

Non-invasive Optical Detection of Intracranial Hypertension with Machine Learning

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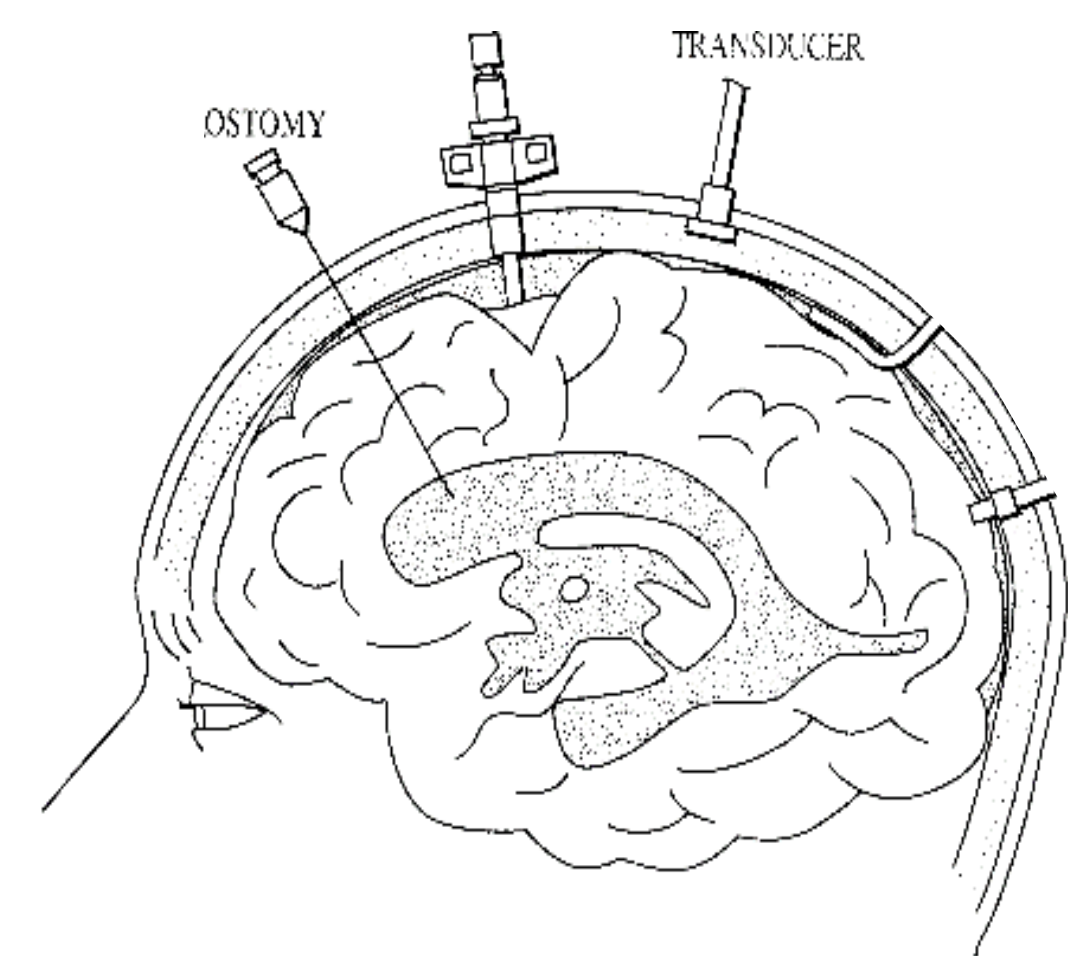
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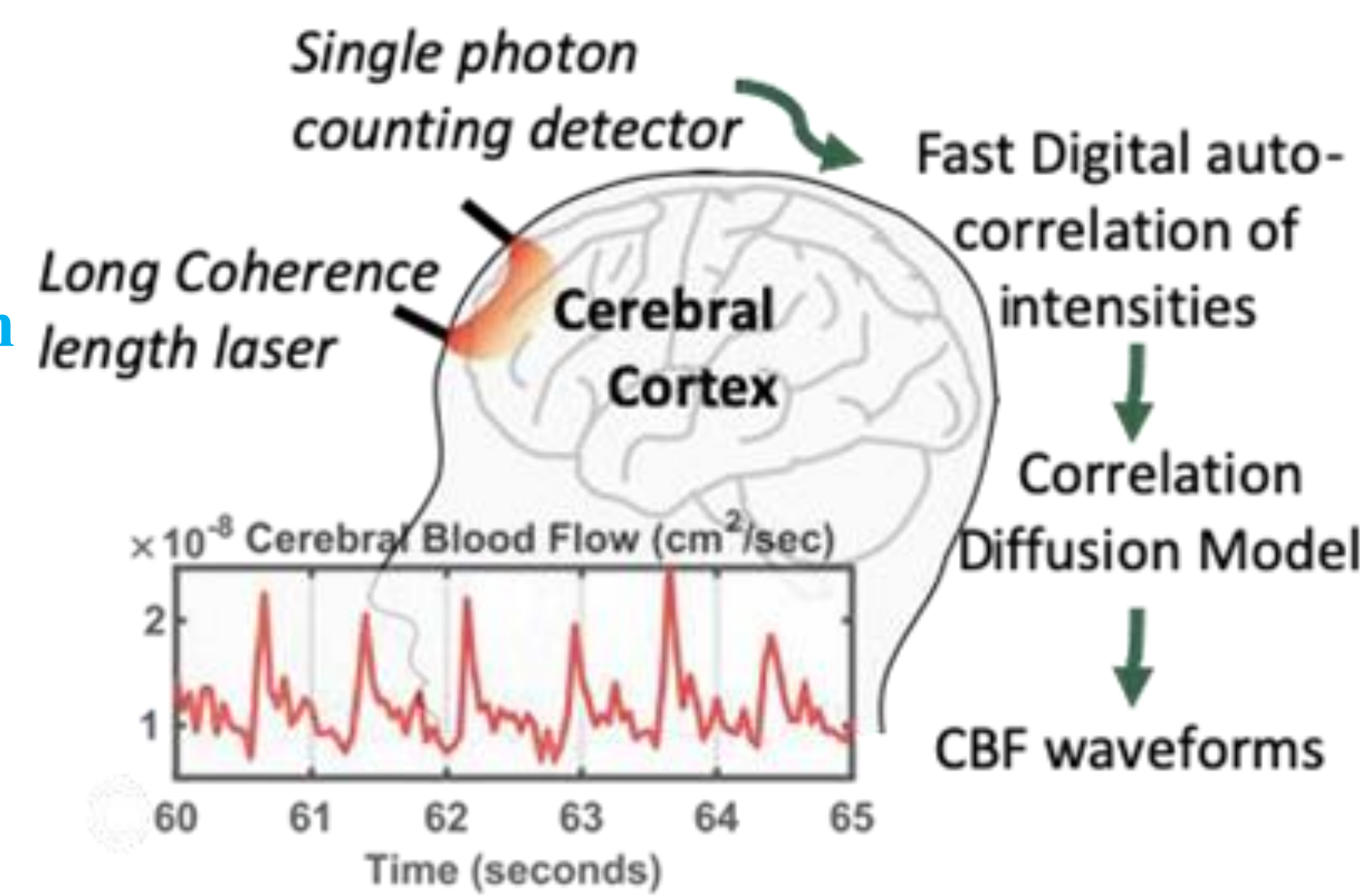
Introduction

