Prediction of Cardiac Arrest From Physiological Signals in the Pediatric ICU

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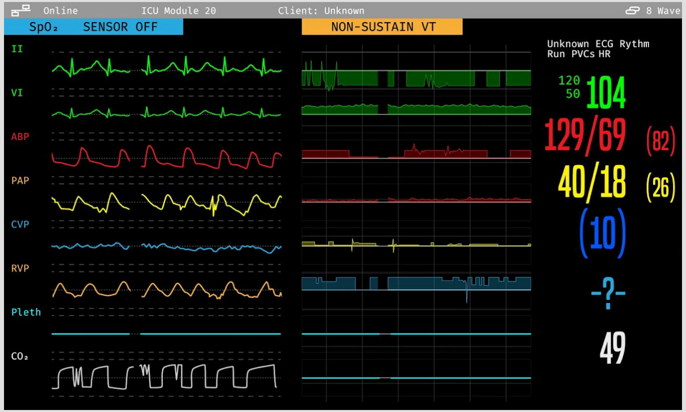
Cardiac Arrest in Pediatric ICU

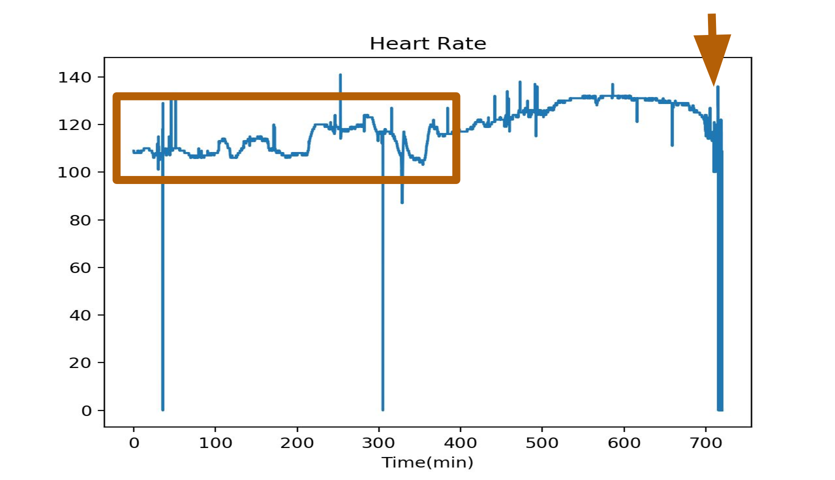
- Many patients in the ICU are at risk of a sudden cardiac arrest

- In-hospital cardiac arrest is strongly associated with mortality



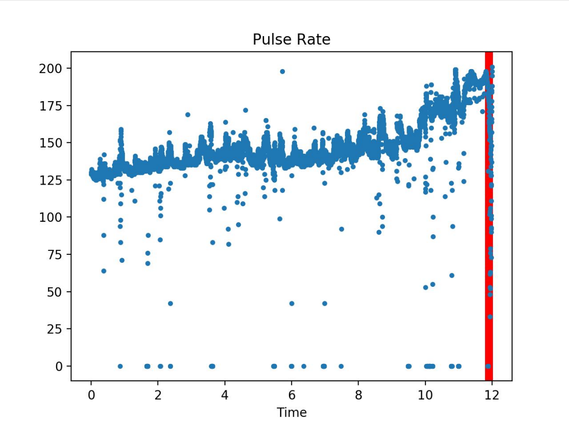
- Only a limited number of interventions are available to deal with this issue, that do not guarantee disability-free survival

