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Stochastic Processes

Final Project

1. Introduction

1.1 Problem context

Imagine a bustling hospital, its corridors echoing with urgent footsteps and the steady hum of life-saving machinery. Within this medical labyrinth lies the beating heart of critical care: the Intensive Care Unit (ICU). Here, amidst the controlled chaos, lives hang in the balance, tended to by a dedicated team of healthcare professionals.

Yet, within this high-stakes environment, a challenge looms large: the delicate orchestration of patient flow. With a capacity of just 15 beds, the ICU operates on a knife's edge, where every admission and discharge must be meticulously managed.

1.2 Problem framing

Picture this scenario: a patient arrives at the ICU doors, their condition dire and in need of immediate attention. However, with all beds occupied, the harsh reality dawns: they face rejection, their fate uncertain in the face of limited resources. This pivotal moment underscores the pressing need for an efficient simulation model, one that can accurately replicate the intricate dance of patient flow within the ICU's confines.

But the challenges don't end there. Once admitted, each patient becomes a nexus of care, assigned a dedicated nurse whose vigilance is paramount to their recovery. And yet, even after their stay within the ICU, the journey may not end. Some patients may return, their conditions fluctuating and requiring further intervention, a complex dynamic that adds layers of complexity to an already intricate system.

To navigate these complexities, our simulation model draws upon a rich amount of data, capturing the nuances of arrival rates, lengths of stay, return rates, and more. It is through this lens that we embark on a journey to understand, to optimize, and to ultimately enhance the delivery of critical care within the ICU.

1.3 Objectives

In this project, our primary objective is to develop a comprehensive simulation model that accurately represents the patient flow dynamics within the ICU of a hospital. With a capacity of 15 beds, our simulation will capture the intricate interplay of patient admissions, discharges, and potential re-admissions, considering constraints such as bed availability.

Furthermore, we aim to leverage real-world data to inform our simulation parameters, including arrival rates, lengths of stay, and return rates. Through rigorous data analysis, we will derive insights to define key performance indicators (KPIs) essential for evaluating the efficacy of our model.

In the second part of our project, we shift focus to predictive modeling, specifically targeting the prediction of a patient's readiness for discharge from the ICU. Utilizing attributes such as Simplified Acute Physiology Score, Glasgow Coma Scale, and others, we aim to build a predictive model capable of distinguishing between patients ready to leave the ICU and those who should remain.

2. Modeling the ICU on AnyLogic

2.1 Data Exploration

2.1.1 Description of the dataset

The dataset provided contains information regarding patients admitted to the ICU. Here's a comprehensive description of the dataset:

id: An identifier for each unique patient.

codes: A unique code associated with each patient.

age: The age of the patient.

gender: The gender of the patient (1 for male, 0 for female).

dates: The date of admission to the ICU.

bad: A binary attribute indicating the outcome of the patient.

Outcome: Describes the final outcome of the patient (e.g., "Alive", "Dead").

last: Indicates the status of the patient (still in CHU or not).

SAPS: Simplified Acute Physiology Score, an estimation of the probability of mortality.

Glasgow: Glasgow Coma Scale, describing the extent of impaired consciousness.

TISS: Therapeutic Intervention Scoring System, quantifying the amount of intensive care treatment needed.

PA: Blood pressure.

FC: Heart rate.

Temp: Body temperature.

dayIn: The day number of stay in the ICU.

It's important to note that there are null values present in the dataset, particularly evident in the rows where certain attributes such as SAPS, Glasgow, TISS, PA, FC, and Temp are empty.
Additionally, the dataset comprises 6228 observations.
These observations provide a rich source of data for analysis, offering insights into patient demographics, clinical indicators, and outcomes within the ICU setting. However, to ensure accurate analysis and modeling, handling of null values and rigorous data preprocessing will be necessary.

2.1.2 Patient arrivals per day

In order to build our simulation of this ICU service, we needed different values that would define the behavior of our Patient agents within it.
The first is the rate at which new customers enter the service, in other words, the starting point for our simulation.

To do this, from the dataset we keep only entries where the “day in” is 1, to keep only hospital arrivals. Then we look at all unique entries over one year (in our case, the year 2019).

Finally, we divide the average number of entries for each day of the year by 365 days to obtain a daily rate.

3	Date	Count of Patient arrival	Daily Patient per day	1,67
4	**2019**	**444**		
5	02/01/2019	1		
6	03/01/2019	2		
7	04/01/2019	1		

Figure 1: Excel analysis for the Daily Patient per day

This way, we can define that our daily patient rate is about 1.67 patient per day.

Figure 2: Implementation of AnyLogic of the Daily patient per day

2.1.3 ICU patient length of stay

Once the patient is accepted in the service, we need to be able to estimate how long he or she will stay there.
To do this, all we need to do is group together the number of Day In spent in the hospital for each patient.

3	Patient ID	DAYIN count	Average ICU patient length of stay	7,59
4	20017421	4		
5	40026409	8		
6	40169517	7		
7	50001723	7		

Figure 3: Excel analysis for the Average ICU patient length of stay

From this analysis, we arrive at an average of 7.59 days. In order to keep the simulation and analysis relatively simple, we decided to apply a normal distribution with 7.59 as the mean and a variance of 3 high enough to obtain low and very high values, but keeping most of our patients staying between 6 and 10 days.

