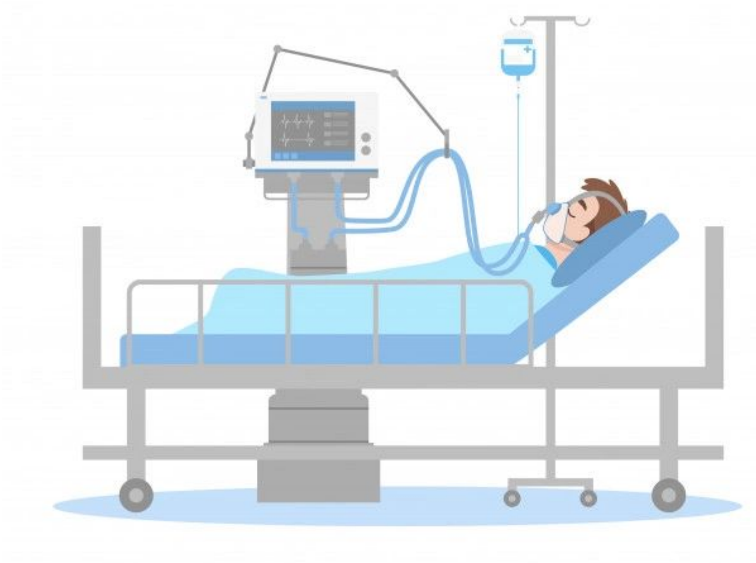


https://www.freepik.com/

Clinical Decision Support for planned Extubations in the ICU

Capstone Presentation

Data Science Team: Mirko Knoche, Jacqueline Gabriel, Niko Stergioulas & Nina Notman

TABLE OF CONTENT

01

EXTUBATION TRADE-OFF

Extubate too late...

... high risks associated with invasive ventilation

... complicated weaning

Extubate too early...

... higher risk of re-intubation

... increased stress for patient and staff

02

GOAL OF THE PROJECT

*Our goal with this project is to **support** the **decision** of physicians regarding the **timing of extubations** so that fewer patients are being extubated too early.*

03

DATASET

MEDICAL INFORMATION MART FOR INTENSIVE CARE

DATABASE

Freely available critical care data for researchers

DATA SOURCE

Beth Israel Deaconess Medical Center, data collection from 2001 until 2012

DATA COLLECTION

53,423 distinct hospital admissions from adult patients

MEASUREMENTS

Vital signs, medications, laboratory measurements, fluid balance, procedure codes, diagnostic codes, imaging reports

03

PATIENT SELECTION

ARDS patients

Selected adult ICU stays with an ICD diagnosis of **A**cute **R**espiratory **D**istress **S**yndrome.

Mechanical Ventilation

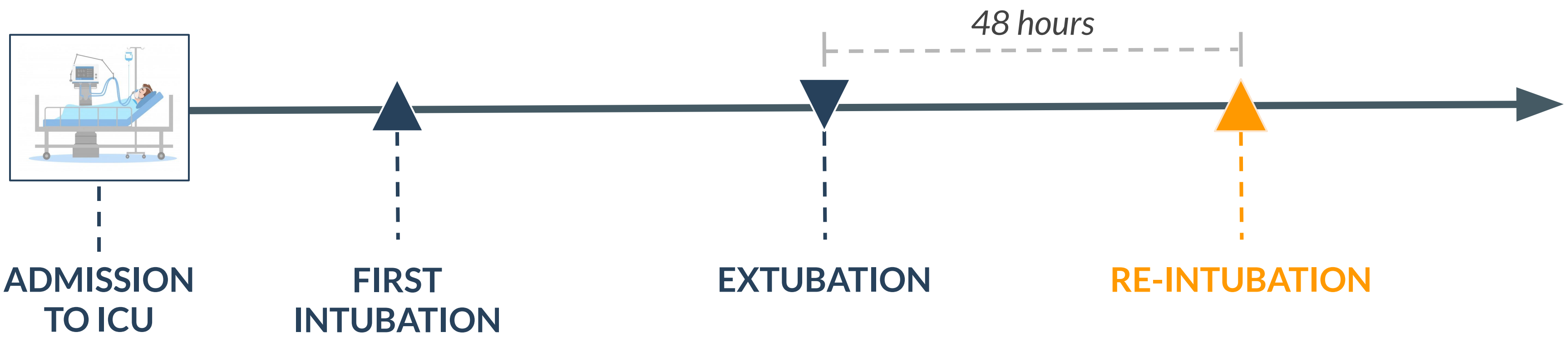
Further selection of ICU stays with patients that were ventilated.