Learning the Existing Pattern in Pre-arrest Physiological Signals



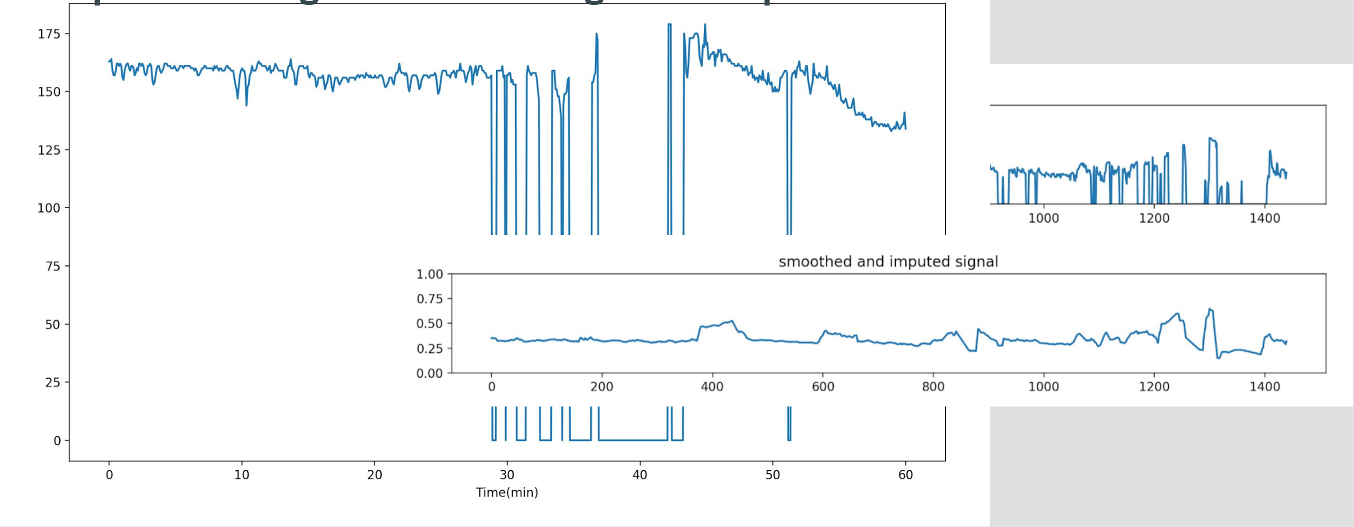
Challenges:

1. Clinical data is usually corrupted by noise or missing values
2. Time-series physiological recording is densely packed with information.
3. Typical ICU practice is to record vital signs based on perceived patient needs, so not all patients have a consistent set of measurements in their records



1) Missing Signal Imputation

Low-pass filtering method missing value imputation

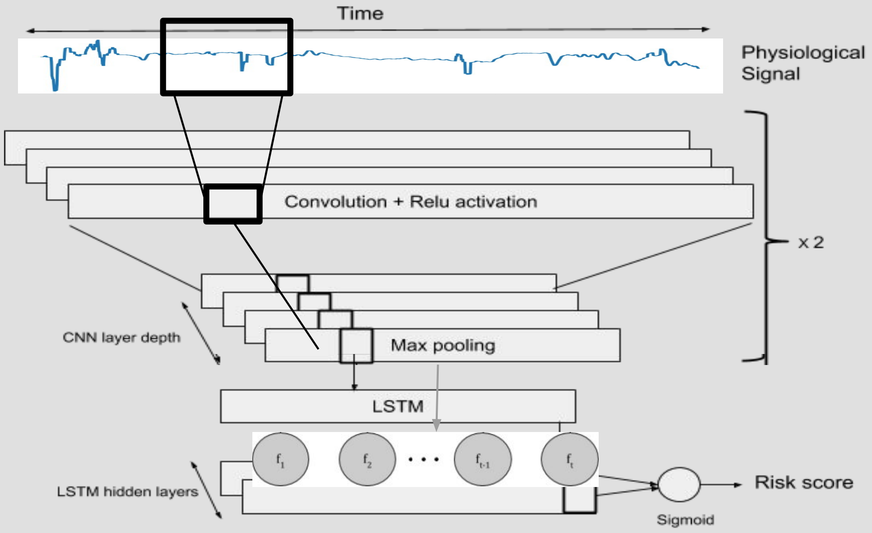


Major benefits:

- It can be online
- Smoothens signal t
  frequency variatio

2) Risk Predictor Model Architecture:

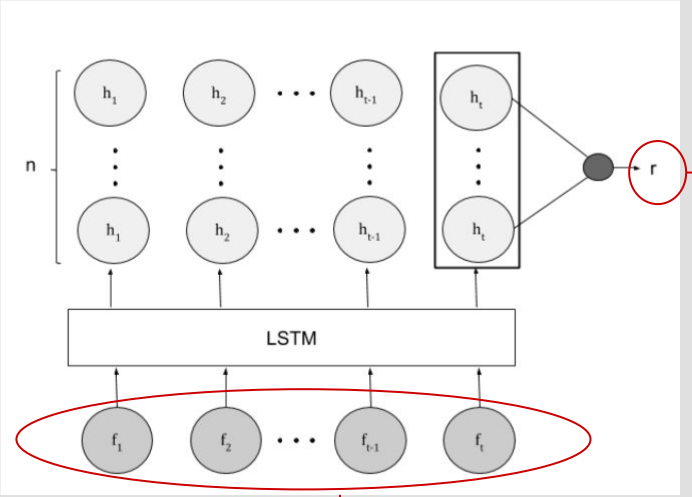
Combining Convolutional and Recurrent networks for the analysis of longitudinal physiological signals



- <u>CNN</u>: Extracts a **compact latent representation** of the window of recording.

