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Remote Blood Oxygen Estimation From Video Using Neural Networks

Joshua Mathew,*[1] Xin Tian,*[2] Chau-Wai Wong,[1] Simon Ho,[3]
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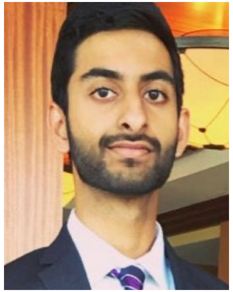
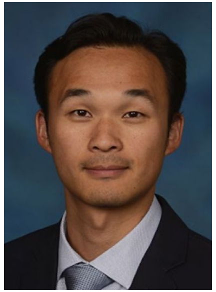
[1] NC State Univ., [2] Univ. of Maryland, College Park, [3] Univ. of Maryland School of Medicine
* Equal contributions



Blood Oxygen Saturation (SpO2)

- SpO_2: Important indicator of lung functions
  - Ratio of concentration of oxygenated hemoglobin to total hemoglobin

$$SpO_2\,(\%) = \frac{C(HbO_2)}{C(Hb) + C(HbO_2)}$$

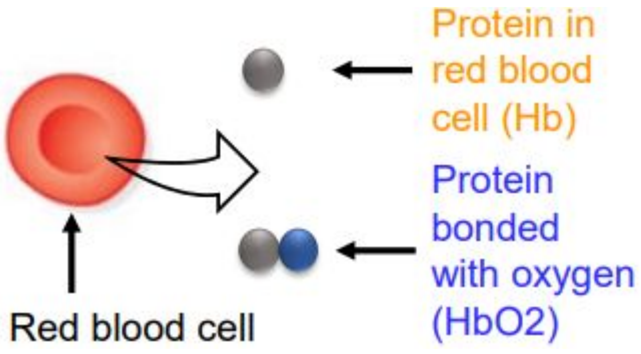
- SpO_2 Range ~95–100% in healthy people
  - COVID-19 clinical findings: Considerable # of patients had dangerously low SpO_2 w/o looking ill before conditions worsening

Pulse Oximeter

- Noninvasive, much less painful
- Convenient for daily use
- Less accurate (±2% error)

Pulse Oximetry

- Exploits difference in light absorption of oxygenated (HbO_2) vs deoxygenated hemoglobin (Hb) to measure blood oxygen saturation (SpO_2)



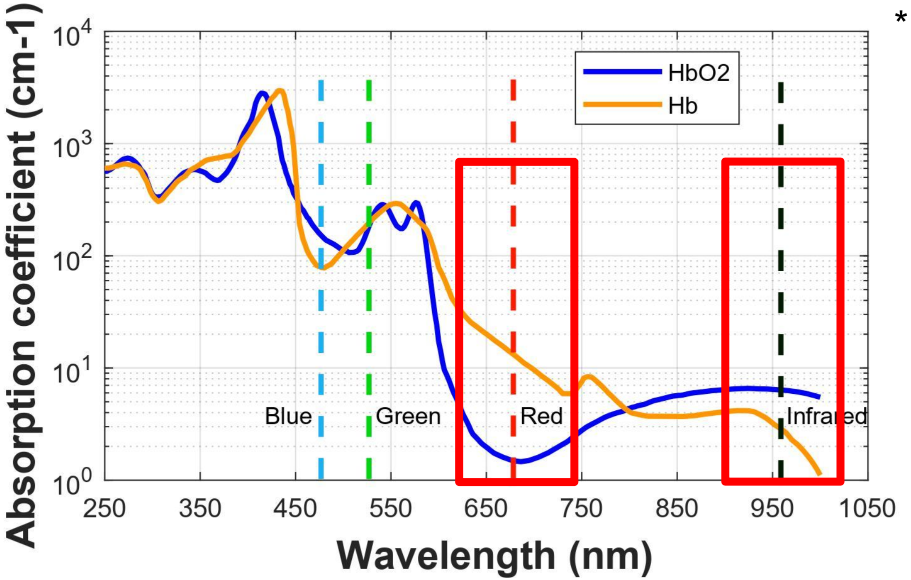


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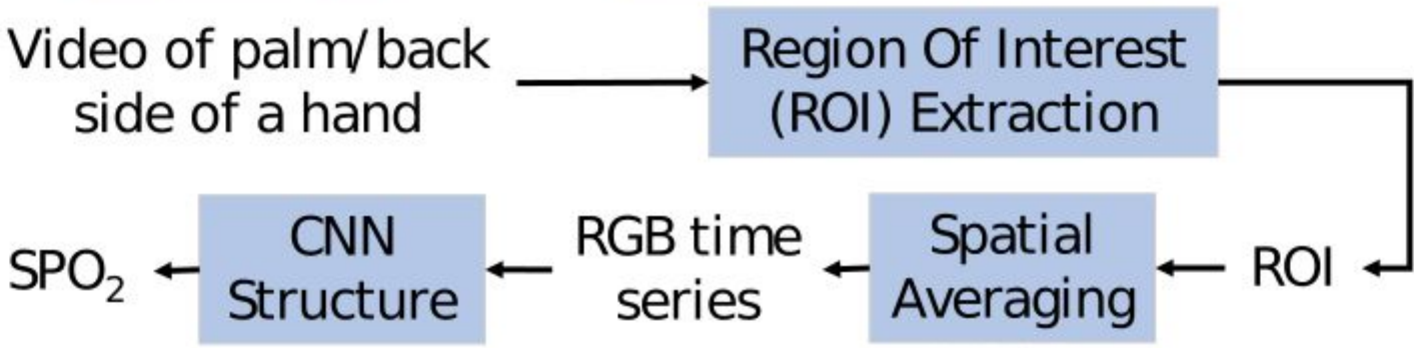
*Fig. 2 from J. Mathew, X. Tian, C.-W. Wong, S. Ho, D. K. Milton, and M. Wu, "Remote blood oxygen estimation from videos using neural networks", *IEEE Journal of Biomedical and Health Informatics*, 2023.

