Sepsis detection from pletismography

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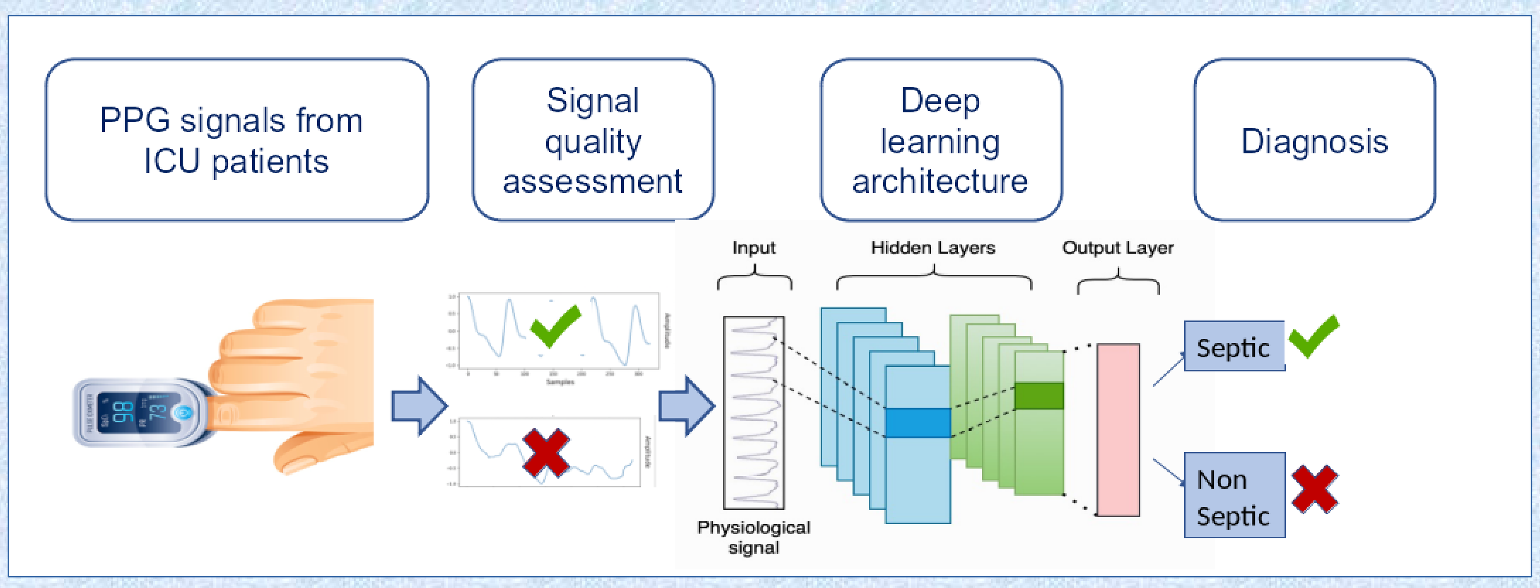
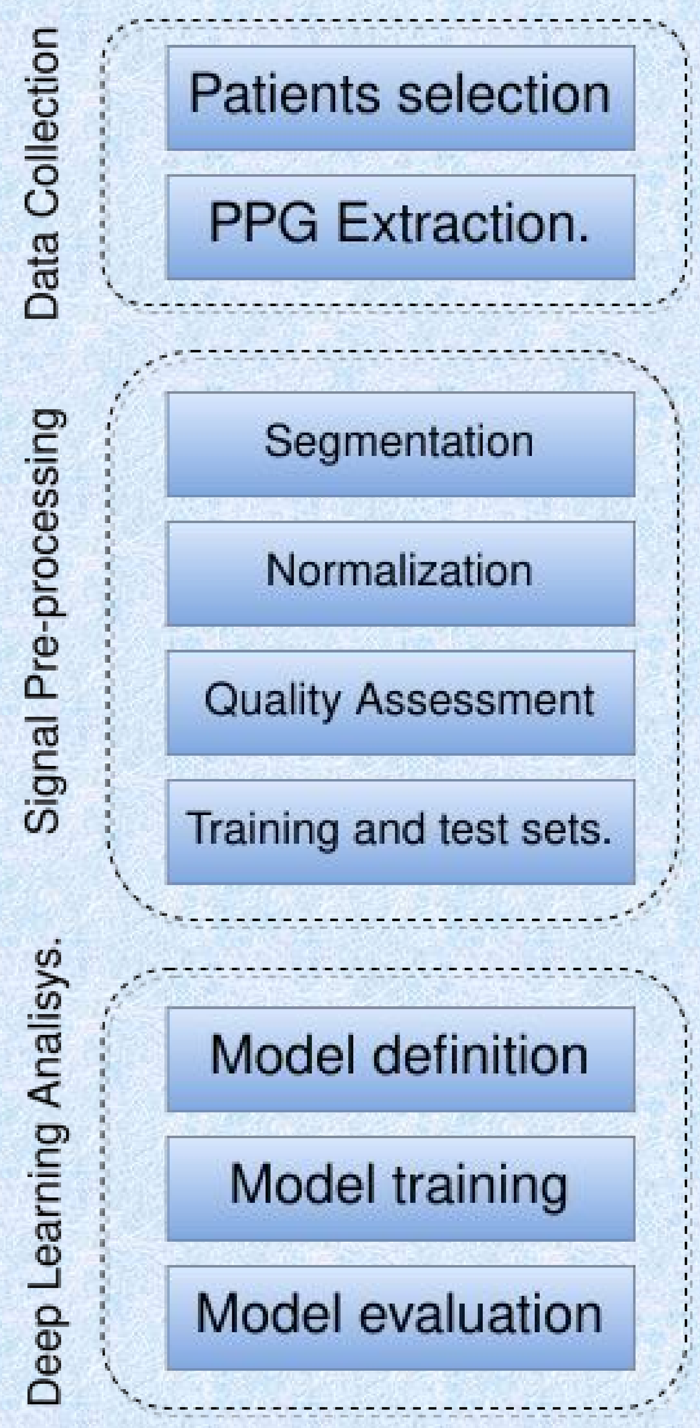
Objectives

