

SHAP summary plot [Figure 4], comprising o set of beeswarm plots, demonstrates the more detailed behavior, magnitude, and direction of the impact of the risk factors on the model's prediction for the patient. As illustrated in Figure 4, Length of Stay and Anesthesia Duration were significant predictors of ICU admission risk, with longer durations/values of these variables resulting in a higher likelihood of ICU transfer. Also, Discharge Disposition plays a key role; patients not discharged directly to their home—such as those discharged to rehabilitation or long-term care facilities—are at a higher risk of ICU admission. Further, ASA Physical Status and Age contribute meaningfully to ICU risk predictions, with higher ASA scores (indicating poorer preoperative health status) and older age both correlating with increased ICU admission likelihood. BMI is another important factor, as higher BMI values increase ICU admission risk, reflecting the known complications associated with obesity in surgical settings. Abnormal findings in Lab Tests and Abnormal Flag values show that abnormally high values in liver damage tests also correlate with higher ICU admission risk. Lastly, although gender has a smaller impact relative to other features, the model indicates a tendency for male patients to be more likely to require ICU admission compared to female patients.

3.3 Individual Risk Analysis

SHAP (SHapley Additive exPlanations) force plots were utilized to interpret the impact of individual clinical variables on the likelihood of ICU admission by showing the top 3 and bottom 3 patients. These force plots visually represent how each feature either increases or decreases the probability of ICU admission relative to a base value, which serves as a reference point. The base SHAP value is computed as the mean predicted probability of ICU admission across all test samples, reflecting the expected likelihood of ICU admission before incorporating patient-specific characteristics. Mathematically, this is expressed as:

$$\text{Base Value} = \frac{1}{N} \sum_{i=1}^{N} P(Y = 1 \mid X_i)$$

where $P(Y = 1 \mid X_i)$ is the predicted probability of ICU admission for each test sample, averaged over the entire test set. This base value serves as a benchmark, and the SHAP values quantify how each feature modifies this probability.

In Figure 5(a), the probability of ICU admission is the highest, with key contributing factors being anesthesia duration (5.68 hours), ASA Physical Status (3.0), and a hospital stay of 6 days. A longer anesthesia duration indicates a more extensive or high-risk surgical procedure, which aligns with an increased likelihood of postoperative ICU admission. Figure 5(b) highlights a higher ICU admission probability driven by ASA Physical Status (3.0), discharge disposition (3.0), and a hospital stay of 10 days. An ASA score of 3.0 signifies that the patient has a severe systemic disease, which inherently increases the risk of complications requiring intensive care. A prolonged hospital stay further suggests complications, reinforcing the need for ICU monitoring. In Figure 5(c), factors such as anesthesia duration (2.73 hours), patient age (71 years), length of hospital stay (7 days), and discharge disposition (3.0)contribute to an increased probability of ICU admission. Longer anesthesia duration and extended hospital stays are associated with more complex surgical or post-operative conditions, making ICU admission more likely. Additionally, the discharge disposition of 3.0 indicates a clinical status necessitating intensive care.

The probability of ICU admission is significantly lower in Figure 6 due to key protective factors, including a short anesthesia duration (1.5 hours), no hospital stay (0 days), lower ASA Physical Status (2.0), and a discharge disposition of 1.0. The discharge disposition (1.0) signifies a routine discharge without complications. The lower ASA status suggests better preoperative health, reducing the risk of severe postoperative complications. Furthermore, a short anesthesia duration and immediate hospital discharge indicate a low-risk, uncomplicated procedure, which strongly decreases the need for ICU admission.

3.4 Evaluation Metrics and Model Performance with Train and Test Datasets

TABLE 2 presents the performance metrics of five machine learning models used to predict admission to the ICU after laparoscopic cholecystectomy (LC) using 5-fold cross-validation. The metrics analyzed include recall, accuracy, false negative rate (FNR), F1 score, and Matthews correlation coefficient (MCC) for both the training and test datasets.

The Random Forest model exhibited perfect performance on the training set (recall and accuracy of 1.00, FNR of 0.00, F1 score and MCC of 1.00), indicating potential overfitting. On the test set, however, its performance decreased, with a recall of 0.69, an accuracy of 0.75, an FNR of 0.31, an F1 score of 0.64, and an MCC of 0.45. Similarly, the Decision Tree model also showed near-perfect results during training (recall of 0.99, accuracy of 0.99, FNR of 0.01, F1 score of 0.99, and MCC of 0.99), but it underperformed in the test set, with a recall of 0.61, accuracy of 0.69, FNR of 0.39, F1 score of 0.55, and MCC of 0.32.