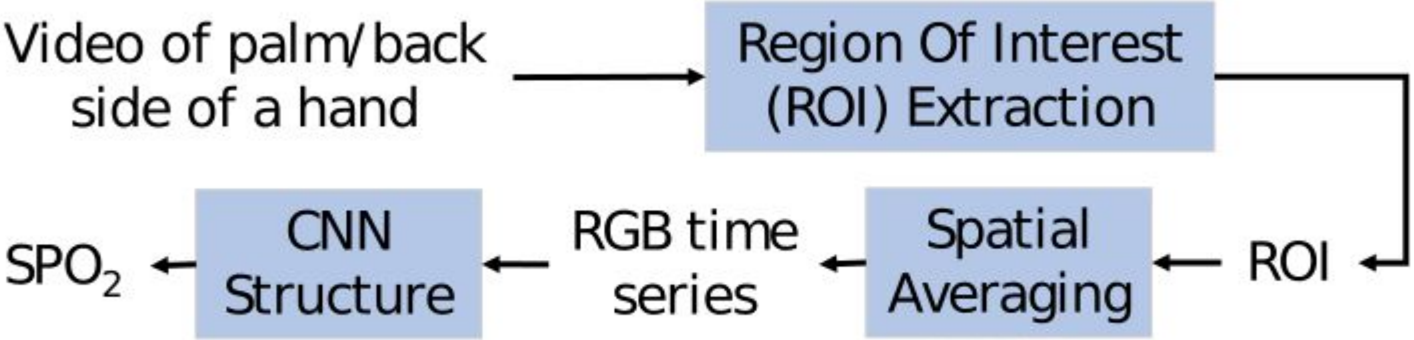
Drawbacks

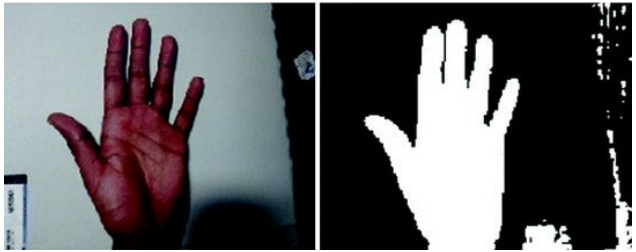
- Requires direct physical contact

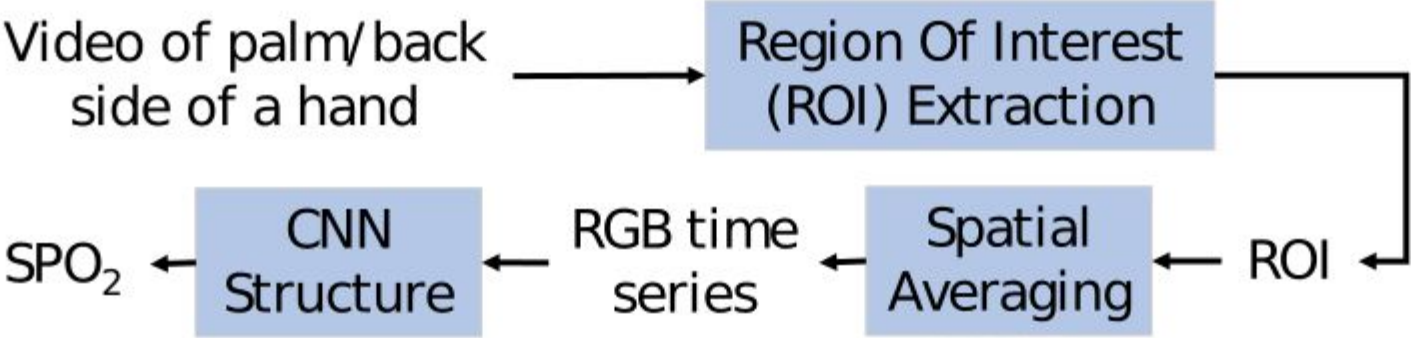
- Pulse oximeters not widely accessible, such as in marginalized communities and some undeveloped countries

Proposed Method




Video of palm/back side of a hand
Region Of Interest (ROI) Extraction
ROI
Spatial Averaging
RGB time series
CNN Structure
SPO_2





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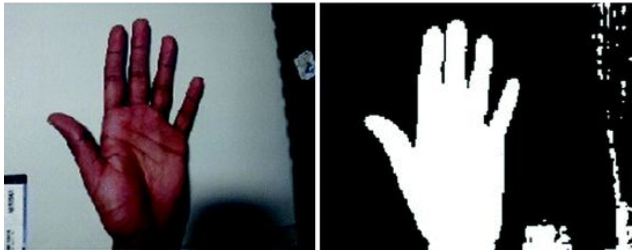

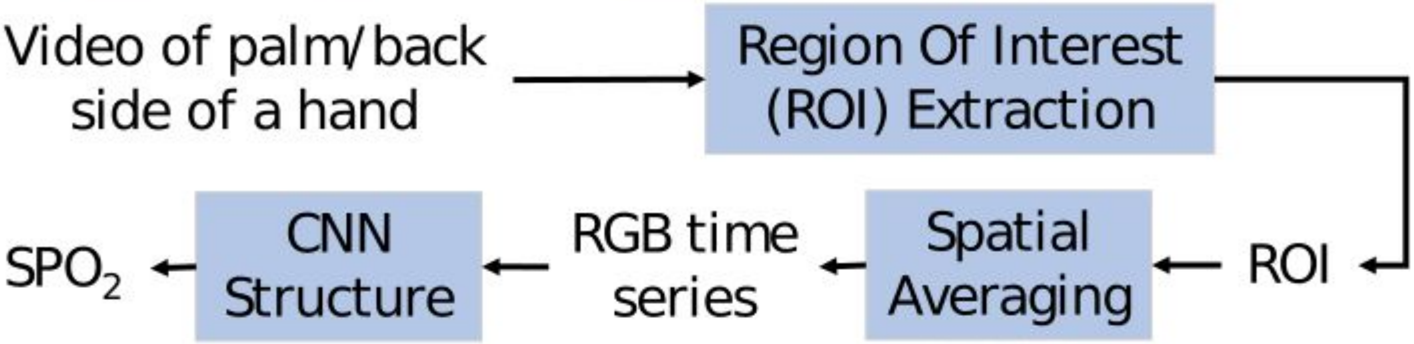
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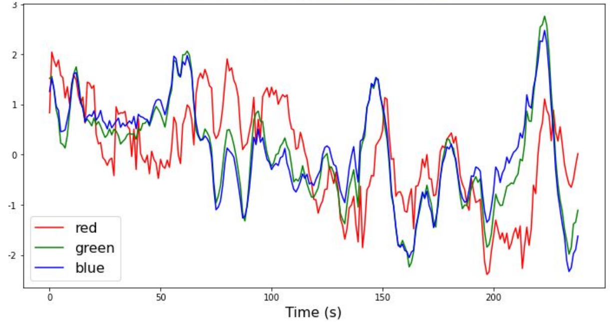
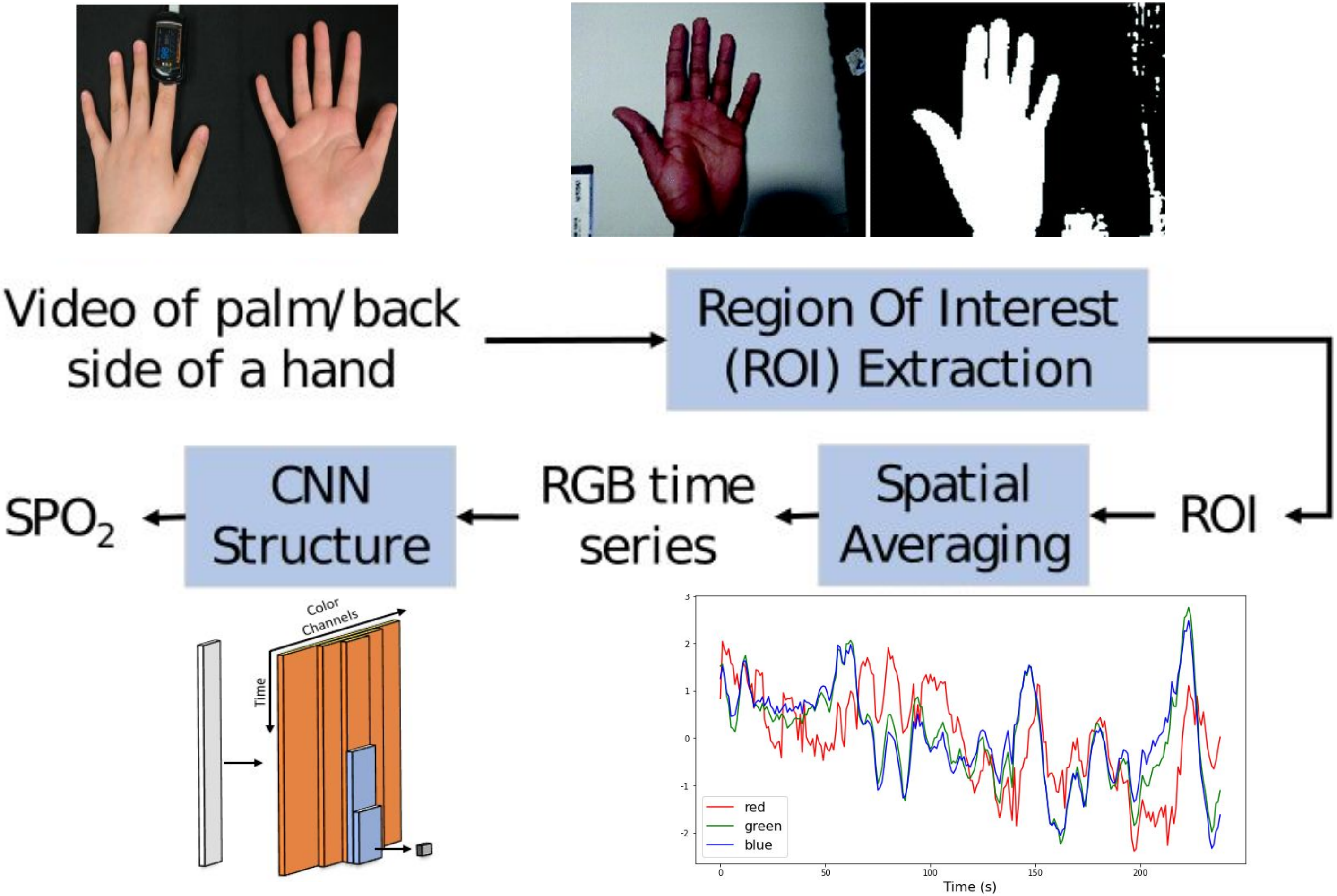