The study investigates the possibility of identify the insurgency of sepsis using only plethismographic signal (PPG). Alterations of microcirculatory flow induced by sepsis reflect themselves on subtle modification of the signal measured by the pulsioxymeter.
This solution constitutes a valuable tool for the clinician, due to several factors: PPG is a completely non invasive technique, commonly used in any clinical settings, and thus does not include any additional cost; moreover, PPG allows continuous monitoring without causing discomfort. Finally. the method constitutes a valid alerting system for obtaining a rapid diagnosis and therapy, as recommended by current guidelines [1].

Methods

The study adopts an Artificial Intelligence system (Deep Neural Network, DNN) that learns to discriminate patients in two groups, namely a septic group and a control group, using only a PPG waveform.
PPG signals belonging to selected patients are split into segments of fixed length and normalized. The optimal segment length has been determined experimentally.
Data quality has been assessed by a specific procedure, discarding segments of poor quality. Finally, patients were subdivided in a training set, used for creating the decision model, and in a test set, for assessing its performance.
Training and test set were used for defining and optimizing the DNN in order to obtain optimal performance.

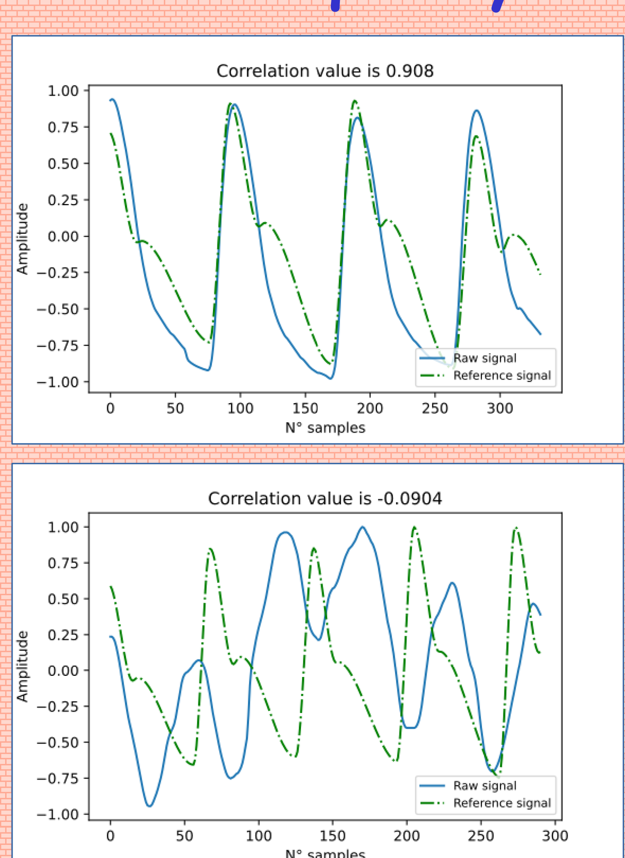




Patient selection

Patients were selected from the publicly available database “MIMIC-III” [2], a clinical database collecting more than 40000 patients from ICUs of Beth Israel Deaconess Medical Center.
Inclusion criteria are:
Controls: single stay in ICU, non-deceased patients, non-sepsis related ICD,
Sepsis: singles stay in ICU, deceased patient, sepsis-related ICD
The restriction on single stay reduces the probability of a severe comorbidity that may act as confounding variable.
The selection of deceased patients for the sepsis group is related with the lack of timing information in the MIMIC data: patient deceased with a sepsis-related diagnosis are very likely affected by that disease during the last few days of stay.