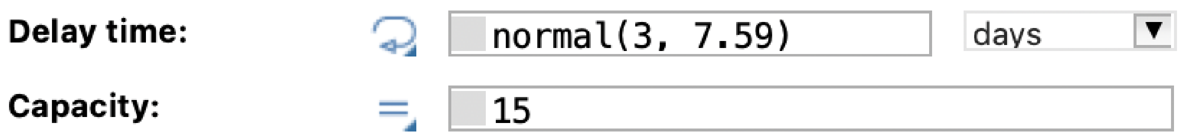


Figure 4: Implementation on AnyLogic of the average ICU patient length of stay

This study would require an in-depth look to define a distribution law closer to the truth, the one currently in place being due solely to heuristic reasoning.

2.1.4 ICU patient return rate

To find out what percentage of our patients will return to the ICU, we follow the following logic:
If a patient arrives as a first day on several different dates, then he's one of them. We therefore carried out this analysis in Excel.

Total number of patients	707
Patients who came back to the ICU	58
ICU patient return rate	8%

Figure 5: Excel Analysis of the ICU Patient return rate

This enabled us to identify an 8% return rate for our patients.

Now, at the end of our simulation, we can add an if condition with an 8% probability of returning our patient to the waiting room.

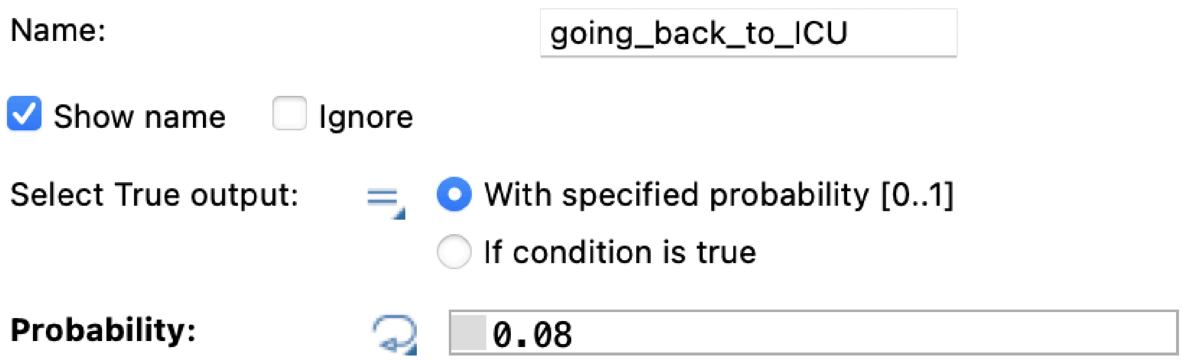


Figure 6: Implementation on AnyLogic of the ICU Patient return rate

2.2 Modelling and 3D Visualization

2.2.1 Model Logic

To build the ICU simulation, we had in mind to construct a linear flow passing through the various real-life operational stages: registration on arrival at the hospital, waiting in the waiting room, then arrival in the ICU room.
In this model, there are two decisions that determine the choice of patient pathway: firstly, if all beds are occupied, then the customer is sent home, as the hospital simply cannot provide the necessary care at that moment.

Secondly, we know that a proportion of patients discharged from ICU will return. If this is the case, our model's approach is to send the patient straight back to the waiting room, without having to check in again. However, this places him at the end of the queue waiting for a bed, a choice that will be discussed later in this report.
Within this model, we find the pool of nurses (remember that one nurse is assigned to each patient) who are automatically assigned to customers according to ICU arrivals and discharges.

Last but not least, Move blocks enable us to trace the patient's journey through our hospital department. It is therefore essential to have a clear idea of the reality of the business and of what happens in the hospital, in order to get as close as possible to reality in its representation.

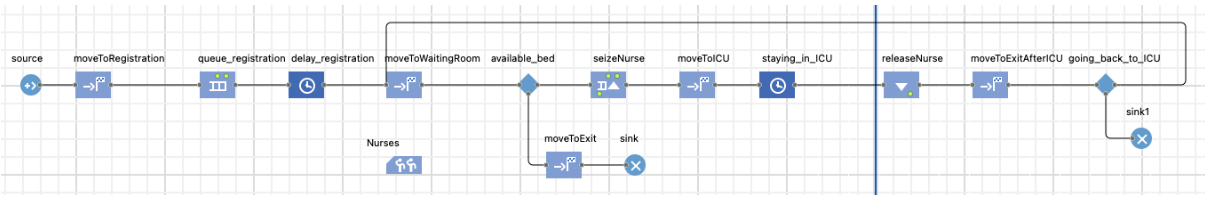


Figure 7: Logical representation of the model with its blocks on AnyLogic

2.2.2 Model Operations

We define the variables we are interested in capturing in this simulation: the number of patients and nurses available (which should always be equal), the number of patients accepted and refused, and the number of patients with long ICU stays.
Next, we need to understand where in the model these variables need to be modified in order to apply the corresponding changes.