The Support Vector Machine (SVM) model showed a training recall of 0.81 and an accuracy of 0.73, along with an FNR of 0.19, an F1 score of 0.74, and an MCC of 0.46. On the test set, the SVM achieved a recall of 0.72, an accuracy of 0.70, FNR of 0.28, F1 score of 0.60, and MCC of 0.38. The Artificial Neural Network (ANN) model performed consistently across both datasets, with a training recall of 0.84, accuracy of 0.78, FNR of 0.16, F1 score of 0.79, and MCC of 0.57, and a test recall of 0.79, accuracy of 0.65, FNR of 0.21, F1 score of 0.58, and MCC of 0.34. Lastly, the Logistic Regression model demonstrated moderate performance during training (recall of 0.76, accuracy of 0.72, FNR of 0.24, F1 score of 0.72, and MCC of 0.44) and similar test performance, with a recall of 0.72, accuracy of 0.68, FNR of 0.28, F1 score of 0.59, and MCC of 0.36.
Overall, the Random Forest model demonstrated the best performance in terms of recall and FNR, indicating its strength in identifying positive ICU admission cases while maintaining a low false negative rate.

Figure 7 shows the AUROC score for five models with the test dataset. Combined with the performance on the training dataset, the random forest was chosen as the optimal mode, and Bayes search with a 10 cross-fold validation was used to find the best hyperparameters that can yield optimal predictive performance with minimal overfitting. The resultant hyperparameters were bootstrap: False, Max Depth: 574, Max Features: log2, Min Samples Leaf: 1, Min Samples Split: 2, and Estimators: 458. After applying the best hyperparameters, the AUROC score improved to 0.83. Under the new threshold obtained from the ROC curve set at 0.32, the final model yielded a recall value of 0.92, accuracy of 0.70, F1 score of 0.64, MCC of 0.45, and FNR of 0.13

CHAPTER 4: DISCUSSION

Laparoscopic cholecystectomy (LC) has been one of the most popular surgeries performed in different populations[31]. However, it is difficult to assess the individual patient's risk of postoperative complications after LC. Developing a clinical decision-support tool to identify risk factors for ICU admission after LC will be helpful for surgeons and hospitals to make better decisions on patient-specific risk evaluation. This study found that the random forest model performed the best with an AUROC of 0.83 after hyperparameter optimization, indicating good discrimination ability to evaluate risk factors for ICU after LC. Furthermore, the most important patient risk factors identified by the random forest model, in order of significance, were the length of stay (days), anesthesia duration (hours), discharge disposition, ASA physical status, age, BMI, lab test, gender, and abnormal flag.

This is the first study to utilize AI-driven models to predict admission to the ICU after LC. Previous studies on the subject focused on the use of statistical models or scoring systems to predict difficult laparoscopic cholecystectomy. For example, Vannucci et al[32]. studied statistical models to predict the operative difficulty in laparoscopic cholecystectomy AUROC of 0.70 and 0.76. Kemal Beksac et al[2]. used logistic regression to predict conversion to open cholecystectomy with 0.7 sensitivity and 0.79 specificity. Nikhil Gupta et al[4]. utilized a scoring system to analyze risk factors and predict specific degrees of difficulty during surgery. The AUROC was 0.86, but the sample size was too small to ensure its validity. Thus, it is necessary to develop AI-driven models to tackle the problems from different perspectives. The findings of this study that AI-driven models, such as Random Forest, can perform well in predicting admission to the ICU after laparoscopic cholecystectomy are consistent with previous studies. For example, Ke Lin et al[33]. built a mortality prediction model using ML algorithms for acute kidney injury (AKI) patients in the IC and found that Random Forest has the best performance with an AUROC of 0.866 (95% CI: 0.862 - 0.870). Similarly, Linda Lapp et al[34]. used several ML models to predict severe postoperative complications after cardiac surgery. Their study demonstrated that AdaBoost has the best overall performance (AUROC = 0.731). However, based on the sensitivity and negative predictive value, it was the Random Forest (negative predictive value = 0.923) and gradient boosting model (sensitivity = 0.875) that performed well in severe postoperative complications. In addition, Qiuying Chen et al[35]. developed ML models to predict prolonged ICU lengths of stay after acute type A aortic dissection surgery. They found that Random Forest produced the highest performance, with an AUROC of 0.837 (95% CI: 0.766–0.908) in the test dataset. Further studies utilizing AI for predicting non-ICU admission complications after laparoscopic cholecystectomy are needed.

This study also found that the length of stay was a significant predictive variable in the Random Forest model. A longer hospital stay may be associated with more severe illness or complications, increasing the likelihood of ICU admission. This is consistent with several studies that have shown an extended hospital stay as a risk factor in high-risk patients after laparoscopic cholecystectomy. For example, Musbahi et al[36]. used negative binomial regression to model hospital stay duration and identified it as a significant factor influencing postoperative outcomes. Moreover, Kieran Stone et al[37]. in their systematic review, highlighted how reducing the length of stay was associated with cost savings and did not increase the risk of complications. These findings showed that the length of stay could influence postoperative complications and, in turn, affect whether the patient will be transferred to the ICU.