2) Risk Predictor Model Architecture

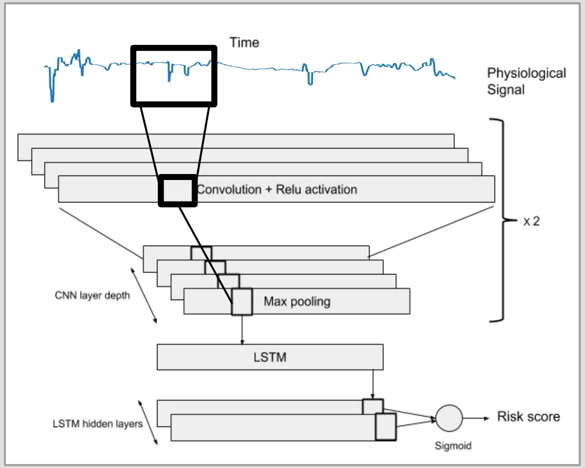
- LSTM: Learn the existing temporal dependencies to predict the probability of an arrest in the future



r is feed into a simple regression model along with the **age** of a patient, to generate **risk**, that is the risk score associated to a time window of a certain physiological signal.

f is the condensed latent representation of the original physiological signal extracted by the CNN

2) Risk Predictor Model Comparison:



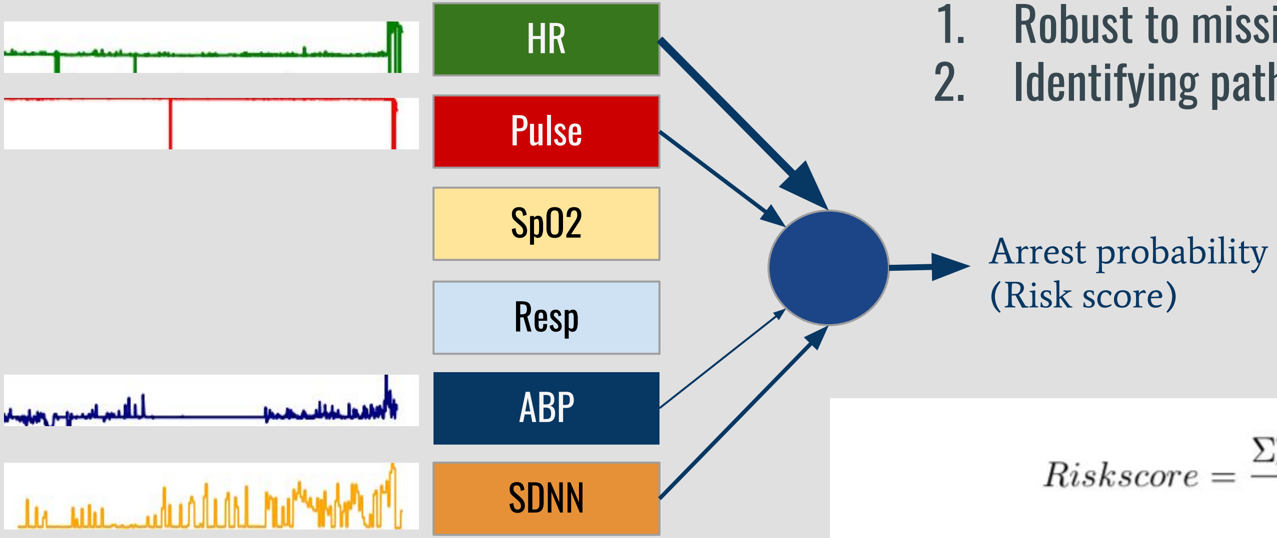
Signal Type	CNN	LSTM	CNN+LSTM
Heart rate (HR)	0.753 ± 0.075	0.666 ± 0.118	0.816 ± 0.034
Respiratory rate (Resp)	0.739 ± 0.043	N/A	0.67 ± 0.05
Pulse rate (Pulse)	0.720 ± 0.093	0.698 ± 0.06	0.746 ± 0.092
Oxygen Saturation level (SpO2)	0.714 ± 0.078	0.617 ± 0.101	0.723 ± 0.055
Ambulatory Blood Pressure (ABP)	0.675 ± 0.17	0.647 ± 0.17	0.76 ± 0.13
SDNN Heart Rate Variability Metric (SDNN)	0.663 ± 0.080	N/A	0.692 ± 0.07