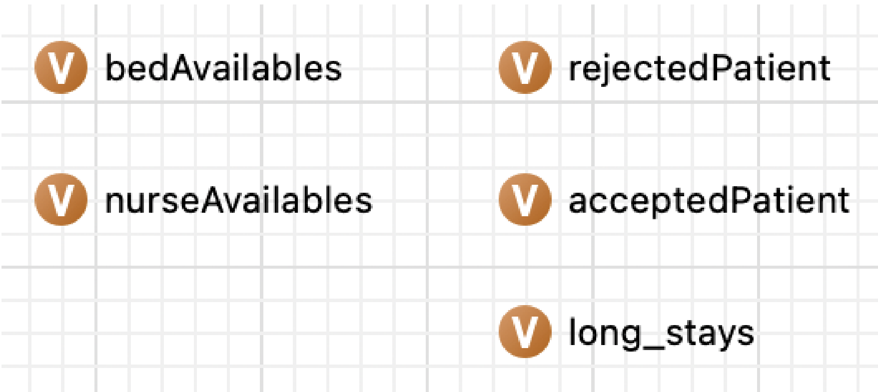


Figure 8: Captured variables that vary within the model

In the first part (registration), there are no variations on these variables, only a queue with three desks to see your registration completed. The duration of this stage is defined by a normal distribution with a mean of 5 minutes. In fact, we assume that the average registration time is 5 minutes to collect all the necessary information, but that a small number of patients will require less or more time, depending on the severity of their symptoms, whether they express themselves clearly, or whether they are complicated cases.
In the waiting room, the duration is not explicitly defined. It depends solely on the number of beds and nurses that become available over time.
In the situation where at least one bed is available, a nurse picks up the first patient in the queue and takes him or her to the ICU room (reducing the numbers of these two entities by one).

Similarly, when a patient's stay is over, we increment these variables to restart the process of fetching a patient from the waiting room.

In this context where the client is taken to his bed, we take the opportunity to increase the number of patients accepted by one. However, according to the hospital policy if the beds are full then the patient is sent home, so this is when the number of rejected patients increases.
As the beds are limiting for the number of patients that the service can treat, it is also important to monitor the number of patients who make a "long stay" within the service, which is described as a stay longer than 9 days.
Indeed, we define the duration of stay within the simulation as a normal law of average 7.59 days with a large variance.

2.2.3 Model Design

Once the simulation builds either by its flow or by the mathematical operations to be captured, we can now represent it to visually see the reality within the service.

The idea was to build a minimalist representation showing the three stages of the patient journey with clearly the three recording offices, the waiting room and its chairs, as well as the ICU room with its beds.
The service is closed by walls, delimiting the paths that can be used by clients and nurses.

A 3D visualization can add another dimension to the simulation by representing the physical layout of the ICU. This spatial representation can simulate the actual arrangement of beds, medical equipment, and staff stations within the ICU environment. By visualizing the physical space, stakeholders can identify potential bottlenecks, optimize resource allocation, and improve the layout for better efficiency.

Visualizations are powerful communication tools that can effectively convey complex information to stakeholders, including healthcare professionals, administrators, and policymakers. By presenting simulation results in a visually engaging manner, stakeholders are more likely to understand the challenges and opportunities within the ICU environment

Finally, visualizations can aid in the validation and verification of the simulation model. By comparing the visual representation of the simulated system with real-world observations or historical data, stakeholders can assess the accuracy and reliability of the model. This iterative process of validation and verification ensures that the simulation accurately reflects the dynamics of the ICU.