red
green
blue
Time (s)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ROI
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SPO_2
Color Channels
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red
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Time (s)

Data Collection

- Data collected from videos of the hand with palm up or down

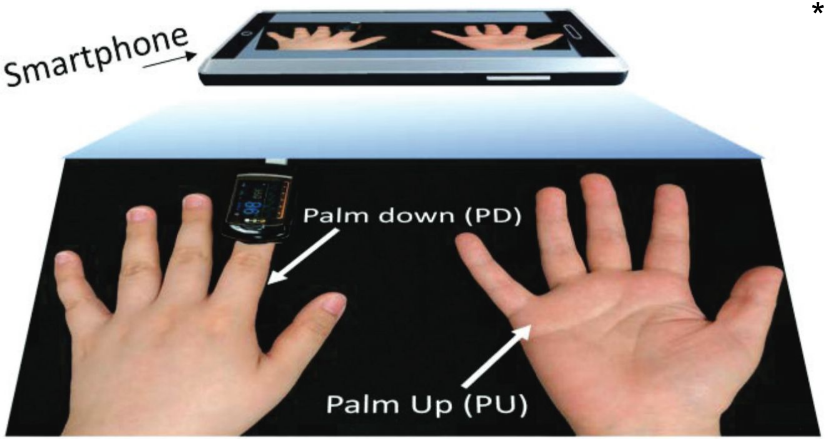

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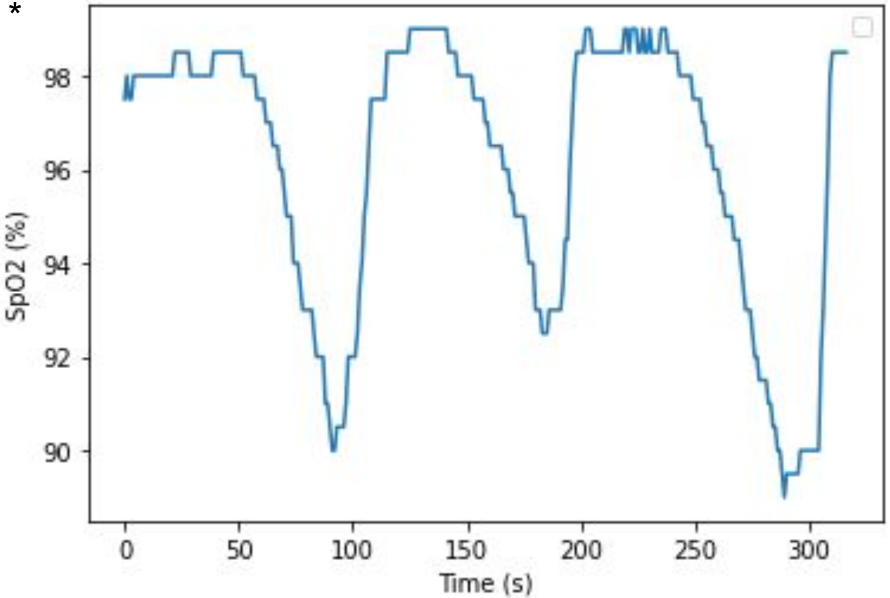
*Fig. 5 from J. Mathew, X. Tian, C.-W. Wong, S. Ho, D. K. Milton, and M. Wu, "Remote blood oxygen estimation from videos using neural networks", *IEEE Journal of Biomedical and Health Informatics*, 2023.

