ReLearn: A Robust Machine Learning Framework in Presence of Missing Data for Multimodal Stress Detection from Physiological Signals

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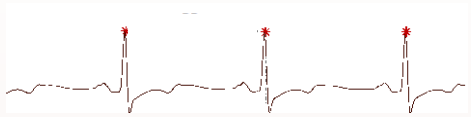
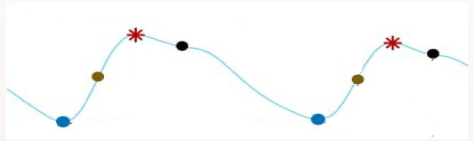
Introduction

- Stress in moden societies
- Continuous and multimodal stress detection and recognition improves life quality [2]-[5]
  - Through wearable devices and embedded Machine Learning (ML) algorithms

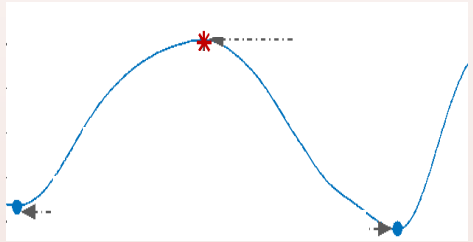


ECG (Electrocardiogram)



PPG (Photoplethysmography)

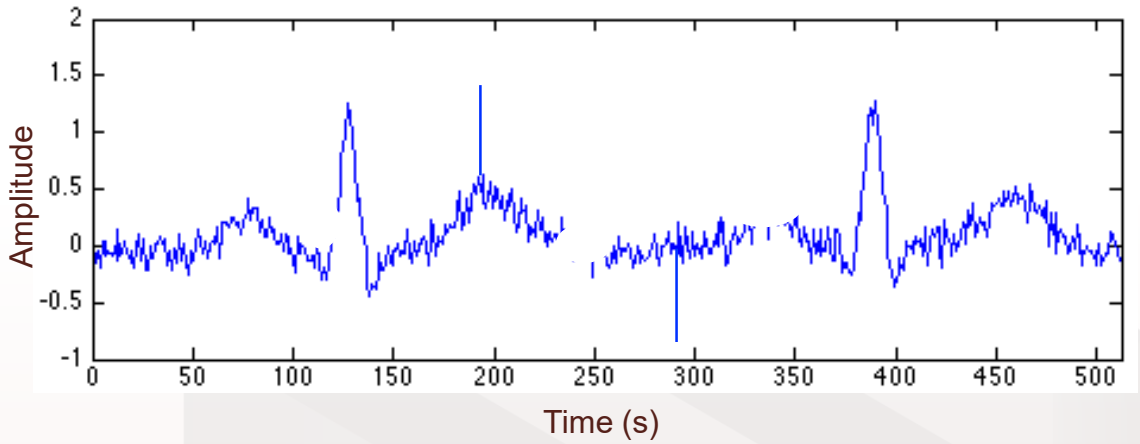
EDA (Electrodermal Activity)



RSP (Respiration)

Problem Definition and Motivation

- Common challenges of physiological signal acquisitions:
  - Noisy data
  - Missing data
  - Outliers



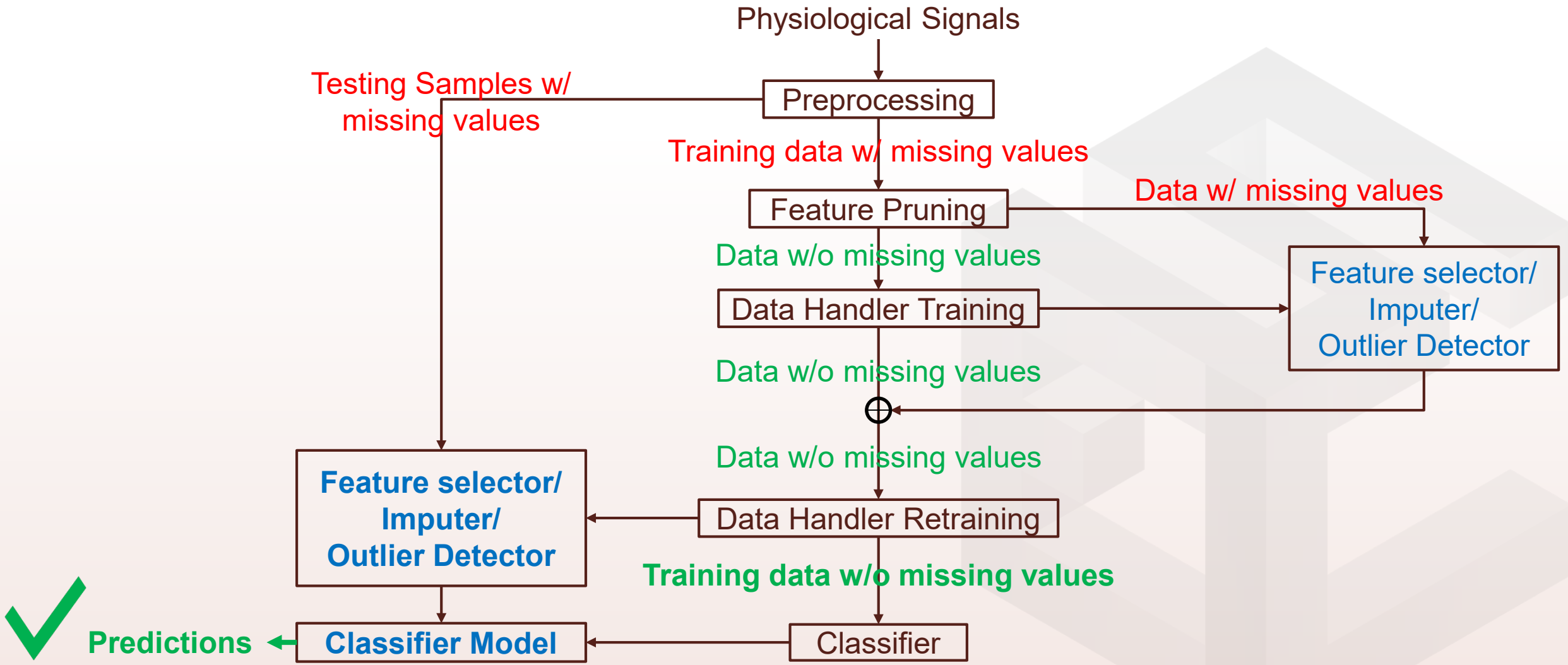
- Conventional remedies:
  - Filtering
  - Ignoring imperfect data and outliers
  - Data imputation
    - Last value
    - Mean/median value
    - Constant value