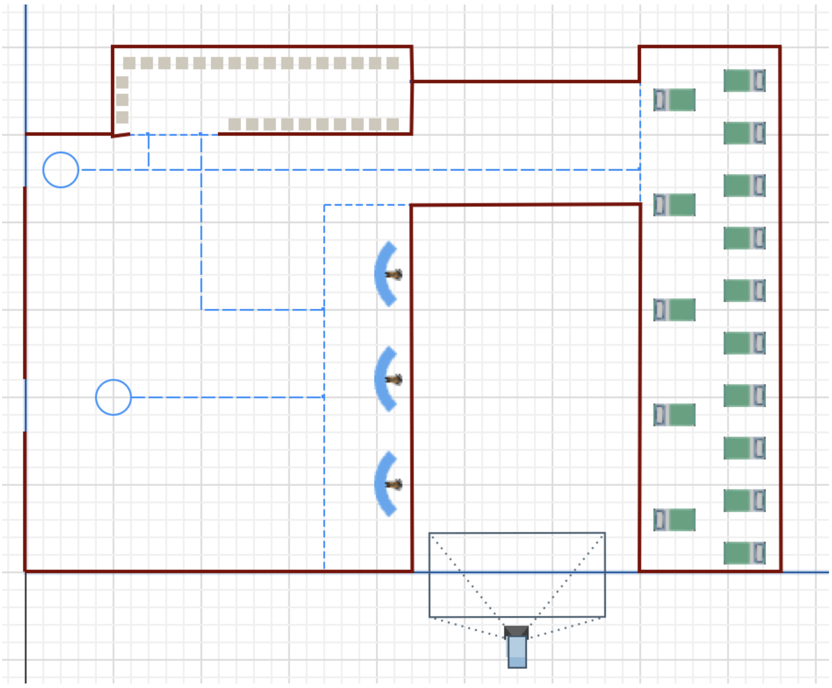


Figure 9: 2D representation of our model

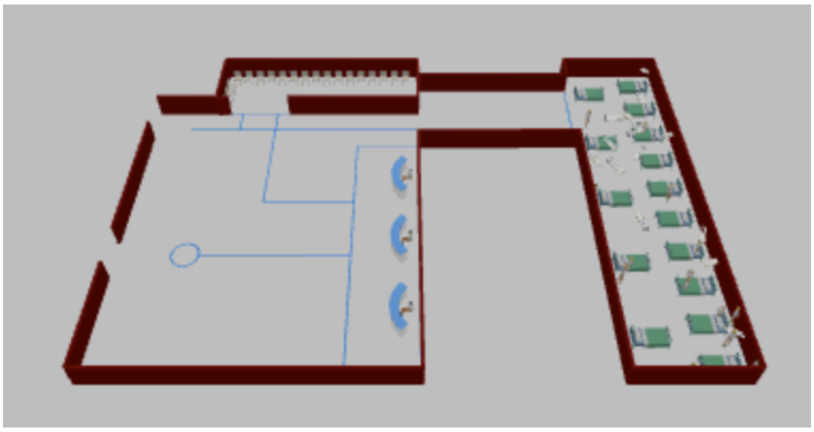


Figure 10: 3D representation of our model

2.3 Key Performance Indicators

2.3.1 Bed utilization rate

As we discussed earlier, beds are the limiting factor of the service, forcing the hospital to reject patients in need of care if all its beds are occupied. It is therefore ESSENTIAL in our model to monitor our bed utilization rate to know if we are just-in-time, and therefore whether it would be beneficial to increase the number of beds and nurses, or if the current number is in line with the flow of patients arriving at the hospital.

We define this rate by : $(1 - \frac{availableBeds}{15}) * 100$

When we run our simulation for dozens of days, we notice that our occupancy rate is almost 100%.
This proves that with 15 beds, the number of beds is really a limiting parameter, and that this causes the department to refuse patients.

Figure 11: Bed Utilization Rate after dozens of days

This KPI should be monitored if internal decisions are taken, such as adding more beds, the aim being to optimize so as not to have “too many beds”, by turning away as few patients as possible.

2.3.2 Percentage of patients rejected

Monitoring the percentage of patients rejected is vital for several reasons. Firstly, it serves as a critical measure of the ICU's capacity and its ability to meet patient demand. A high percentage of rejected patients indicates that the ICU is operating at or beyond its capacity, leading to potential delays in patient care, increased wait times, and compromised patient outcomes.
By closely monitoring this KPI, hospital administrators and healthcare leaders can proactively identify capacity constraints, anticipate resource needs, and implement strategies to optimize patient flow and reduce rejection rates.

We define this rate by : $\frac{rejectedPatient}{(rejectedPatient + acceptedPatient)} \ * \ 100$

When we run our simulation for dozens of days, we notice that our occupancy rate is around 15.46%, which means that close to 1 patient out of 7 is not admitted to the ICU service.

Figure 12: Rejected Patient Rate after dozens of days

Regular data analysis and performance reviews should be conducted to identify trends, root causes of rejections, and opportunities for improvement. By adopting a proactive and data-driven approach to monitoring the "Percentage of patients rejected" KPI, hospitals can enhance patient access to healthcare.

2.3.3 Percentage of ICU “long stays”

Monitoring the percentage of ICU “long stays" is essential due to its significant implications for resource utilization within the ICU.
Indeed, long stays tie up ICU beds, limiting access for new admissions and potentially leading to the rejection of critically ill patients who require immediate care. Monitoring this KPI allows healthcare providers to identify patients at risk of prolonged ICU stays early in their course of treatment, enabling proactive interventions to optimize care, facilitate discharge planning, and free up beds for incoming patients.

Prolonged occupancy of ICU beds by patients with extended lengths of stay can strain limited resources, including staffing, equipment, and critical care supplies. This can lead to inefficiencies in resource allocation, increased healthcare costs, and compromised quality of care for both current and future patients. By closely monitoring this KPI, healthcare administrators can identify trends in prolonged ICU stays, assess the impact on resource utilization, and implement targeted interventions to reduce length of stay and improve patient flow.
Furthermore, even if this lack of bed explains our work on this project, this KPI should not be an excuse to bias the model in order to release patient faster. We are pretty much sure that most (if not all) of these "long stay" patient are justified by their health state.

On at exit:

```
if (self.getDelayTime(self.get(0), DAY) > 8) {
    long_stays++;
    longStayPatientRate = (long_stays / (acceptedPatient + rejectedPatient))*100;
}
```

Figure 13: Long Stay is captured when the delay is more than 8 days

We define this rate by : $\frac{longStays}{acceptedPatient} \; * \; 100$
When we run our simulation for dozens of days, we notice that our “long stay” rate is around 26.804%, which means that close to 1 patient out of 4 stays more than 8 days in the service (and so is occupying a bed for that length).

Figure 14: Long Stay Patient Rate after dozens of days

3. Machine Learning model for ICU departure decision

3.1 Upstream work on data

3.1.1 Dropping useless features

Knowing that our model is trying to predict the target variable bad to determine if a patient is either ready to leave the ICU or if he should stay, we understood that we were not able to exploit all the features within the dataset to create the model.
This is the case for the id, the codes, the dates and the last columns which are not helping us be able to predict the target bad.

3.1.2 Handling null values

We then add to handle the numerous missing values of the remaining features.
For that we used the simple imputer function that replaced the NA values with the median of the column. There are a lot of method to handle NA values, by dropping the column for example but we would have a lack of features in the end to develop our model which did not really make sense, and we used median because the number is more representative than the mean.

We then checked that no features were highly correlated together, because in that case we could have removed some features.

3.1.3 Eliminating outliers

We then eliminated outliers using the Interquartile Range method, a common technique used in statistics that shows efficiency by being robust, non-parametric and simple while preserving the data.
While creating a machine learning model we should eliminate outliers as they are data points that significantly differ from the rest of the data in the dataset. They have an impact on the statistical analysis we made, such as Exploratory Data Analysis and they affect the model performance in a negative way.