Extubation

Selected ICU stays where an extubation occurred.

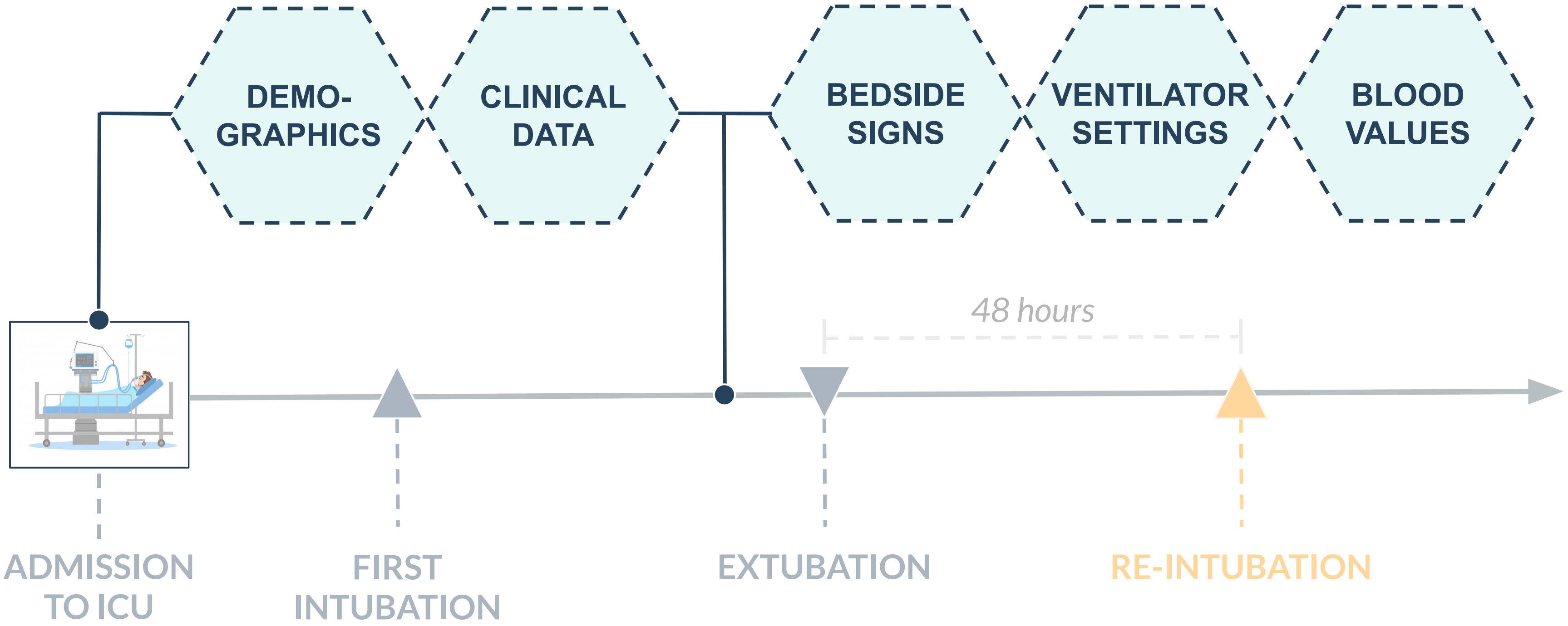
5.425 Patients

DEFINITION OF A SUCCESSFUL EXTUBATION



04

FEATURES



DEMO-
GRAPHICS
CLINICAL
DATA
BEDSIDE
SIGNS
VENTILATOR
SETTINGS
BLOOD
VALUES
48 hours
ADMISSION
TO ICU
FIRST
INTUBATION
EXTUBATION
RE-INTUBATION

04

EVALUATION METRIC

I'd rather have patients intubated longer than extubate too early...