→
- No prediction for discarded segments
- Reduced prediction accuracy due to lack of sufficient data, esp. in Machine Learning solutions

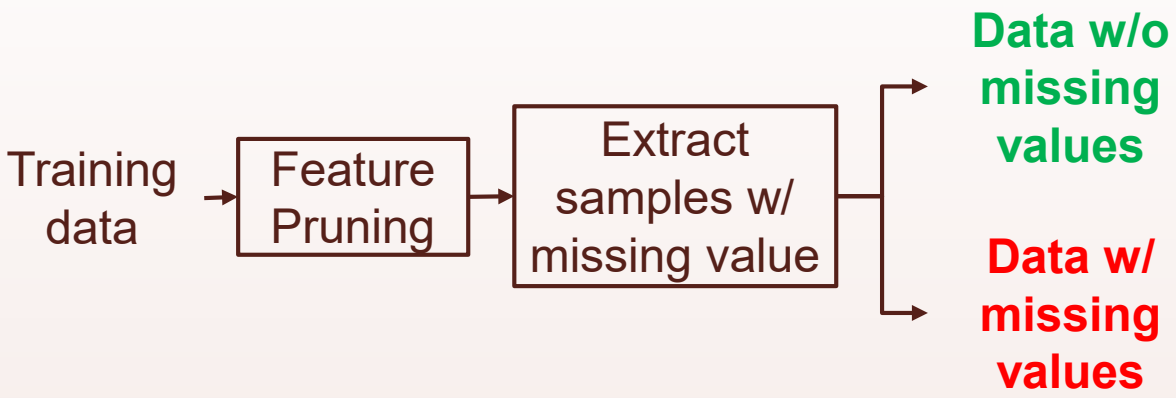
→
- Reduced prediction accuracy due to inaccurate data

A more comprehensive solution is requied to deal with outliers and missing data!