3.1.4 Oversampling

We then oversample our features and target variables using SMOTE because our dataset was imbalanced, we had one class that was underrepresented compared to the other class which created an awful accuracy for the model. In our context it was the class 1 representing the positive values; after using SMOTE we were able to see an improvement in the F-Score of our models for class 1, sometimes increasing from 0.19 to 0.9.

3.2 Benchmarking different machine learning models

3.2.1 Choosing models

We created 5 machine learning models, Multi-Class Logistic Regression , K-Nearest Neighbors, Support Vector Classifiers, Random Forest and Decision Trees.
All of them are classification algorithms because predicting the target bad is a classification problem, the result is either 0 or 1.

We tried those 5 models as they allow us to compare the different classes of machine learning algorithm, we have logistic regression that is really useful for binary classification, KNN that is non parametric and use for classification and sometimes regression tasks, SVC used for binary and multi-class classification tasks,DT that are simple and and easily interpretable models that permit to capture some complex tasks and RF that is an ensemble learning model using multiple decision trees and combining them to improve the generalization of the model.

3.2.2 Model training

The model learned the patterns and relationships in the data by adjusting its parameters or weights iteratively to minimize a predefined loss function, as these are classification models we used cross-entropy loss. The training process continues until the model reaches a maximum number of iterations, every model has different parameters dictionary depending on the parameter needed to give the model an optimal result. This explains why we have different computing time depending on the model.

3.2.3 Model evaluation

We evaluated our 5 models using 3 evaluation methods, a confusion matrix, a classification report and the ROC curve for the 5 models. The confusion matrix is used to describe the performance of a classification model on a set of test data for which the true values are known. It allows visualization of the performance of an algorithm, particularly in terms of the model's ability to correctly classify instances into different classes.The classification report is a summary of the performance of a classification model, we have several metrics, such as the precision metrics, it is calculated as TP / (TP + FP), the recall is calculated as TP / (TP + FN), the F1 score is calculated as 2 * (precision * recall) / (precision + recall), the support is calculated as the number of actual occurrences of each class in the test dataset while accuracy measures the proportion of correct predictions among all predictions.and is calculated as (TP + TN) / (TP + TN + FP + FN) . The ROC curve is a graphical representation of the performance of a binary classification model across different discrimination thresholds. It illustrates the trade-off between the true positive rate (sensitivity) and the false positive rate (1 - specificity) as the discrimination threshold varies.

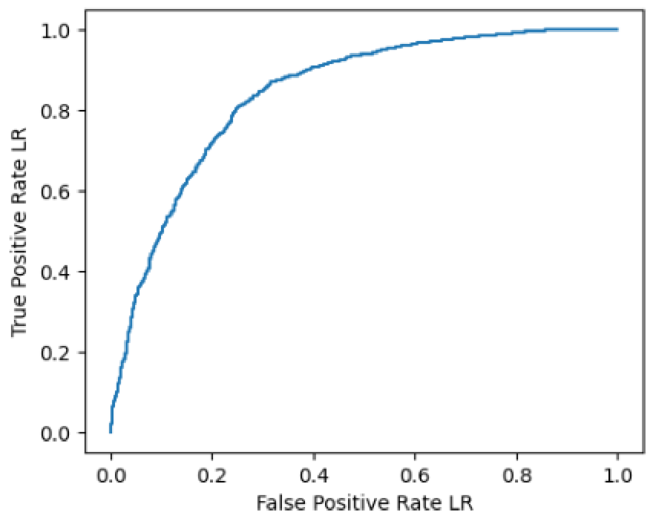
3.2.4 Analysis of the results

For the Logistic Regression we have a confusion matrix such [[1164, 404],
[302, 1300]],

We display the results of the classification report and the ROC curve below for evey models and we can see for this model that the accuracy is 0.77

Classification report Multi-Class Logistic Regression :

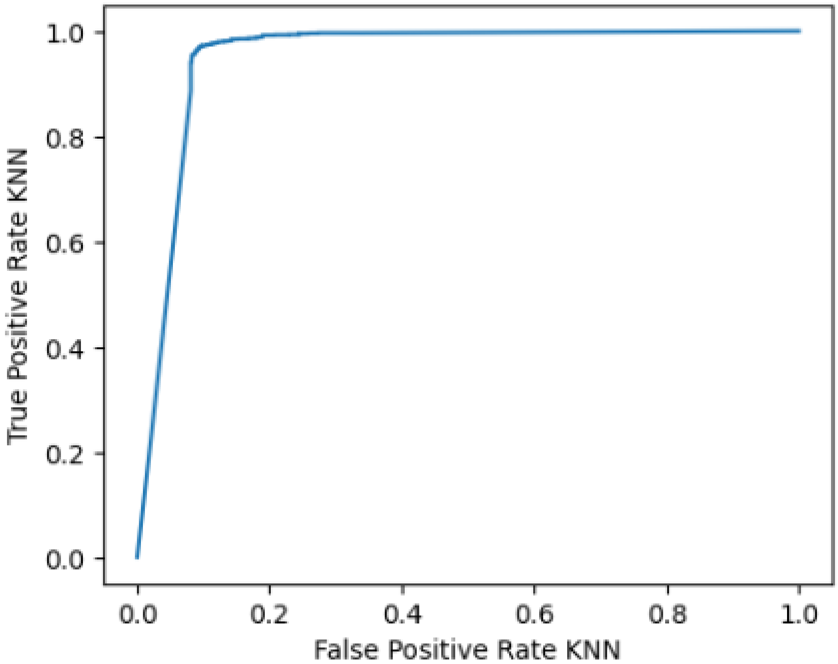
	precision	recall	f1-score	support
0.0	0.79	0.74	0.77	1605
1.0	0.75	0.80	0.78	1565
accuracy			0.77	3170
macro avg	0.77	0.77	0.77	3170
weighted avg	0.77	0.77	0.77	3170



For the KNN the confusion matrix is such as [[1273, 295],
[18, 1584]] with an accuracy of 0.9.