Intracranial Pressure (ICP): Fluid pressure on the brain tissue
Elevated ICP: A cause of brain injury in traumatic brain injury & other illnesses



Current clinical ICP monitors are **invasive**
- Risk of infection/tissue damage
- Only performed in very sick patients

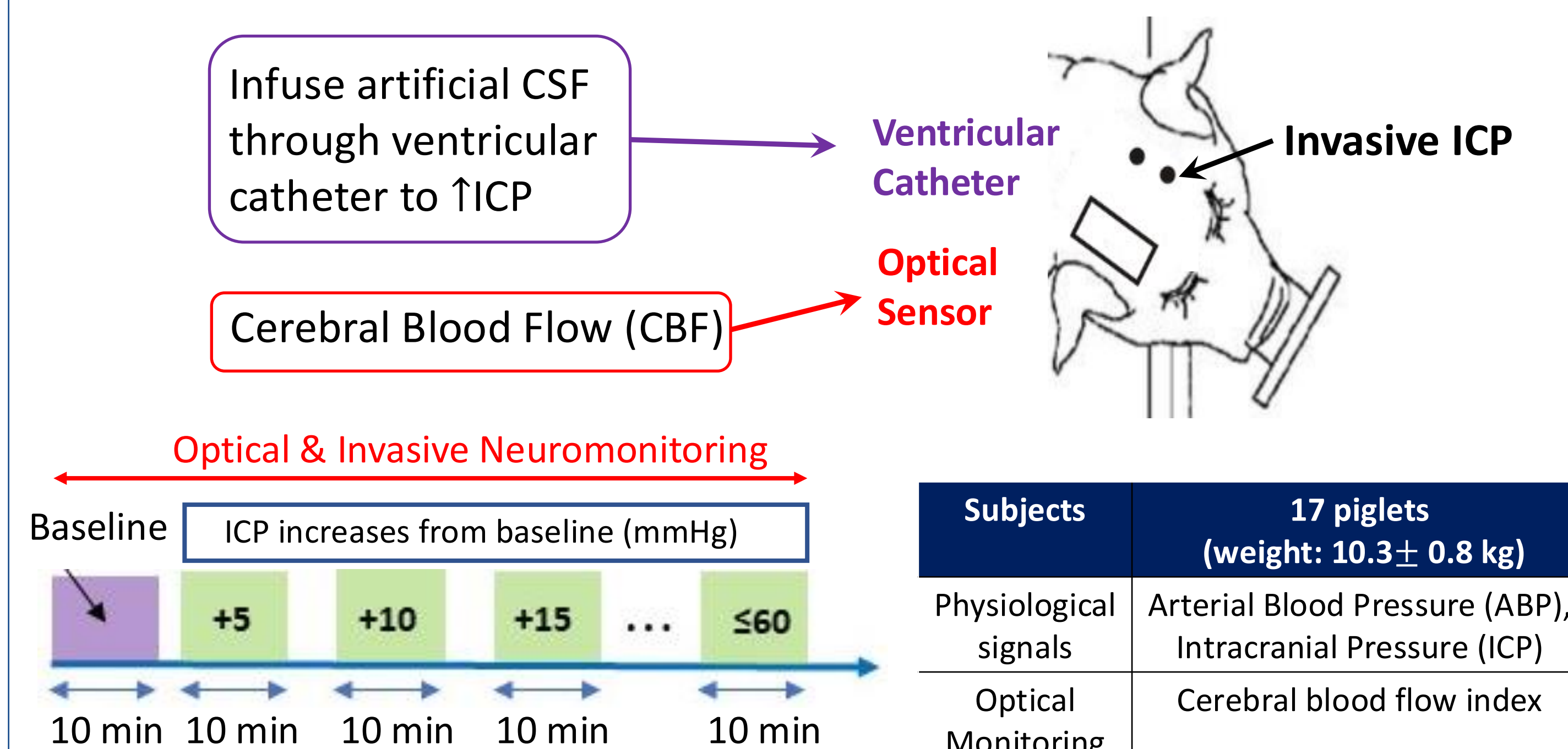
Noninvasive microvascular cerebral blood flow waveform measured with Diffuse Correlation Spectroscopy is sensitive to ICP



T. M. Flanders et al., "Optical Detection of Intracranial Pressure and Perfusion Changes in Neonates With Hydrocephalus," J Pediatr (2021).
K. C. Wu et al., "Validation of diffuse correlation spectroscopy measures of critical closing pressure against transcranial Doppler ultrasound in stroke patients," J Biomed Opt 26 (2021).
A. Ruesch et al., "Estimating intracranial pressure using pulsatile cerebral blood flow measured with diffuse correlation spectroscopy," Biomed Opt Express (2020).
J. B. Fischer et al., "Non-Invasive Estimation of Intracranial Pressure by Diffuse Optics: A Proof-of-Concept Study," J Neurotrauma (2020)