This study also found that anesthesia duration was the second most important predictive variable in the Random Forest model. An extended duration of anesthesia can indicate a more complicated or prolonged surgery, which could increase the risk of postoperative complications and admission to the ICU. V Kanakala et al[38]. wanted to identify risk factors for laparoscopic cholecystectomy by conducting a multivariable analysis. The study found that anesthesia duration is a significant predictor of postoperative complications, highlighting its impact on the overall risk profile of patients undergoing LC. Similarly, JU Chong et al[39]. evaluated factors influencing the length of postoperative hospital stay in patients undergoing laparoscopic cholecystectomy. They found anesthesia duration as a significant predictor, suggesting that longer anesthesia duration was associated with extended hospital stays and increased risk of postoperative complications. These findings emphasize the importance of monitoring anesthesia duration as a potential risk factor for ICU admission.

This study also found that discharge disposition was the third important predictive variable in the Random Forest model, highlighting its importance and significant role as a risk factor for surgery. This is consistent with prior studies showing the influence of discharge disposition on conversion from laparoscopic to open cholecystectomy. For example, Sakowitz et al[40]. found that patients requiring post-surgical ICU care often had complex cases that precluded direct home discharge, suggesting a correlation between the need for ICU-level care and non-home discharge dispositions. Similarly, Huang Lau et al[41]. demonstrated that patients discharged home after laparoscopic cholecystectomy had fewer complications, with minimal need for intensive postoperative interventions. This implies that when a patient is discharged directly to home, they are less likely to be readmitted to the ICU, as they are considered to have a stable postoperative course. Integrating this finding into AI-driven predictive models could help healthcare providers more accurately stratify post-surgical care needs, allowing for more efficient allocation of ICU resources to patients at higher risk of complications.

This study has some limitations. The MOVER database, as with any large database, may have inaccuracies in data entry. The database lacks certain socioeconomic variables, such as income and education levels, which can be important for comprehensive risk factors analysis. The data set used in this study may not include diverse populations or settings, limiting the generalizability of the findings. Medical practices and patient demographics can change over time, potentially affecting the relevance of the data. In addition, more data sets should be included to validate whether these models can be applied to clinical settings when there are diversified populations. Also, laparoscopic cholecystectomy is often considered a routine and minimally invasive procedure, leading to less emphasis on comprehensive vital signs monitoring compared to more invasive surgeries.

In conclusion, this is the first study to develop and validate AI-driven models to predict admission to the ICU after LC with good performance. Specifically, the Random Forest model demonstrated good discriminative ability with an AUROC of 0.83, surpassing the performance of conventional predictive methods. The model identified patient-specific risk factors that contribute to a higher risk of admission to the ICU, and these are hospital length of stay (days), anesthesia duration (hours), discharge disposition, ASA physical status, age, BMI, lab test, gender, and abnormal flag.

Furthermore, patients who are older males with higher BMI, abnormally high values in liver damage tests, and poor health status before surgery are at an increased risk of ICU admission. Additionally, these patients often experience longer anesthesia duration and extended hospital stay and are more likely to have a non-home discharge disposition, all of which further elevate the likelihood of requiring ICU care after LC. For example, a patient with an anesthesia duration of 5.68 hours and an ASA score of 3.0 was identified as having a particularly high likelihood of ICU admission. In contrast, the SHAP force plots for low-risk patients showed protective patterns such as short anesthesia duration (1.5 hours), no hospital stay, low ASA scores (2.0), and routine discharge dispositions. This research effort serves as a groundwork for future research that can translate into an excellent performing, externally validated, AI-driven clinical decision support tool to be utilized by hospitals and surgeons to improve patient outcomes.