Classification report KNN :

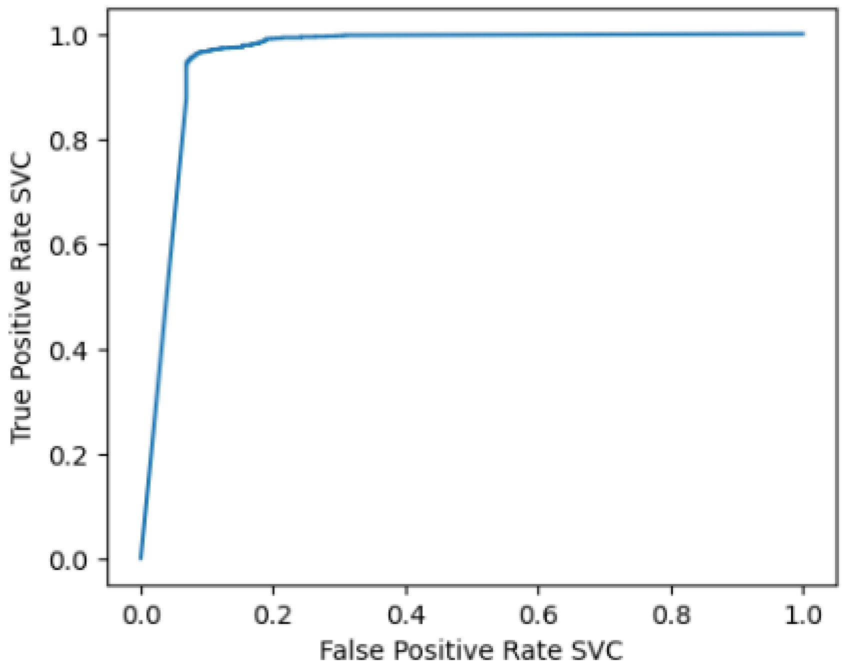
	precision	recall	f1-score	support
0.0	0.98	0.82	0.89	1605
1.0	0.84	0.98	0.91	1565
accuracy			0.90	3170
macro avg	0.91	0.90	0.90	3170
weighted avg	0.91	0.90	0.90	3170



For the SVC the confusion matrix is such as [1319, 249],
[184, 1418]], while the accuracy is 0.86.

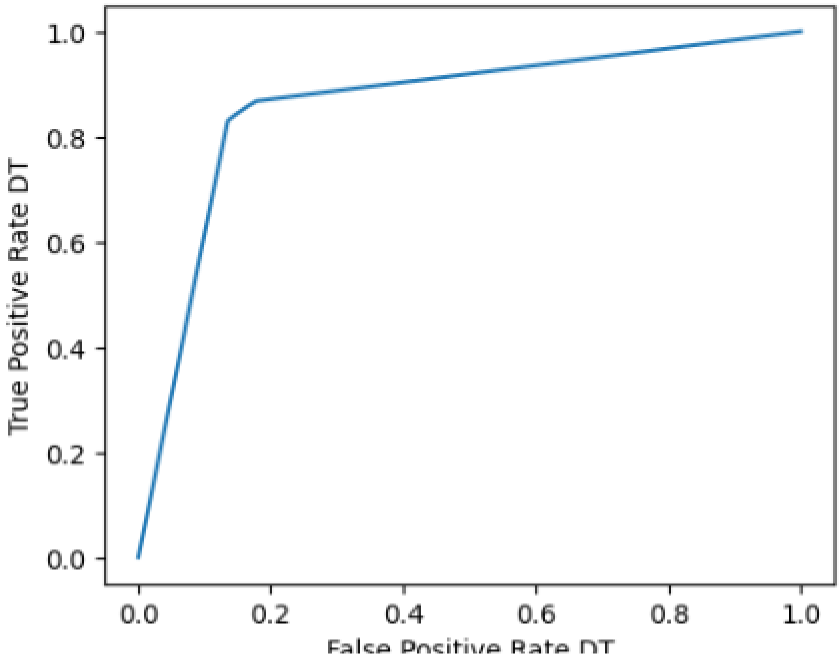
Classification report SVC :

	precision	recall	f1-score	support
0.0	0.88	0.85	0.86	1605
1.0	0.85	0.88	0.86	1565
accuracy			0.86	3170
macro avg	0.86	0.86	0.86	3170
weighted avg	0.86	0.86	0.86	3170



For the DT the confusion matrix is [[1337, 231],
[253, 1349]] and the accuracy is 0.86.