Breathing Protocol

- Participants asked to follow a breathing protocol to vary SpO_2
- Increased range of SpO_2 values

*



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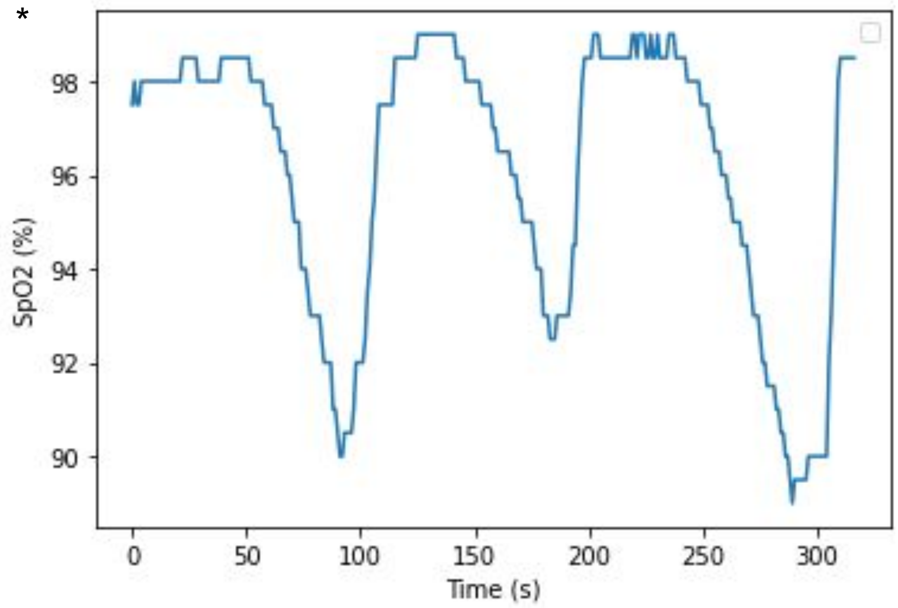

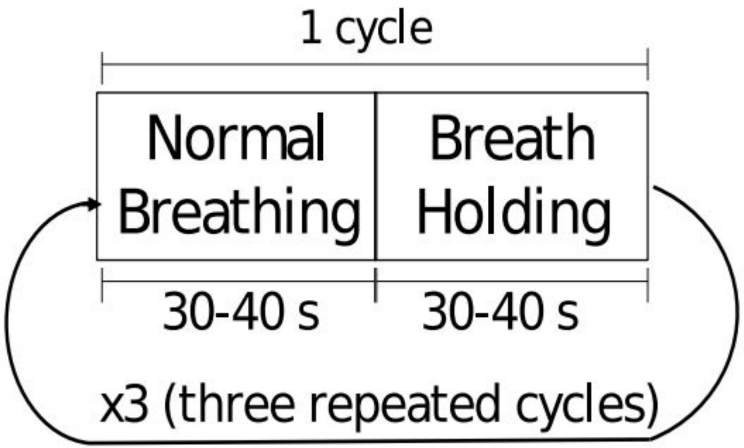

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Model Structures

- Model 1 - Channel mixing then feature extraction
- Model 2 - Feature extraction then channel mixing
- Model 3 - Interweaving channel mixing and feature extraction

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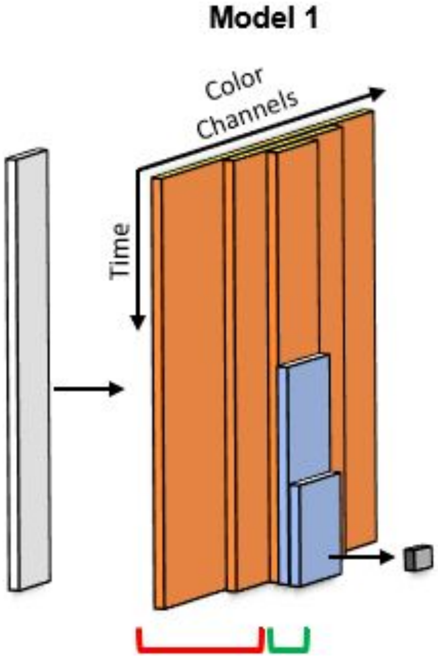

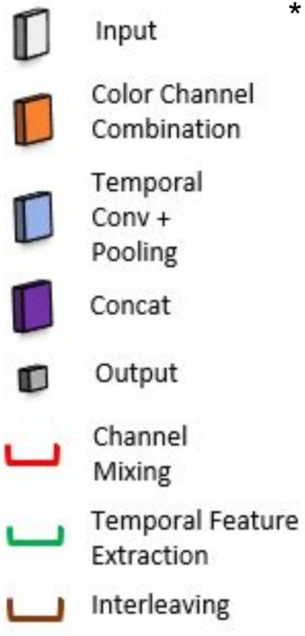

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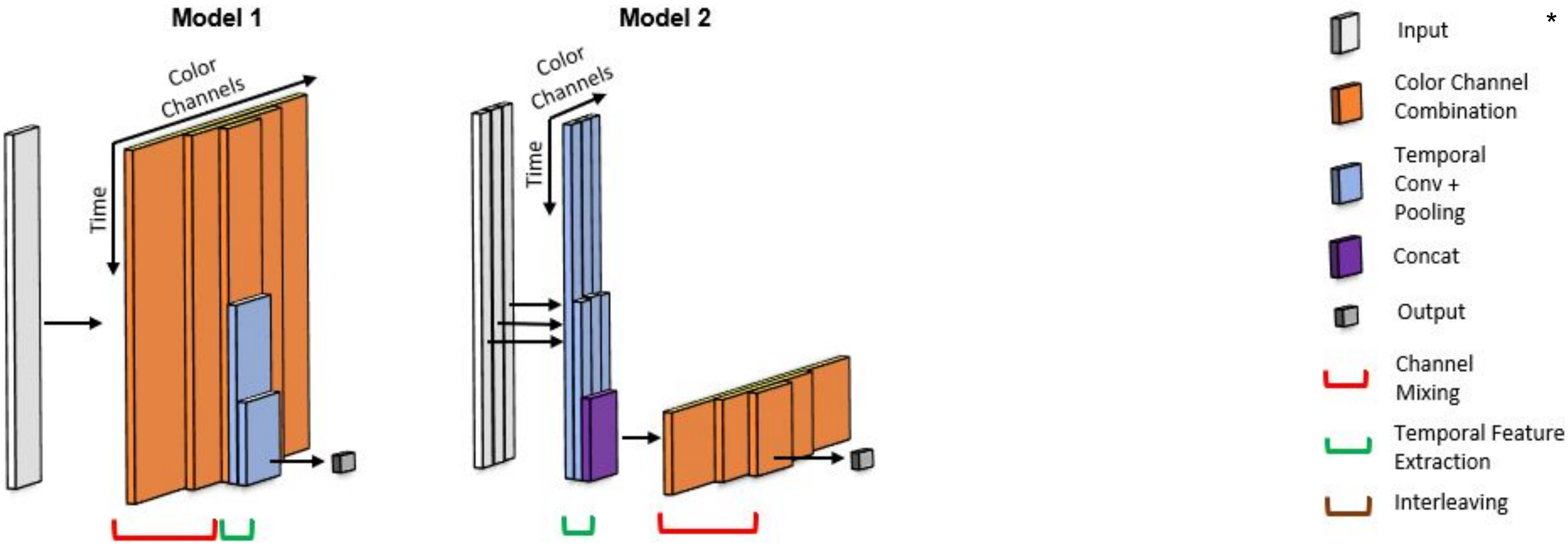