** Numbers reported are the F1 scores

3) The Ensemble Structure

Major Benefits:

1. Robust to missing measurements
2. Identifying pathways resulting in an arrest

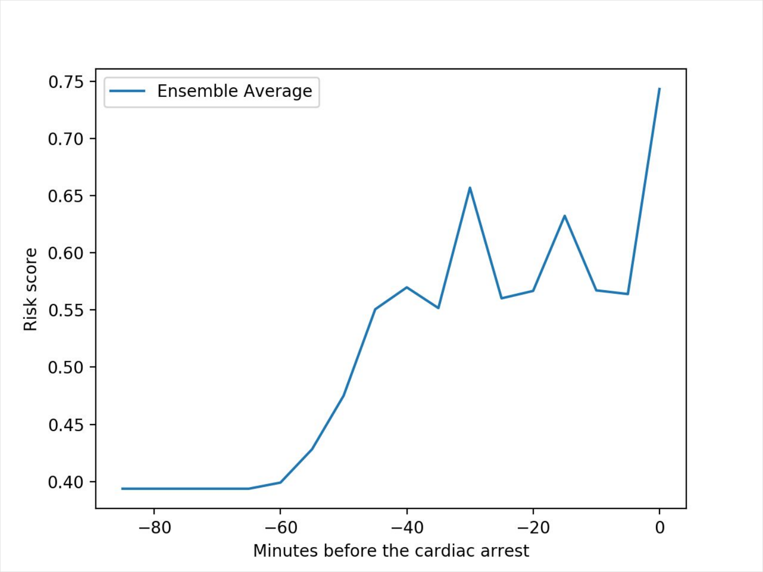


$$Riskscore = \frac{\Sigma_{i=1}^{n}(W_i * risk_i)\mathbb{1}_i}{\Sigma_{i=1}^{n}(W_i)\mathbb{1}_i}$$

Where $\mathbb{1}_i = 0$ if signal i is missing and $\mathbb{1}_i = 1$ otherwise

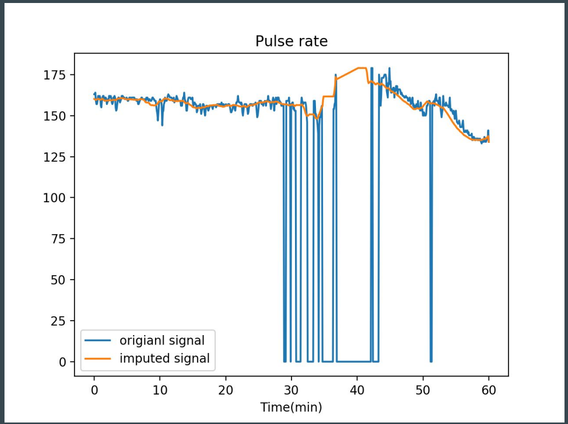
Future direction:
Towards Predictive Personalized Medicine

Approaches that offer promising future for **predictive** rather than **reactive** medicine, in a personalized framework where clinical decision support can be provided at the level of individual patients.



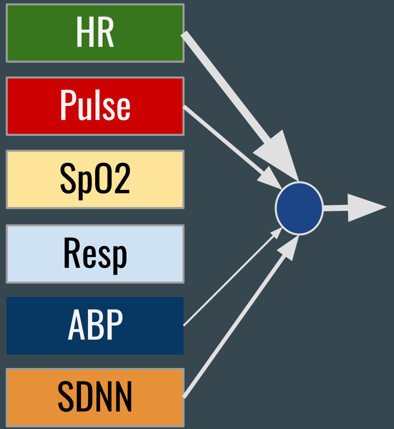
Major Takeaways:

- The low-pass filtering method is a robust technique for missing value imputation in temporal signals



- CNNs are powerful tools for extracting features from high-dimensional space data and in combination with RNNs, it can also model temporal dependencies

- Ensemble models are helpful tools in cases where samples might have inconsistent set of features.



Thank you!

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