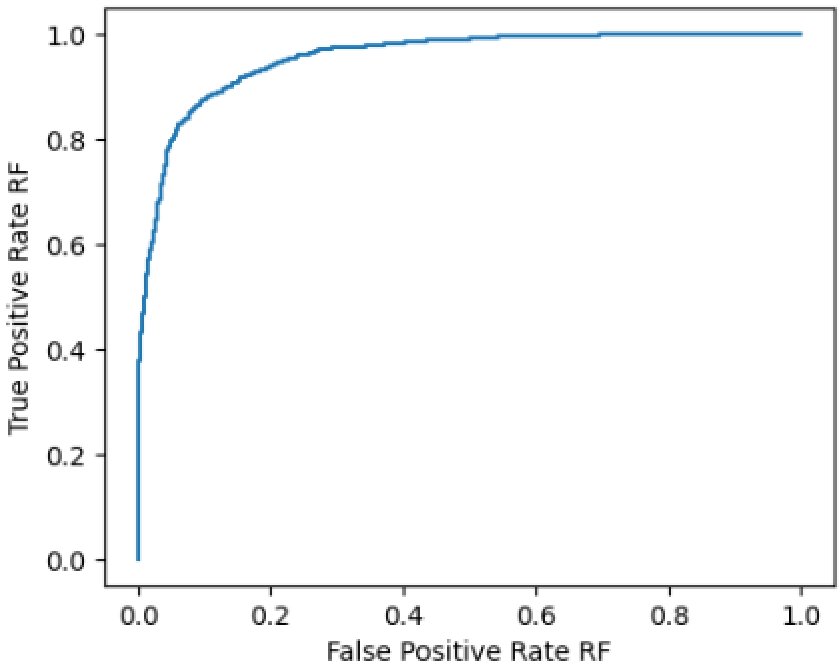
```
Classification report Decision Trees :
              precision    recall  f1-score   support

         0.0       0.85      0.87      0.86      1605
         1.0       0.86      0.85      0.85      1565

    accuracy                           0.86      3170
   macro avg       0.86      0.86      0.86      3170
weighted avg       0.86      0.86      0.86      3170
```



For the RF the confusion matrix is [[1367, 201],
[169, 1433]] and the accuracy is 0.88

Classification report Random Forest :

	precision	recall	f1-score	support
0.0	0.89	0.87	0.88	1605
1.0	0.87	0.90	0.88	1565
accuracy			0.88	3170
macro avg	0.88	0.88	0.88	3170
weighted avg	0.88	0.88	0.88	3170



3.3 Decision and Conclusion

3.3.1 Study limitations

We have some limitations, the data, they are incomplete and we had to transform the missing values to be able to exploit them, we could also use some other features that could capture all the relevant information to predict the outcome of the ICU, which is not the current case. It could improve the accuracy of our models

3.3.2 Final model selection

First of all we used a Machine Learning Model and not a Deep Learning model because knowing the good scores we have with our models, trying to get better results using Deep Learning models would be a waste of resources.
We picked the KNN model because after looking at our classification report we can for example see that this model have the best accuracy, also the ROC curve over time is looking to be the best one with SVC and we can see from the matrix also that KNN matrix have a really low number of False Negative as the value is 18 and the closet other model is the RF with a value of 169. The false positive value is descent in comparison to other model (295 vs 201 for the best model : DT)
The advantages of KNN are several but this is a non parametric classification model, really flexible with no assumptions about data , which can explain the results that we had, that were the best result within all the models tried.

4. Ethical considerations

4.1 The importance of the decision to release a patient

The decision to release a patient from the Intensive Care Unit is of paramount importance, as it directly impacts the patient's health and well-being. However, when this decision is supported by a machine learning model, ethical considerations become even more crucial due to the potential consequences of erroneous predictions.
The primary ethical principle guiding healthcare decisions is to prioritize patient safety and autonomy. Releasing a patient from the ICU prematurely based on a machine learning model's recommendation poses a risk to patient safety if the patient's condition deteriorates outside the controlled environment of the ICU. Additionally, patients have the right to participate in decisions about their care, including the timing of their discharge from the ICU. It's essential to ensure that patients are adequately informed and involved in the decision-making process to maintaining the human and relational side of health services.

Machine learning models may exhibit bias, leading to disparities in the delivery of healthcare. For example, if the model is trained on data that disproportionately represents certain demographics or healthcare settings, it may produce recommendations that are biased against certain patient groups. Additionally, the use of predictive models may exacerbate existing disparities in access to healthcare services if resources are allocated based on algorithmic predictions without considering broader social determinants of health.

In the context of decision-making in the ICU, it's crucial to emphasize that we are dealing with human lives rather than products on a supply chain. Human life is inherently valuable and irreplaceable. Unlike products in a supply chain, which can be manufactured or replenished, each individual life is unique and precious. Therefore, decisions made in healthcare, especially those concerning patient discharge from the ICU, carry profound ethical implications due to their direct impact on the lives.
Patients in the ICU are often in critical condition, with their health and survival dependent on the care and interventions provided by healthcare professionals. They rely on healthcare providers to act in their best interests and prioritize their health and safety above all else (especially operational and/or economic interests!).

To conclude, healthcare decision-making is inherently complex, involving not only clinical considerations but also ethical, emotional, and social factors. Unlike decisions about products in a supply chain, which may primarily focus on cost-effectiveness, efficiency, and logistical considerations, decisions in healthcare must prioritize patient-centered care, individualized treatment plans, and respect for patient autonomy.