Appendix

Table 1. Baseline characteristics of the study cohort

Variable	ICU admission, No, N = 957	ICU admission, Yes, N = 454	Missing
Gender, female	660 (69%)	276 (61%)	0(0%)
Age, years			0(0%)
18-54	626 (65%)	240 (53%)	
55-90	331 (35%)	214 (47%)	
Body Mass Index, lb./in^2			0(0%)
1-25	2 (0.2%)	1 (0.2%)	
25-35	111 (12%)	44 (9.7%)	
>35	844 (88%)	409 (90%)	
ASA physical status classification			0(0%)
Healthy	68 (7.1%)	20 (4.4%)	
Mild systemic disease	609 (64%)	214 (47%)	
Severe systemic disease	273 (29%)	207 (46%)	
Incapacitating disease	7 (0.7%)	13 (2.9%)	
Discharge disposition			0(0%)
Home Healthcare IP Admit Related	18 (1.9%)	54 (12%)	
Home Routine	931 (97%)	363 (80%)	
Other	8 (0.8%)	37 (8.1%)	
Patient Class, Inpatient	596 (62%)	433 (95%)	0(0%)
Lab Category			0(0%)
Alanine aminotransferase	91 (9.5%)	63 (14%)	
Albumin	65 (6.8%)	36 (7.9%)	
Calcium	45 (4.7%)	35 (7.7%)	
Other	756 (79%)	320 (70%)	
Abnormal flag			0(0%)
Low	59 (6.2%)	43 (9.5%)	
Normal	835 (87%)	349 (77%)	
High	63 (6.6%)	62 (14%)	
Anesthesia type			0(0%)
Epidural	0 (0%)	1 (0.2%)	
General	952 (99%)	450 (99%)	
Regional	5 (0.5%)	3 (0.7%)	
Postoperative complications, anesthesia complications	885 (92%)	430 (95%)	0(0%)
Duration of anesthesia, hours	2.71 $\pm$ 0.88	3.26 $\pm$ 1.29	0(0%)
Length of stay, days			0(0%)

0-2	498 (52%)	48 (11%)
2-5	363 (38%)	248 (55%)
5-10	86 (9.0%)	119 (26%)
>10	10 (1.0%)	39 (8.6%)

Note: Percentage for categorical variables; mean and std for continuous variables; ASA: American Society of Anesthesiologists