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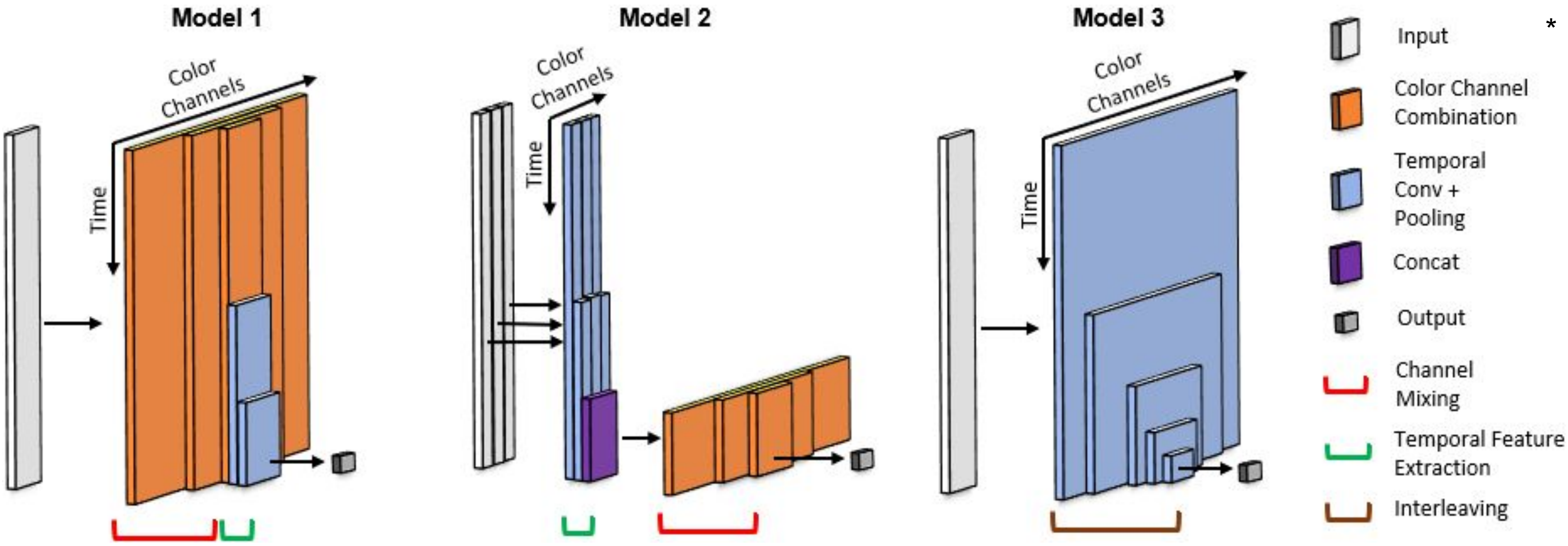

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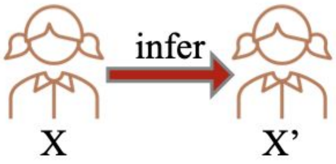
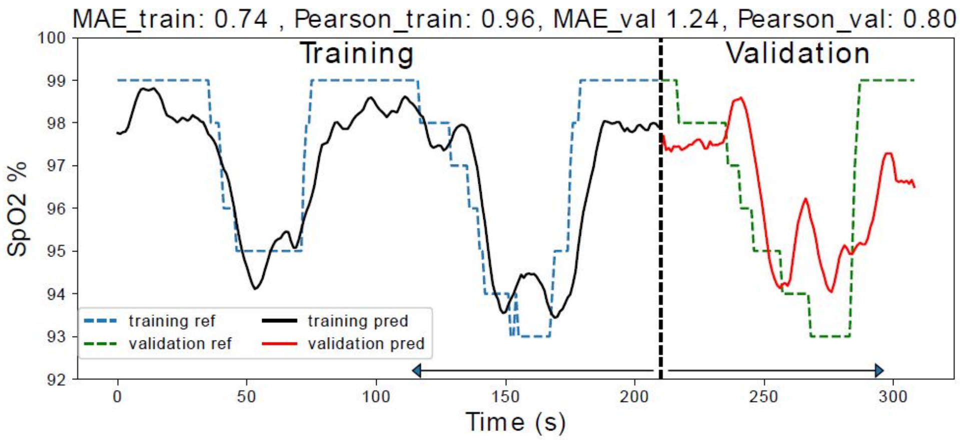
Participant Specific Testing

- 1 recording for training/validation and 1 for testing
- 2 breathing cycles for training and 1 for validation
- Train multiple instances for each model and select instance with highest validation Pearson correlation





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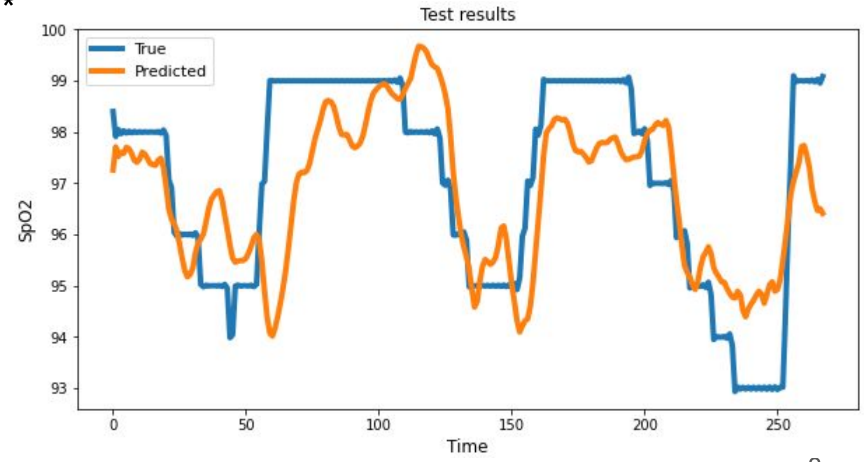

*Fig. 6b from J. Mathew, X. Tian, C.-W. Wong, S. Ho, D. K. Milton, and M. Wu, “Remote blood oxygen estimation from videos using neural networks”, *IEEE Journal of Biomedical and Health Informatics, 2023.*

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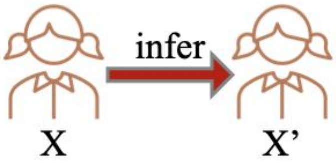