04

EVALUATION METRIC

… so let's focus our model evaluation on $\mathbf{F}_{0.5}$

Extubate too early…

Extubate too late…

05

MODELLING

BASE MODEL

24 Features
Various Classifiers
Best model:

XGBoost (F_{β}= 0.76)

FEATURE ENGINEERING

DEMO-GRAPHICS | CLINICAL DATA | BEDSIDE SIGNS | VENTILATOR SETTINGS | BLOOD VALUES | ... | ... | ...

05

FEATURE ENGINEERING

DISTRIBUTION	Statistical parameters that resemble the course of a measurement
DURATION OF MECHANICAL VENTILATION	Amount of hours the patient has been ventilated until extubation
COMORBIDITIES	Heart failure, diabetes, kidney failure, pneumonia and embolism
FRACTIONS AND PRODUCTS	Work of breathing, Rapid Shallow Breathing Index and respiratory instability

05

MODELLING

BASE MODEL

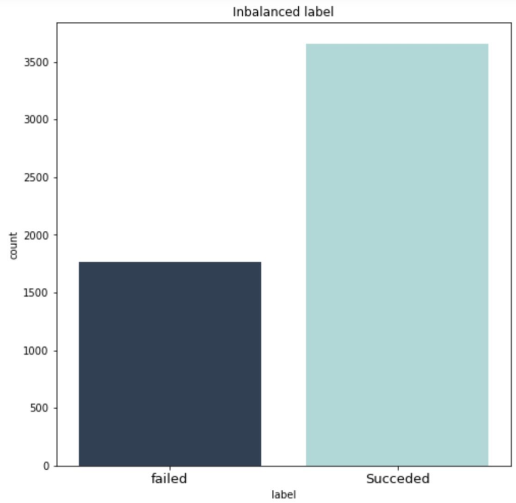
24 Features
Various Classifiers
Best model:

XGBoost (F_β= 0.760)

ADVANCED MODEL

77 Features
Various Classifiers
Best model:

XGBoost (F_β= 0.783)



05

MODELLING

BASE MODEL

24 Features
Various Classifiers
Best model:

XGBoost (F_β= 0.760)

ADVANCED MODEL

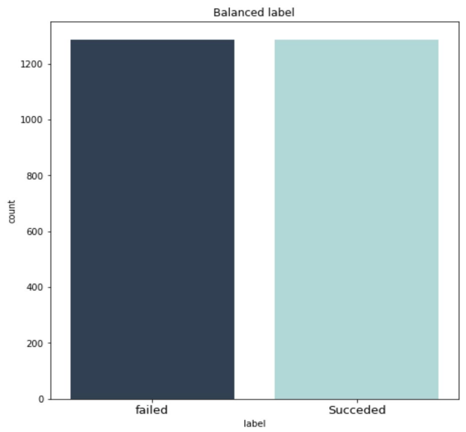
77 Features
Various Classifiers
Best model:

XGBoost (F_β= 0.783)

BALANCED MODEL

77 Features
Balanced Label
Various Classifier

No improvement



05

MODELLING

BASE MODEL

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ADVANCED MODEL

77 Features
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Best model:

XGBoost (F_β= 0.783)

BALANCED MODEL

77 Features
Balanced Label
Various Classifier

No improvement

REDUCED MODEL

Up to 20 Features
Various Classifier
Best model:

XGBoost (F_β= 0.785)

12 FEATURES

05

FEATURE IMPORTANCE

All good...
but what should I look at when deciding to extubate or not?

01 TRACHEOTOMY

If your patient has had a tracheotomy, the weaning is much harder.