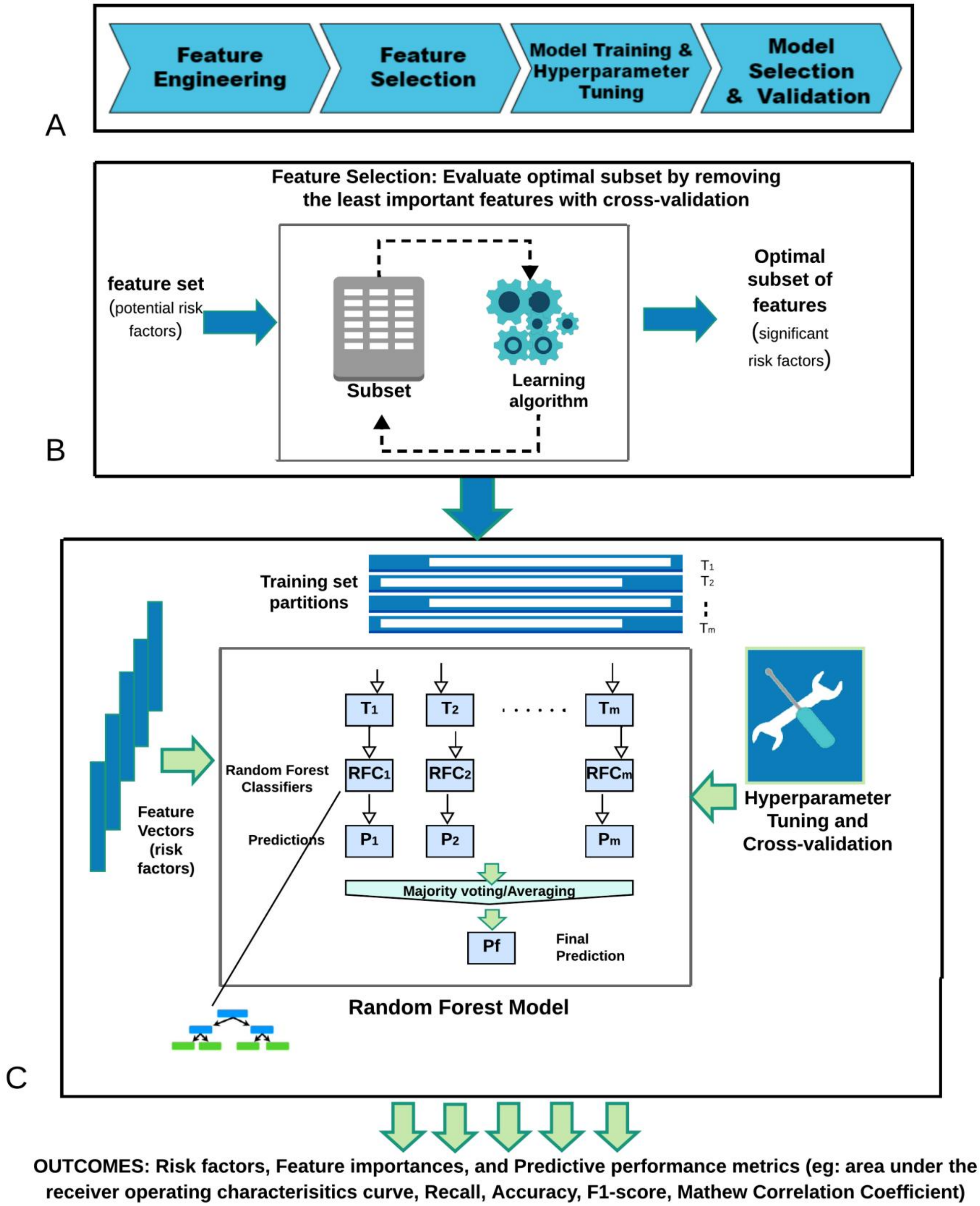


Figure. 1: Proposed Artificial Intelligence-driven Framework.

Table 2. Training and Test Performance on training dataset

Model	Recall	Accuracy	FNR	F1 Score	MCC
Training Performance					
Random Forest	1	1	0	1	1
Decision Tree	0.99	0.99	0.01	0.99	0.99
Support Vector Machine	0.81	0.73	0.19	0.74	0.46
Artificial Neural Network	0.84	0.78	0.16	0.79	0.57
Logistic Regression	0.76	0.72	0.24	0.72	0.44
Testing Performance					
Random Forest	0.69	0.75	0.31	0.64	0.45
Decision Tree	0.61	0.69	0.39	0.55	0.32
Support Vector Machine	0.72	0.70	0.28	0.60	0.38
Artificial Neural Network	0.79	0.65	0.21	0.58	0.34
Logistic Regression	0.72	0.68	0.28	0.59	0.36

Note: FNR: False Negative Rate; MCC: Matthews Correlation Coefficient

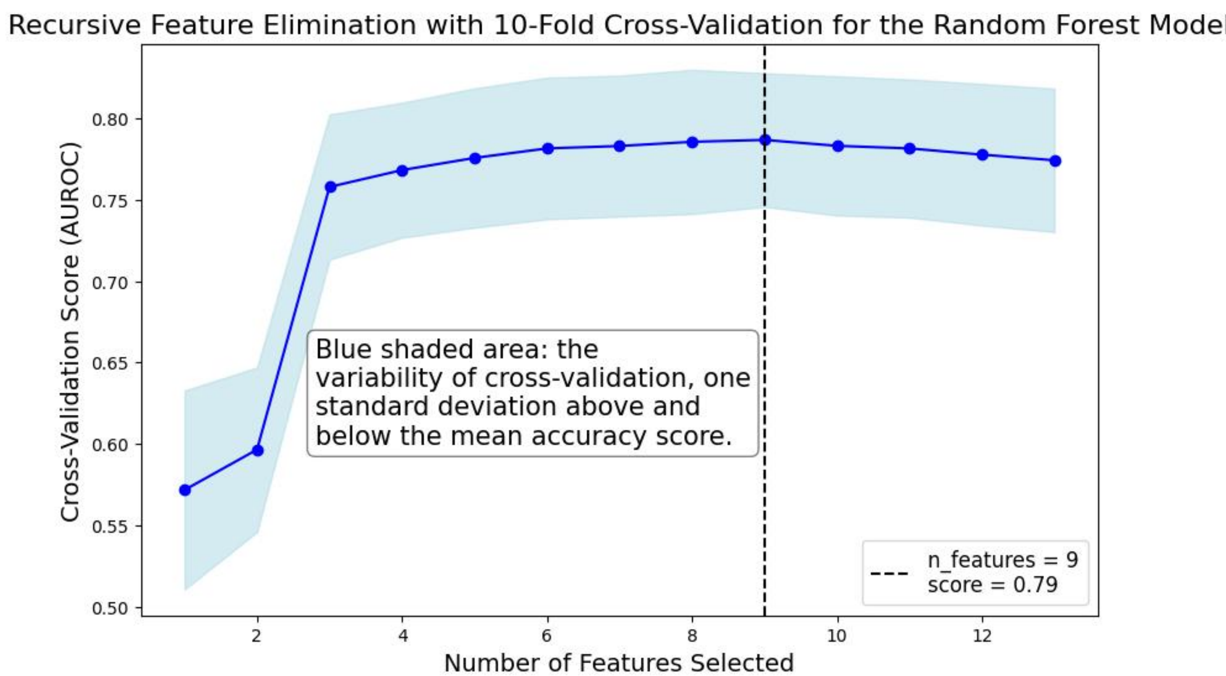


Figure. 2: Predictive ability of the model: Random Forest Classifier's Recursive Feature Elimination with Cross-Validation model shows the number of features VS area under the receiver operating characteristic (AUROC).