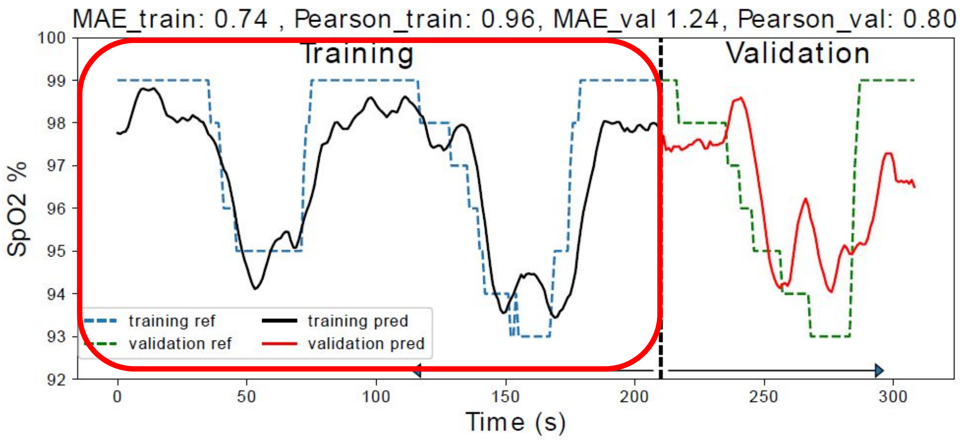

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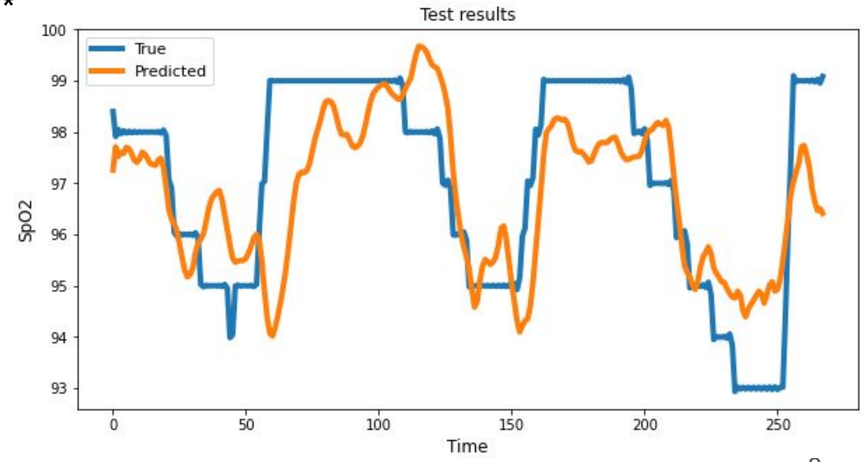

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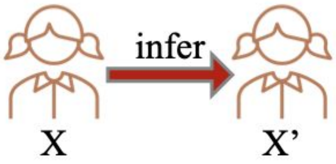

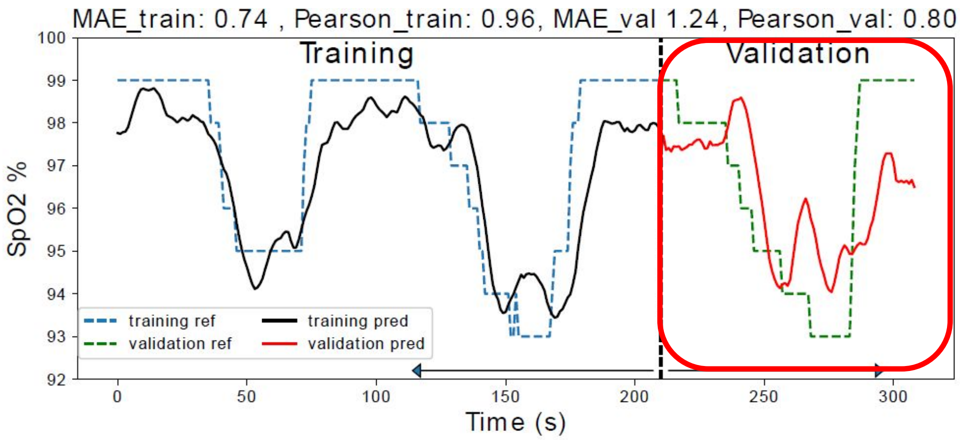

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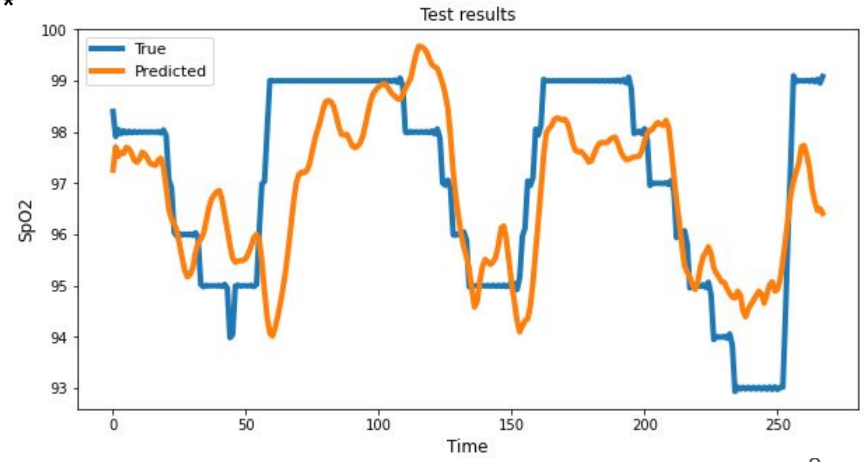

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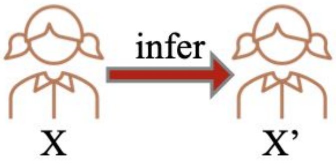