02 MECHANICAL VENTILATION

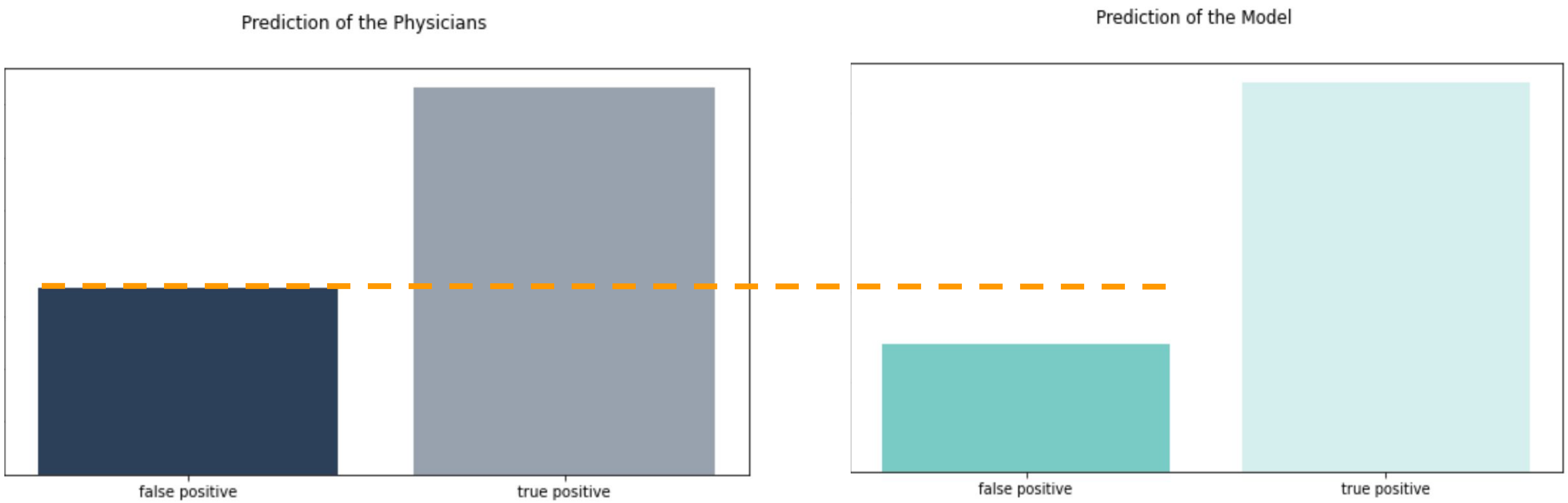
The longer your patient is ventilated, the more cautious you have to be with the extubation.

03 OXYGEN SATURATION

For a successful extubation, make sure that the patient is continuously well supplied with oxygen.

06

CONCLUSION



Our model improved the **precision** from **66% to 75%**.
Implying that it predicts 3 out of 4 extubation successes correctly.

06

FUTURE WORK

Add BMI and weight change as additional features

Add medications, treatments and their application time as features

Take fluid input and output into account

Check falsely classified patients

Use Time-Series-Analysis

Apply Neuronal Network

OUR TEAM

MIRKO KNOCHE

“Data Science Bootcamp means intensive **human** learning.”

JACQUELINE GABRIEL

“It is a satisfying task to support physicians with Machine Learning and improve patient care.”

NIKO STERGIOULAS

“It was fantastic to put my medical knowledge to good use in a data science project. ”

NINA NOTMAN

“It was not only an insightful data science project but also a precious team experience!”

RESOURCES

SLIDES

- Google Slides

TOOLS & TECHNOLOGIES

- DBeaver
- Jupyter Notebook
- Visual Studio Code
- Google Cloud (SQL, Storage, BigQuery)

LITERATURE

Johnson, A. E., Pollard, T. J., Shen, L., Li-Wei, H. L., Feng, M., Ghassemi, M., ... & Mark, R. G. (2016). MIMIC-III, a freely accessible critical care database. *Scientific data*, *3*(1), 1-9.

Mikhno, A., & Ennett, C. M. (2012, August). Prediction of extubation failure for neonates with respiratory distress syndrome using the MIMIC-II clinical database. In *2012 Annual international conference of the IEEE Engineering in Medicine and Biology Society* (pp. 5094-5097). IEEE.

Sadeghi, R., Banerjee, T., & Romine, W. (2018). Early hospital mortality prediction using vital signals. *Smart Health*, *9*, 265-274.

https://github.com/MIT-LCP/mimic-code.git