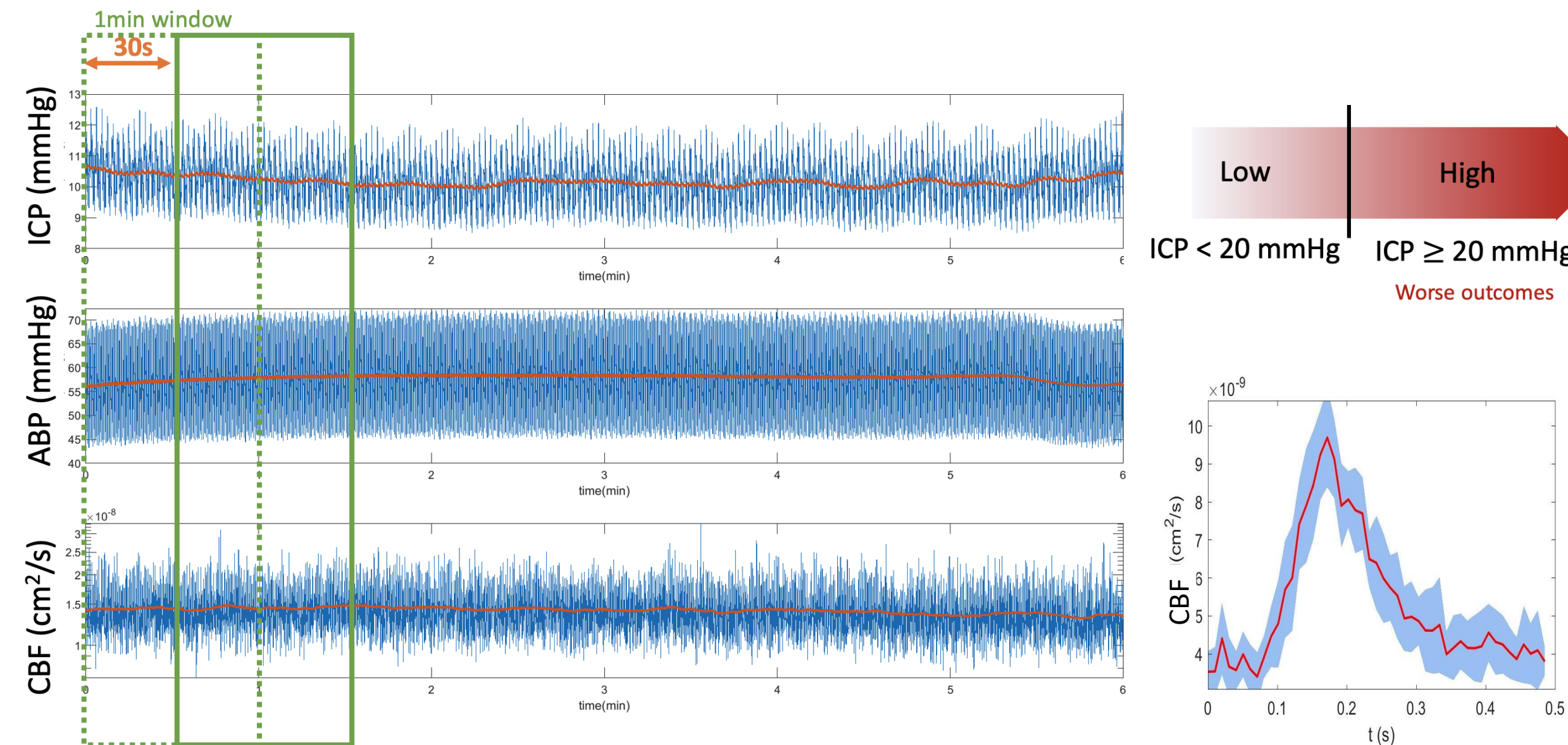
Study objective: Detect elevated intracranial pressure with noninvasive diffuse optical sensor with machine learning