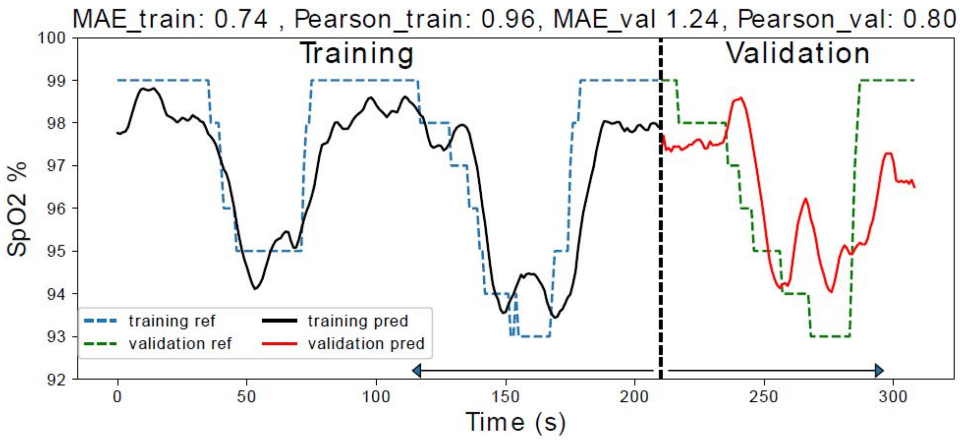

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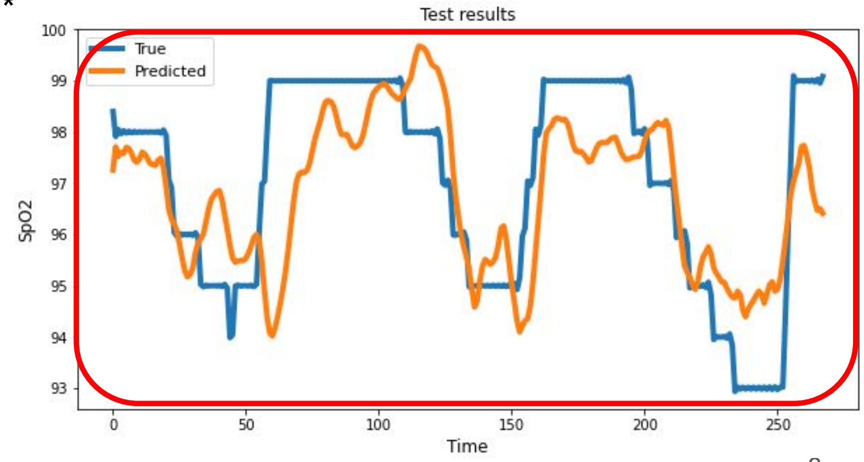

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Participant Specific Correlation Results

- Median correlation across all participants
- Models 2 and 3 achieved best performance

	Hand Mode	Correlation Median	IQR
Model 1 (Proposed)	PD	0.41	0.40
	PU	0.39	0.37
Model 2 (Proposed)	PD	**0.46**	0.44
	PU	**0.41**	0.32
Model 3 (Proposed)	PD	0.44	0.40
	PU	**0.41**	0.46

PU (Palm Up), PD (Palm Down)

IQR (Interquartile Range) = 3rd quartile – 1st quartile

Participant Specific Correlation Results

- Ding et al. [5] – Neural network for contact-based SpO_2 prediction from video
- Scully et al. [7] – Ratio-of-ratios method

	Hand Mode	Correlation Median	Correlation IQR
Model 1 (Proposed)	PD	0.41	0.40
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Model 2 (Proposed)	PD	**0.46**	0.44
	PU	**0.41**	0.32
Model 3 (Proposed)	PD	0.44	0.40
	PU	**0.41**	0.46
Scully *et al.* [5]	PD	0.08	0.37
	PU	0.19	0.24
Ding *et al.* [7]	PD	0.38	0.39
	PU	0.34	0.56

[5] X. Ding, D. Nassehi, and E. C. Larson, "Measuring oxygen saturation with smartphone cameras using convolutional neural networks," *IEEE J Biomed. Health Info.*, 2018.
[7] C. G. Scully, J. Lee, J. Meyer, et al., "Physiological parameter monitoring from optical recordings with a mobile phone," *IEEE Trans. Biomed. Eng.*, 2011.

Participant Specific MAE Results

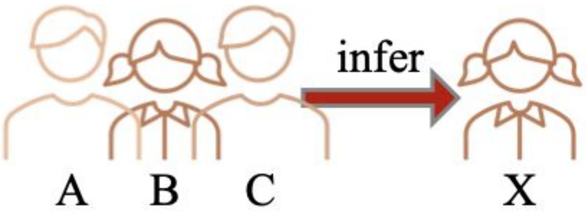
- All models outperformed Ding et al.
- Scully et al. achieves lower mean absolute error (MAE) than some models but has low correlation

	Hand Mode	Correlation Median	Correlation IQR	MAE (%) Median	MAE (%) IQR
Model 1 (Proposed)	PD	0.41	0.40	2.12	0.91
	PU	0.39	0.37	2.16	1.80
Model 2 (Proposed)	PD	**0.46**	0.44	2.09	1.32
	PU	**0.41**	0.32	1.96	0.68
Model 3 (Proposed)	PD	0.44	0.40	**1.93**	1.11
	PU	**0.41**	0.46	**1.81**	1.83
Scully *et al.* [5]	PD	0.08	0.37	1.94	0.92
	PU	0.19	0.24	2.01	0.80
Ding *et al.* [7]	PD	0.38	0.39	3.25	2.85
	PU	0.34	0.56	3.40	3.16

Naïve predictor is not useful

Leave-One-Participant-Out Experiments

- Aim: To test generalizability to unseen participants
- Train on all participant recordings but leave out test participant
- Participant-wise cross-validation



Leave-One-Out Correlation Results

- More difficult than participant-specific case
- Doing channel combination first may be more generalizable

	Hand Mode	Correlation Median	Correlation IQR
Model 1 (Proposed)	PD	**0.33**	0.42
	PU	**0.46**	0.36
Model 2 (Proposed)	PD	0.15	0.50
	PU	0.33	0.39
Model 3 (Proposed)	PD	0.23	0.38
	PU	0.27	0.31

Leave-One-Out Correlation Results

- Proposed models outperform state-of-the-art

	Hand Mode	Correlation Median	Correlation IQR
Model 1 (Proposed)	PD	**0.33**	0.42
	PU	**0.46**	0.36
Model 2 (Proposed)	PD	0.15	0.50
	PU	0.33	0.39
Model 3 (Proposed)	PD	0.23	0.38
	PU	0.27	0.31
Scully *et al.* [5]	PD	0.05	0.43
	PU	0.01	0.54
Ding *et al.* [7]	PD	0.11	0.56
	PU	0.26	0.42

Leave-One-Out MAE Results

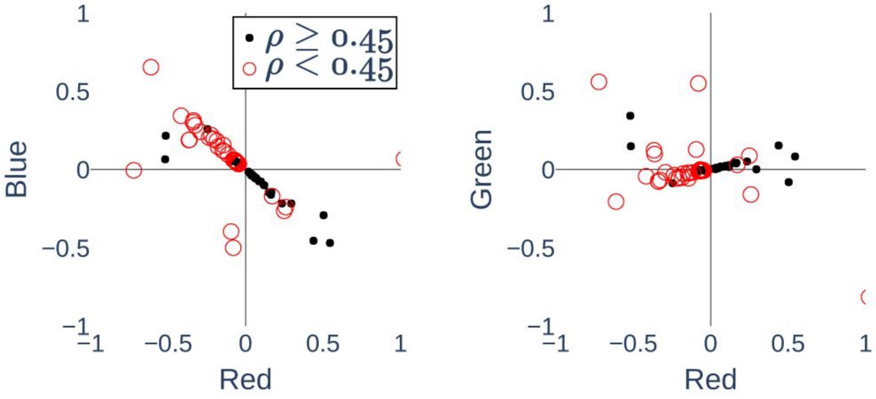
- More difficult than participant-specific case
- Features extracted after channel combination maybe more generalizable