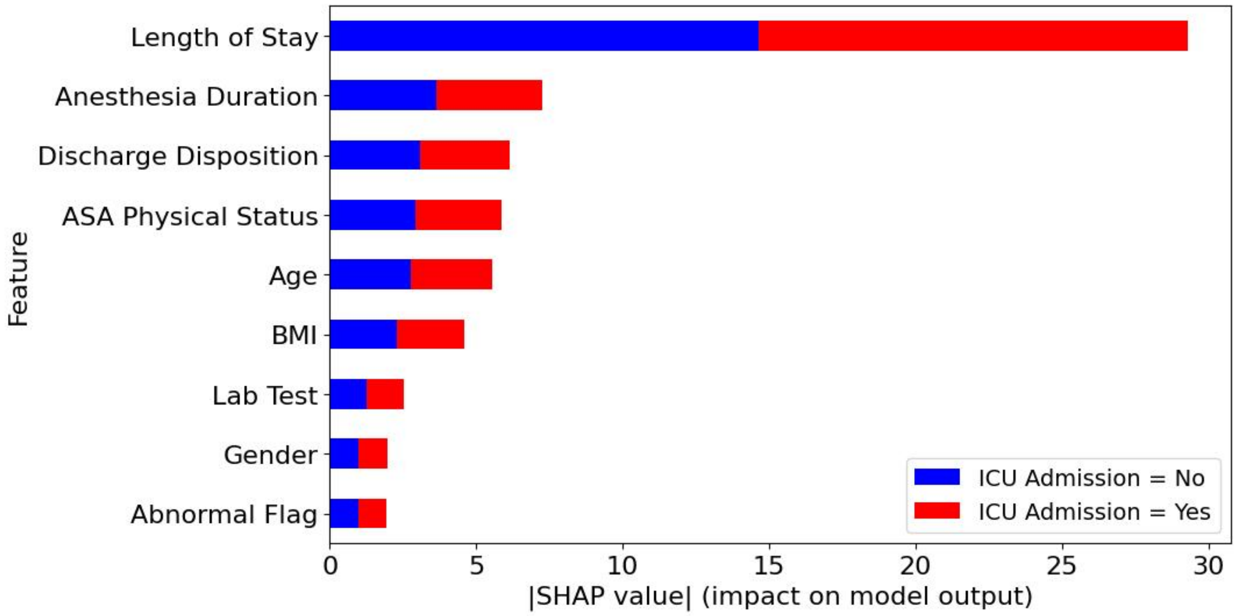


Figure. 3: The feature importance plot demonstrating the relative importance of risk factors in the Random Forest model.

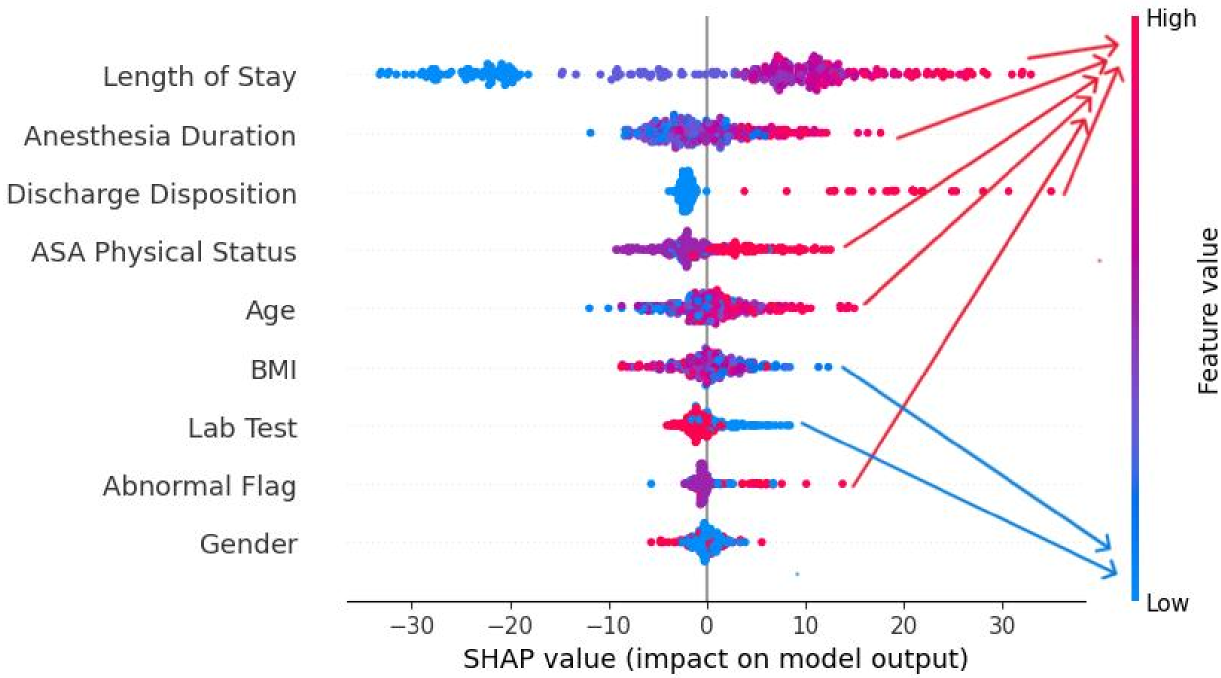
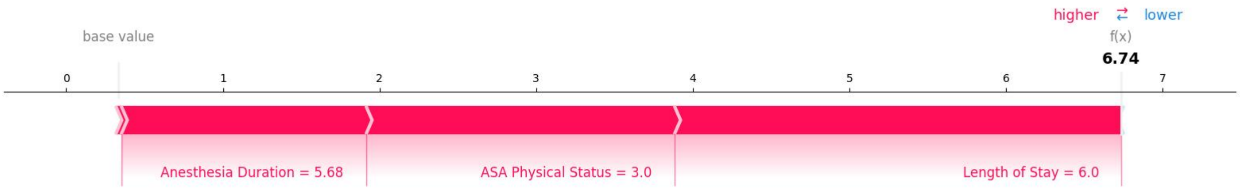
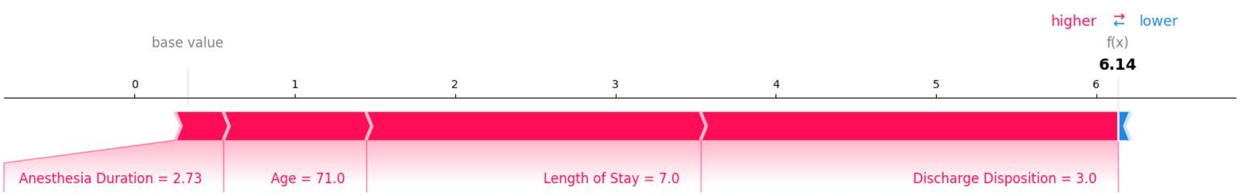