Experiment Design



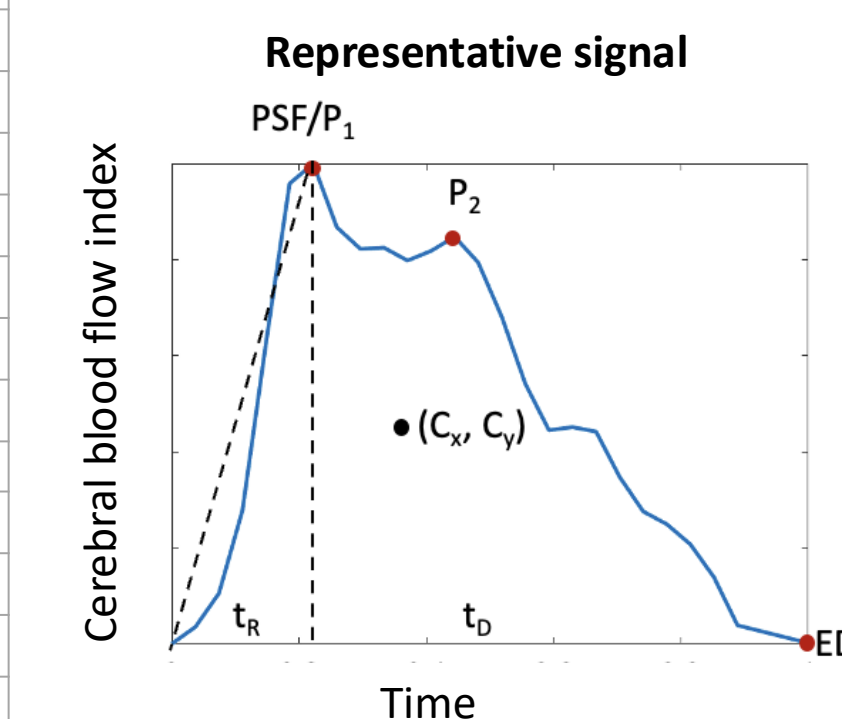
Signal processing & Feature extraction

1. Average 1-min window data: Paired cerebral blood flow waveform & ICP level

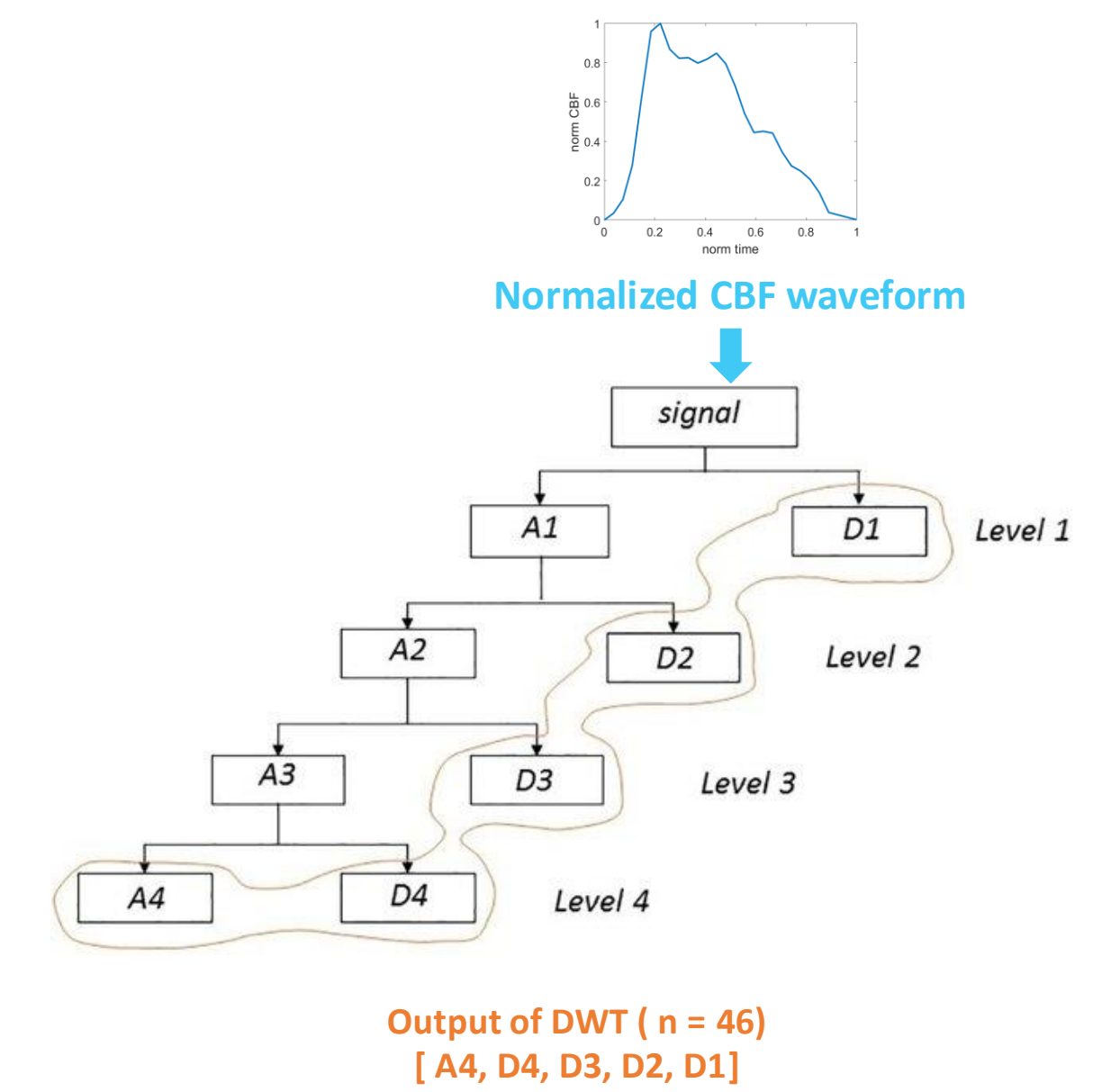


2. Extract morphology Features

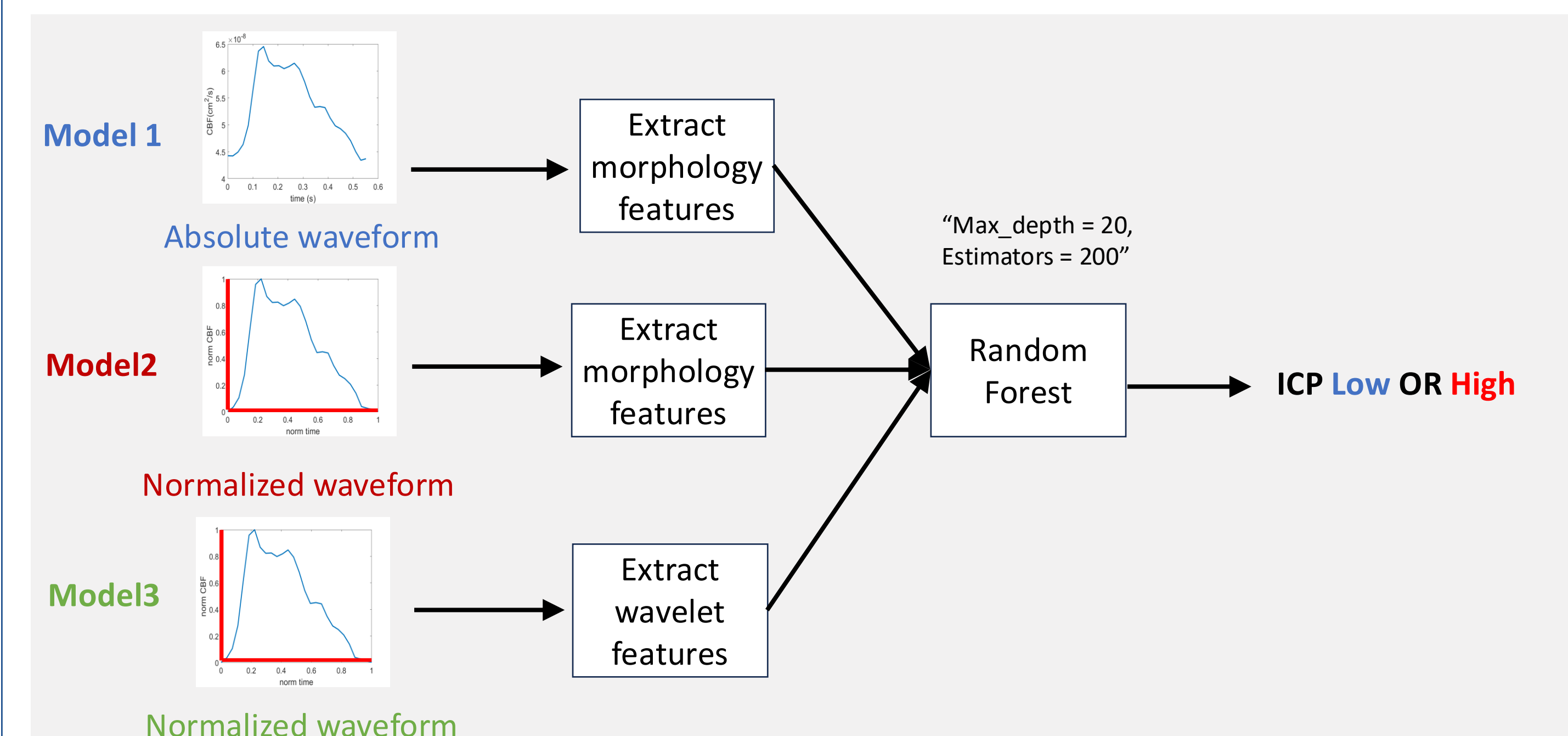
Features (N = 17)	Description
PSF	Peak of systolic flow
EDF	End of diastolic flow
MF	Mean flow
AMP = PSF - EDF	Amplitude
PI = AMP/MF	Pulsatile index
RI = AMP/PSF	Resistive index
AUC	Area under the curve
T _g	Rise time
T _d	Decay time
T _{tot}	Total time
Slope = (PSF - onset)/T _g	The slope of the systolic peak
Centroid x	Center of mass of length
Centroid y	Center of mass of height
P1	First peak
P1 time	First peak time
P2	Second peak
P2 time	Second peak time