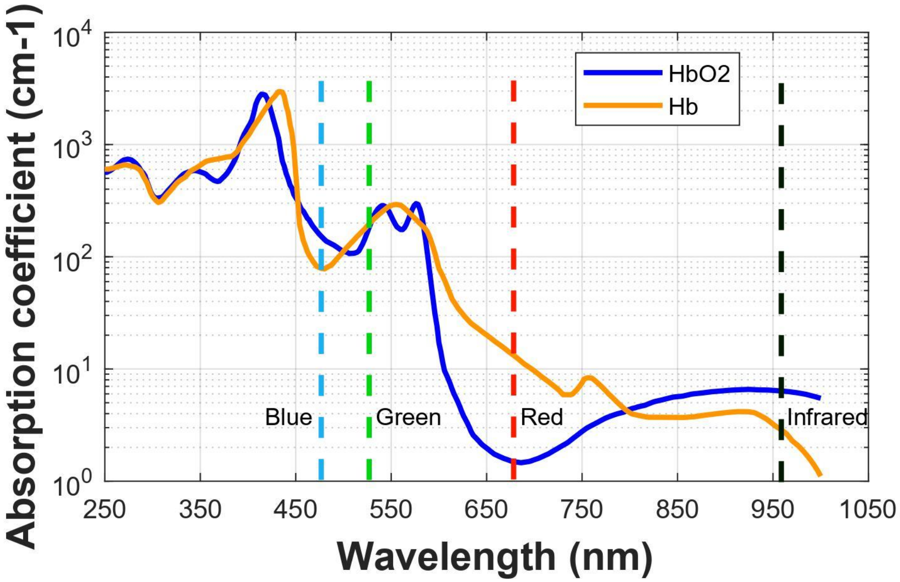
	Hand Mode	Correlation Median	Correlation IQR	MAE (%) Median	MAE (%) IQR
Model 1 (Proposed)	PD	**0.33**	0.42	2.33	1.07
	PU	**0.46**	0.36	**1.97**	0.80
Model 2 (Proposed)	PD	0.15	0.50	2.43	0.94
	PU	0.33	0.39	2.08	0.73
Model 3 (Proposed)	PD	0.23	0.38	2.48	1.18
	PU	0.27	0.31	2.02	1.03
Scully *et al.* [5]	PD	0.05	0.43	**2.08**	0.65
	PU	0.01	0.54	2.08	0.60
Ding *et al.* [7]	PD	0.11	0.56	3.19	1.61
	PU	0.26	0.42	2.43	1.22

Naïve predictor is not useful

Channel Combination Visualization

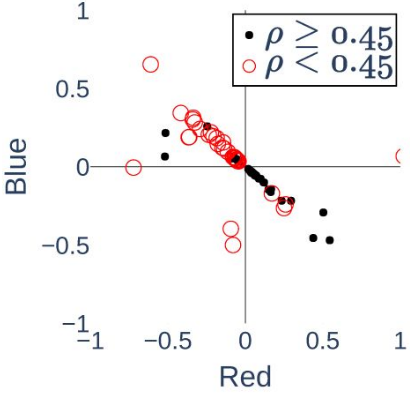
- Visualized model weights

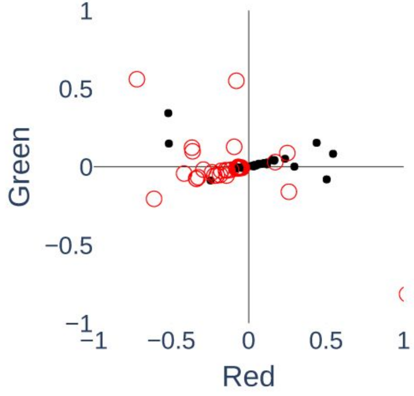


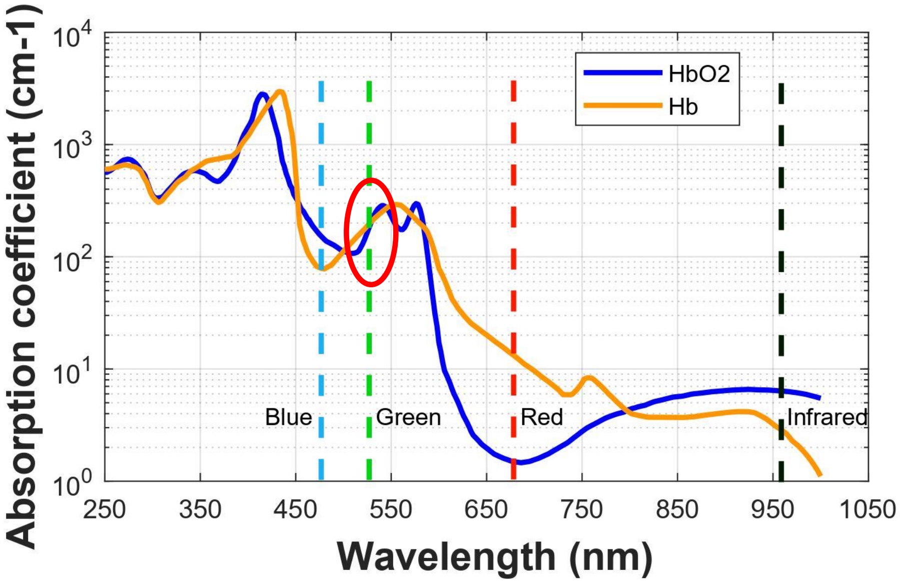


Channel Combination Visualization

- Green channel is given low weight

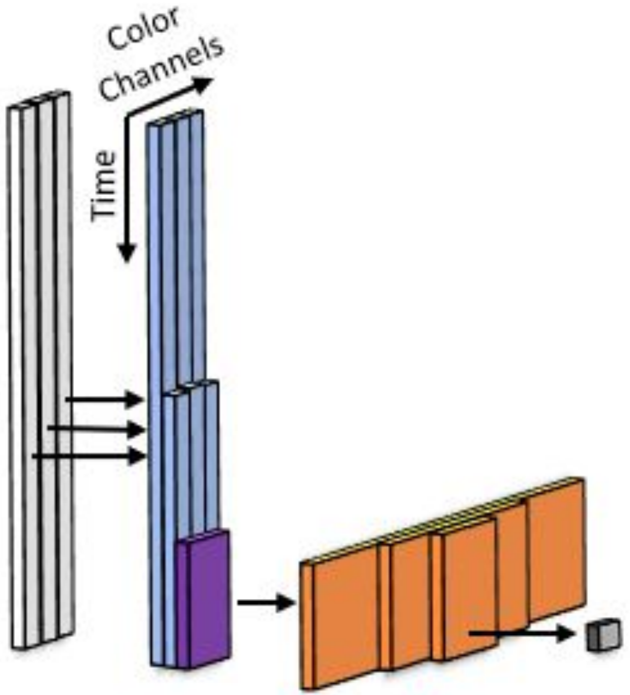






Conclusion

- Measure blood oxygen without physical contact utilizing smartphone videos
- Developeded novel neural network architectures which outperformed state-of-the-art methods
- Showed that learned RGB weights are consistent with optophysiological methods.



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