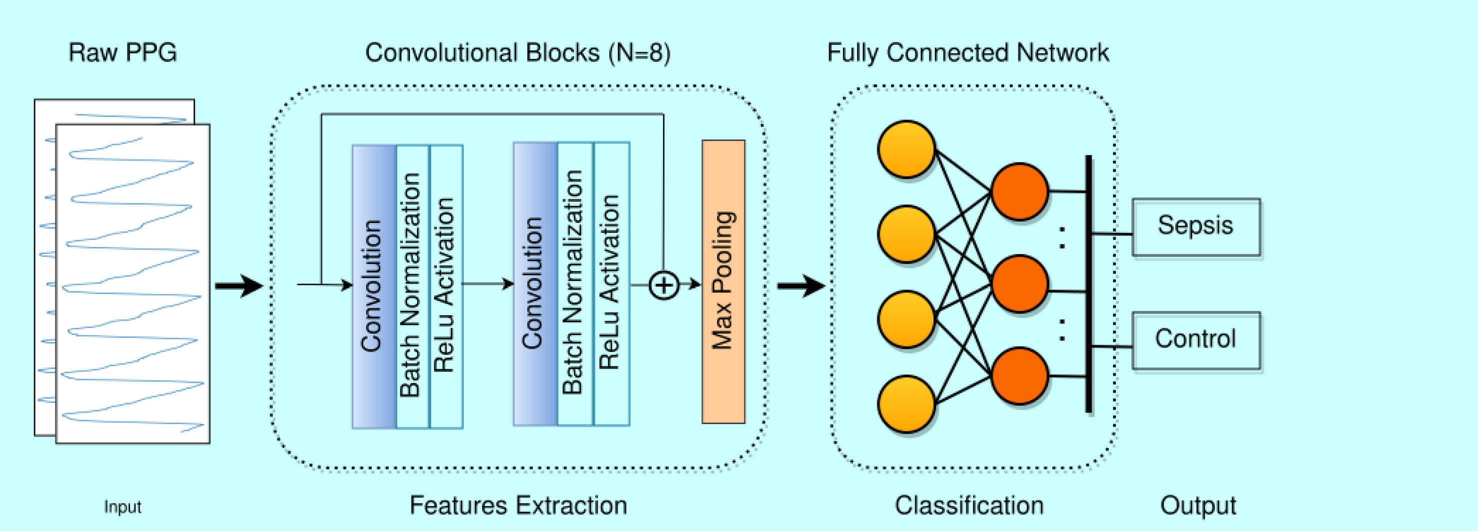
Data quality



During the preliminary analysis of the data, we observed several cases of bad quality data, that may compromise a proper learning of the neural network. Possible causes include bad positioning of the probe, technical problems, clinical manoeuvres, or weak signal due to hypotension, low cardiac output, or hypothermia.
The automatic detection of poor quality signals is based on the correlation between the signal and a reference one, generated with the same cardiac frequency estimated on the signal, and having and “ideal” waveform.
Correlation values below 0.6 are visually associated with poor quality signals, that are removed from the data set.

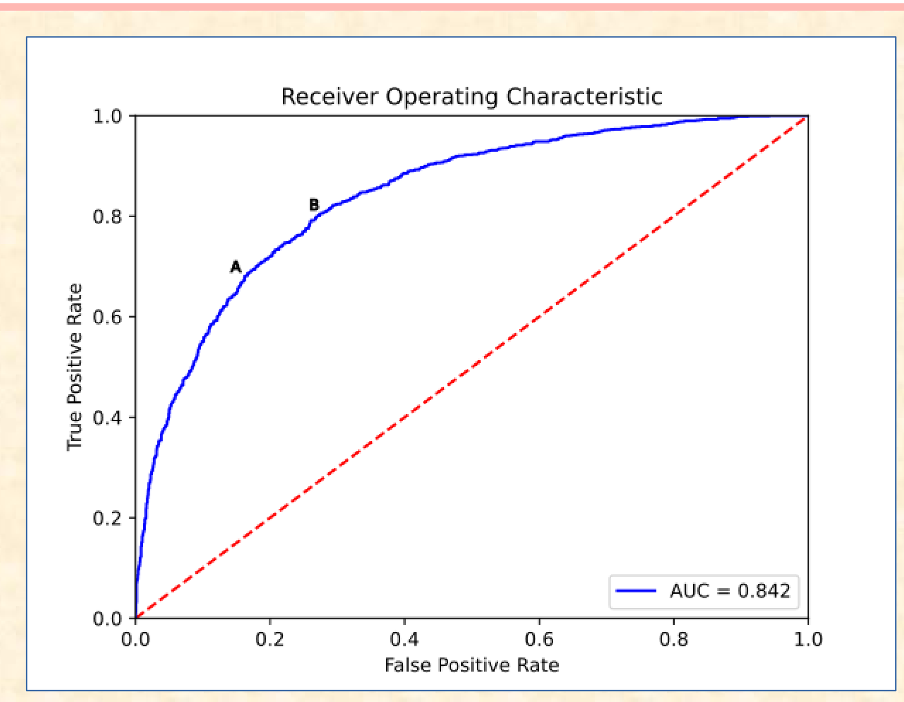
Deep learning model

The final classification model is based on the ResNet architecture [3], schematized in the figure below.
The network receives as input a segment, lasting 2 minutes, of PPG signal. The features extraction blocks precesses the signal in order to extract significant information, and the dense layer associates the information with the correct classification



Results

The output of the DNN provides an index correlated with the probability of sepsis. The introduction of a threshold on the output value allows to balance sensitivity and specificity of the classification system, summarized by the ROC curve. Any threshold value generates a point of the curve, that identifies accuracy, sensibility and specificity of the classification system.
The maximum accuracy (point A on the curve) is slightly over 76%, but it presents higher specificity than sensitivity. Given the aim of the work, we selected a different threshold (point B), with sensibility over 80% and specificity of 70%.



Working point	Accuracy	Sensibility	Specificity
A (max accuracy)	76.37%	70.95%	81.04%
B (optimal)	76.07%	80.68%	72.09%

Acknowledgements

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