4.2 Dealing with decision errors

The implications of the decision errors in the model, where a patient returns to the ICU after being discharged prematurely, are significant and multifaceted. Firstly, from a patient-centered perspective, such errors can lead to detrimental effects on the patient's health and well-being. Returning to the ICU indicates that the patient's condition has worsened or that they were not adequately prepared for discharge, resulting in potential complications, increased morbidity, and prolonged hospitalization. Moreover, the emotional and psychological impact on the patient and their family can be profound, as they may experience heightened anxiety, distress, and loss of trust in the healthcare system.

From an ethical standpoint, it raises questions about accountability, responsibility, and justice. Patients rely on healthcare providers to make informed decisions about their care based on accurate assessments and clinical judgment. When these decisions result in errors that harm the patient, there is a moral obligation to acknowledge the mistake, take corrective action, and mitigate the consequences. Failing to address decision errors effectively can erode trust in the hospital's capacity to provide safe and reliable care, undermine the integrity of the healthcare system, and lead to potential legal and reputational repercussions.
However, if we simply decide that this patient can skip the queue in the waiting room and take a bed as fast as posible, then we raise a new ethical dilemna because the first one in the queue was also in need of health services. It is something extremely tough to deal with to decide if we should heal someone over someone else.

To address these cases, the hospital could implement several measures aimed at mitigating the impact of decision errors and improving patient care. Firstly, transparent communication with patients and their families is essential. Hospitals should openly acknowledge errors, apologize for any harm caused, and provide explanations regarding the steps being taken to prevent similar incidents in the future.
Secondly, a comprehensive review of the discharge process and decision-making protocols should be conducted to identify potential areas for improvement, such as enhancing discharge criteria, implementing standardized assessment tools, and providing additional training for healthcare staff to confirm the machine learning decisions.
Additionally, the hospital could establish a mechanism for monitoring and evaluating the effectiveness of discharge decisions, such as conducting follow-up assessments to track patient outcomes post-discharge and identify patterns of readmission.
Finally, ensuring adequate resources and support services are available to patients

upon discharge, such as access to home healthcare, rehabilitation services, and community support networks, can help facilitate a smoother transition and reduce the likelihood of readmission due to unmet needs. By proactively addressing decision errors and implementing measures to improve patient care, hospitals can uphold their commitment to patient safety, promote accountability, and enhance trust in the healthcare system.

5. Recommendations

5.1 New model for ordering patients

Implementing a new machine learning model to assign a "Grade" of urgency to patients upon registration in the ICU could significantly enhance the prioritization of cases and improve patient outcomes. By considering various parameters such as vital signs, severity of illness, comorbidities, and medical history, the model can systematically evaluate the urgency of each patient's case and allocate resources accordingly. This approach enables healthcare providers to identify and prioritize critical cases requiring immediate attention, thereby reducing the risk of mortality and morbidity in the ICU. Additionally, by incorporating predictive analytics and real-time monitoring, the model can dynamically adjust patient prioritization based on changing clinical conditions, ensuring that resources are allocated efficiently and effectively to those in greatest need.

Furthermore, the implementation of such a model can streamline the triage process, optimize resource utilization, and enhance the overall quality of care delivery in the ICU. By standardizing and automating the assessment of patient urgency, healthcare providers can make more informed and timely decisions regarding patient admission, discharge, and intervention strategies. This not only improves patient outcomes but also enhances staff satisfaction and reduces the burden of decision-making, allowing clinicians to focus on delivering high-quality, patient-centered care. Moreover, by promoting equity and fairness in resource allocation, the model helps mitigate disparities in access to critical care services, ensuring that all patients receive timely and appropriate treatment based on their clinical needs. Overall, integrating a machine learning model to prioritize patient cases based on urgency represents a proactive and innovative approach to optimizing ICU management and ultimately saving lives.

5.2 Managing limiting parameters

Managing limiting parameters in the ICU, such as the availability of beds and nurses, is crucial for ensuring timely and effective patient care while minimizing the risk of rejection due to capacity constraints. One potential solution involves optimizing the workload of nurses by increasing the patient-to-nurse ratio. While this approach may address immediate capacity issues and provide a short-term solution, it comes with inherent risks. Increasing nurses' workload beyond recommended levels can lead to burnout, fatigue, and compromised patient safety. Nurses may struggle to provide adequate attention and care to each patient, potentially resulting in medical errors, adverse events, and suboptimal outcomes. Moreover, overburdened nurses may experience decreased job satisfaction and higher turnover rates, further exacerbating staffing challenges in the long run. Therefore, while adjusting nurse workload may offer temporary relief, it is not a sustainable or ideal solution in the absence of adequate staffing resources.

The preferred and more sustainable solution to managing limiting parameters in the ICU is to address the root cause by increasing capacity through the addition of more beds and recruiting additional nurses. By expanding infrastructure and workforce capacity, hospitals can accommodate growing patient demand, reduce rejection rates, and ensure that patients receive timely and high-quality care. Increasing the number of beds allows for greater flexibility in accommodating patients, especially during periods of high demand or unexpected surges in patient volume. Similarly, recruiting more nurses enables hospitals to maintain optimal patient-to-nurse ratios, ensuring that patients receive the attention, monitoring, and interventions they require. While expanding capacity may entail initial investments in infrastructure, equipment, and staffing, the long-term benefits in terms of improved patient outcomes, enhanced staff satisfaction, and reduced rejection rates justify the investment. Overall, increasing limiting parameters in the ICU represents a proactive and sustainable approach to optimizing healthcare delivery and meeting the needs of patients and healthcare providers alike.