Figure. 4: SHapley Additive exPlanations (SHAP) value summary plot, illustrating the impact of a feature on model output for predicting ICU admission. A set of beeswarm plots, where each dot corresponds to an individual in the study cohort. The dot's position on the x-axis shows the relative impact that the feature has on the model's prediction for that individual. When multiple dots land at the same x position, they pile up to show density. Red dots indicate a high value for that feature, while blue dots represent a low feature value. Red arrows represent the features with high values influencing the outcome most, while blue arrows represent the features with low values influencing the target outcome most.



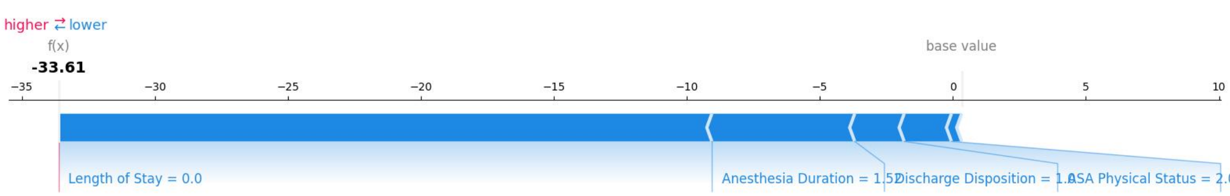
(a) Patient with the highest risk of ICU admission

(b) Patient with the second highest risk of ICU admission

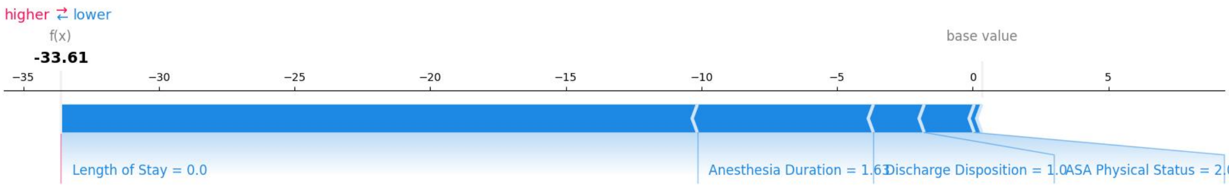


(c) Patient with the third highest risk of ICU admission

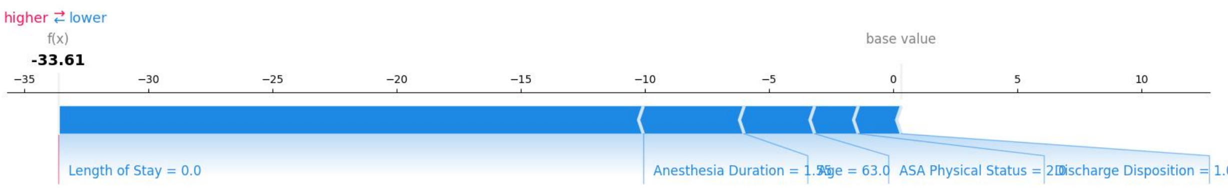
Figure. 5: SHAP force plots for the top 3 patients with the highest predicted risk of ICU admission.