3. Extract Wavelet Features



Machine Learning



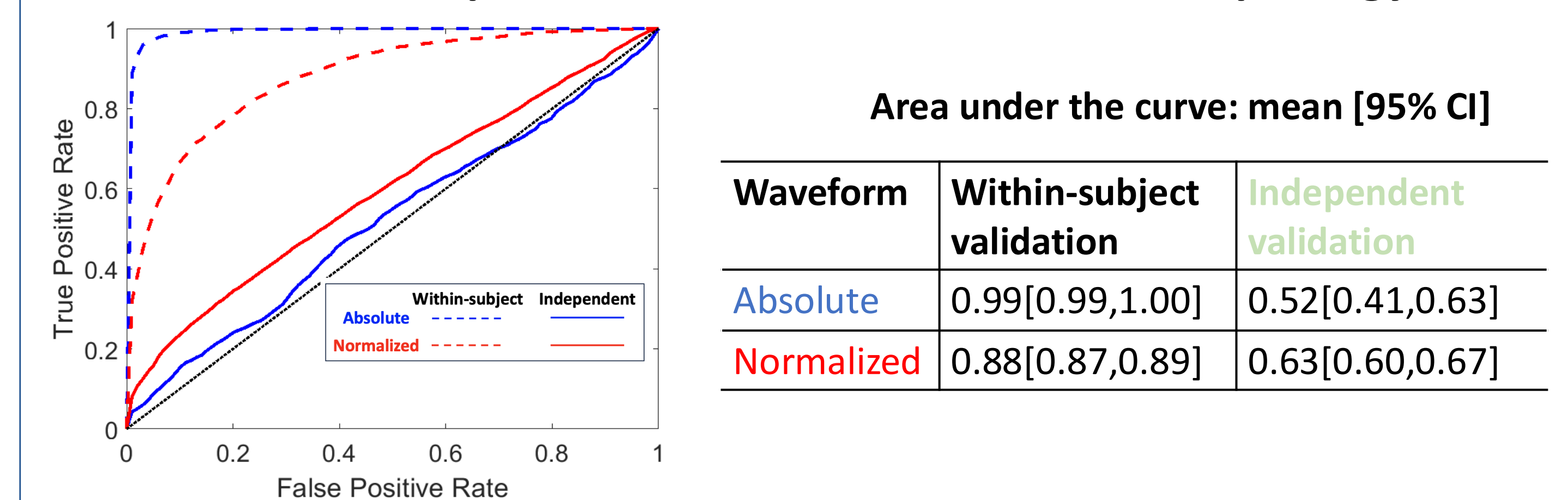
Model Evaluation: 5-fold cross-validation