(a) Patient with the lowest risk of ICU admission



(b) Patient with the second lowest risk of ICU admission



(c) Patient with the third lowest risk of ICU admission

Figure. 6: SHAP force plots for the bottom 3 patients with the lowest predicted risk of ICU admission.

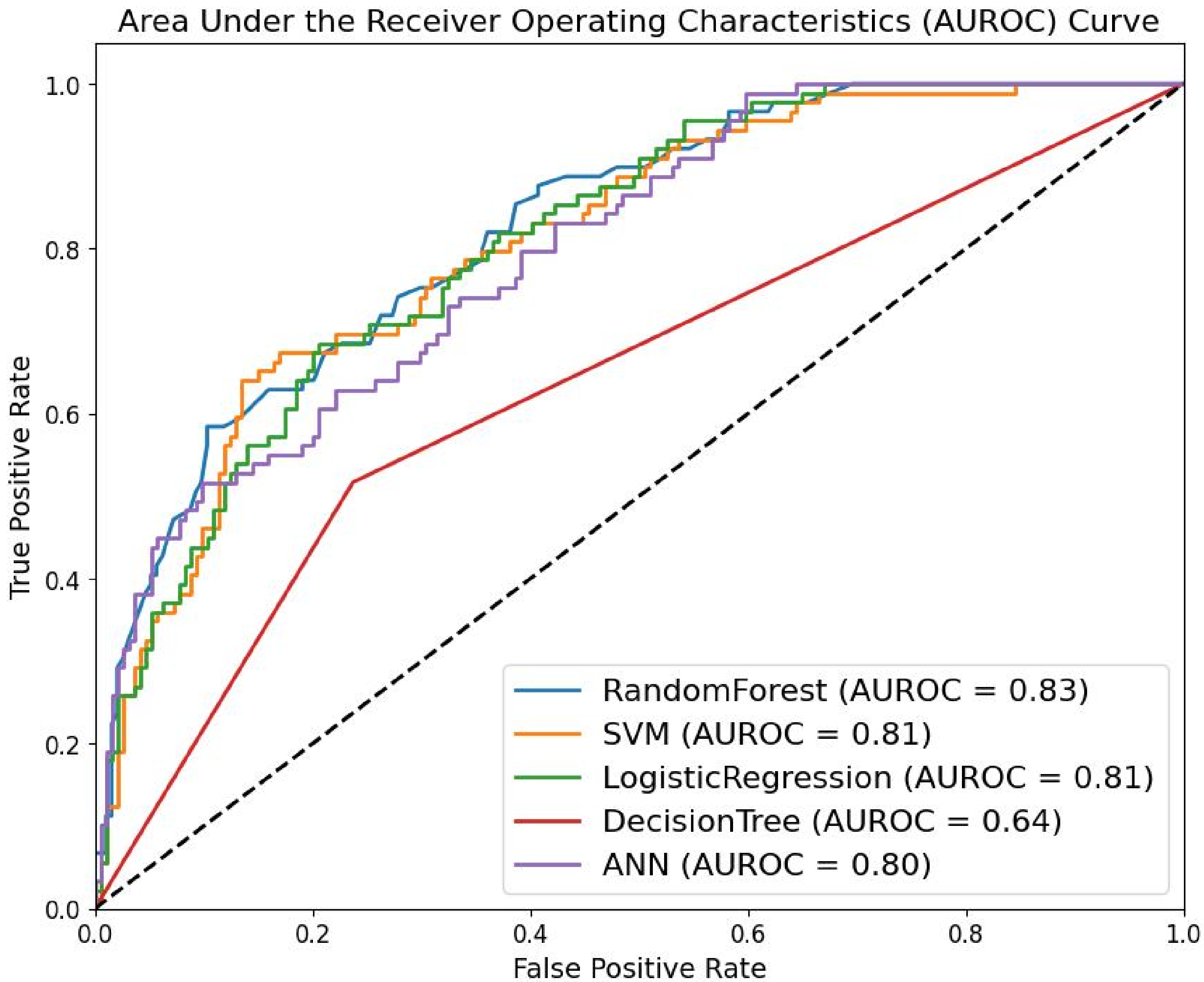


Figure. 7: Area under the receiver operating characteristics plots for five artificial intelligence-driven Models.

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