- **Within-subject cross-validation:** waveforms from each animal are randomly distributed in the training and testing datasets
- **Subject-independent cross-validation:** Each animal's data is exclusively used either for training or testing (**test on unseen animals**)

Absolute vs. normalized waveform

ROC curve for the prediction of elevated ICP with morphology features



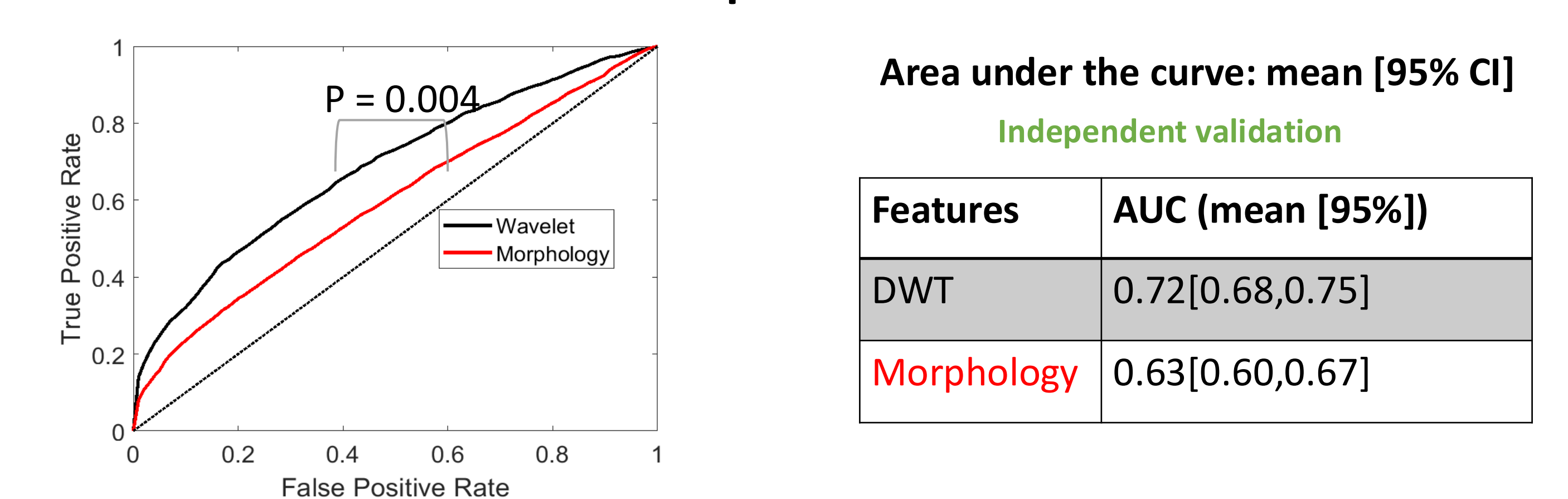
Area under the curve: mean [95% CI]

Waveform	Within-subject validation	Independent validation
Absolute	0.99[0.99,1.00]	0.52[0.41,0.63]
Normalized	0.88[0.87,0.89]	0.63[0.60,0.67]

- Within-subject cross-validation is problematic
- The use of normalized waveforms improves generalizability

Morphology vs. wavelet features

ROC curve for the prediction of elevated ICP



Area under the curve: mean [95% CI]

Features	AUC (mean [95%])
DWT	0.72[0.68,0.75]
Morphology	0.63[0.60,0.67]

Wavelet features significantly outperform morphology features on unseen subjects

Summary

Conclusions:

- Prediction performance using the within-subject cross-validation approach is not generalizable to unseen subjects
- Using normalized CBF waveforms improves the generalizability of the ICP prediction compared to absolute waveforms
- Wavelet features improve prediction performance compared to morphology features

Future directions:

- Improved DCS data quality (temporal resolution, SNR)
- Optimize wavelet transform parameters
- More advanced machine learning methods



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