Proposed Framework: ReLearn

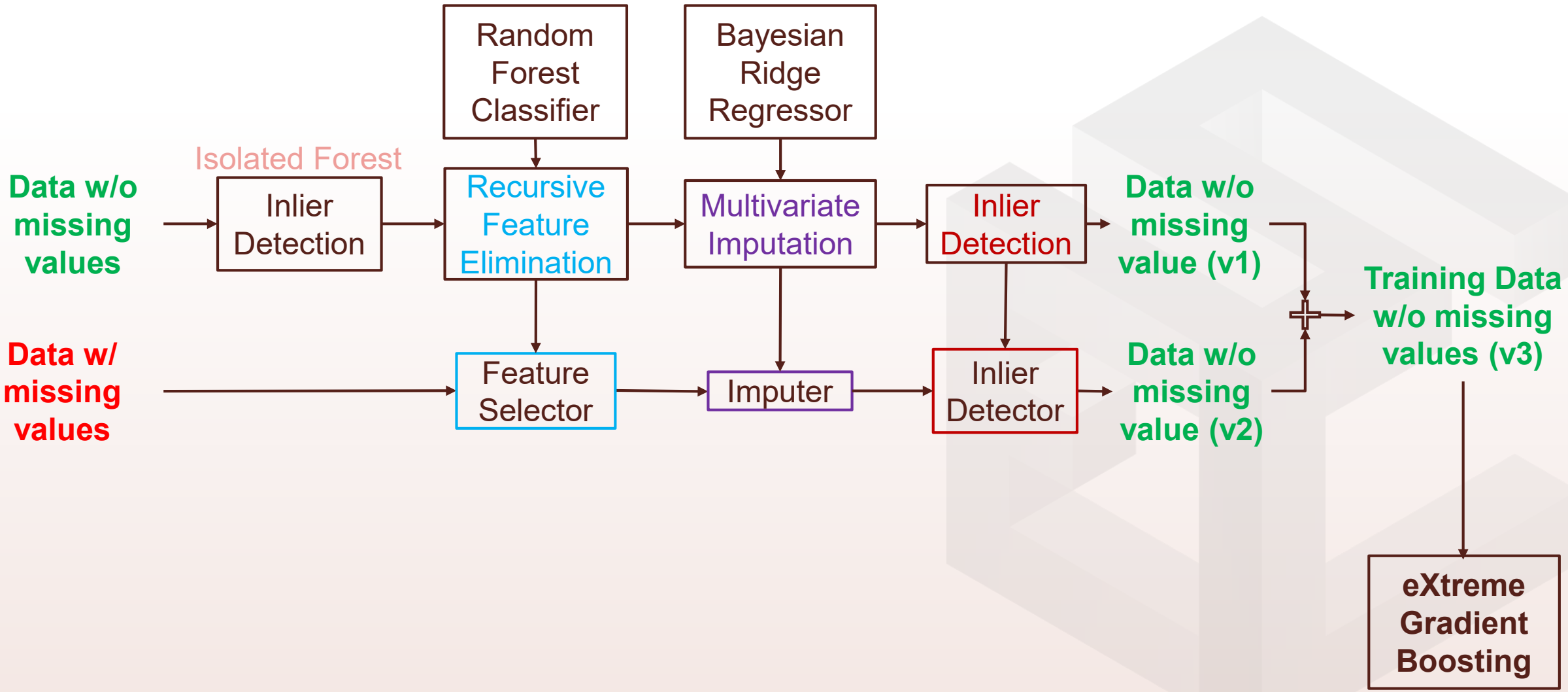


Data Preprocessing



- **Feature Pruning: remove a feature if more than x% of its samples are missing**
  - **Hyperparameter to tune**

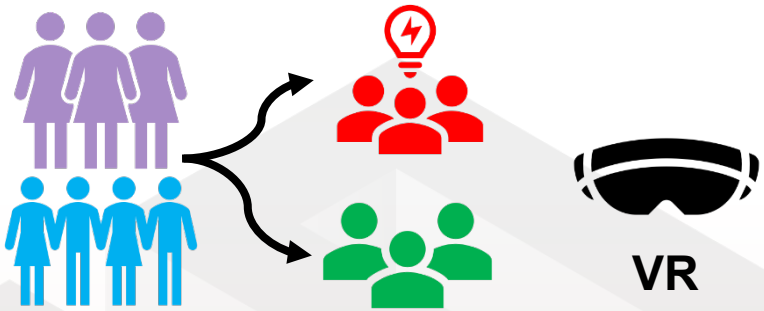
Data Handler and Main Classifier

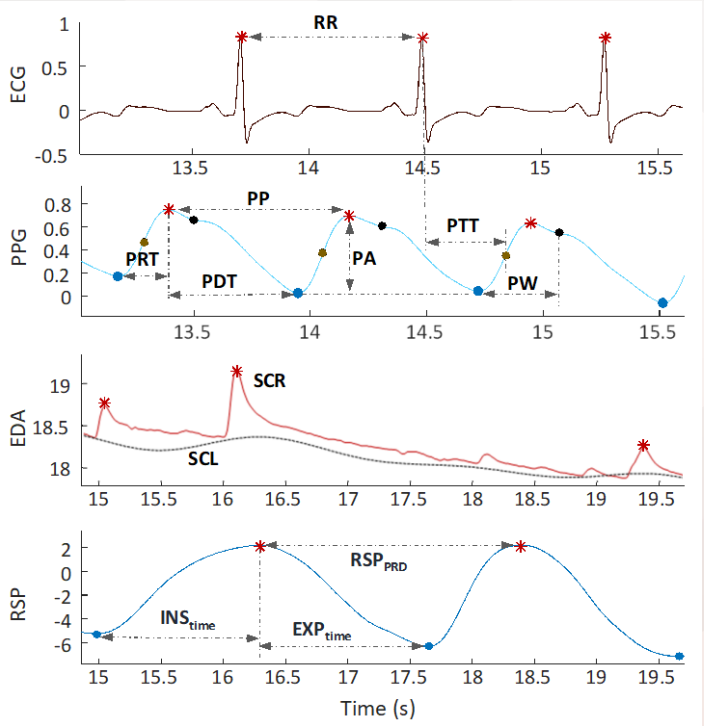


Experiment Protocol and Stress Database

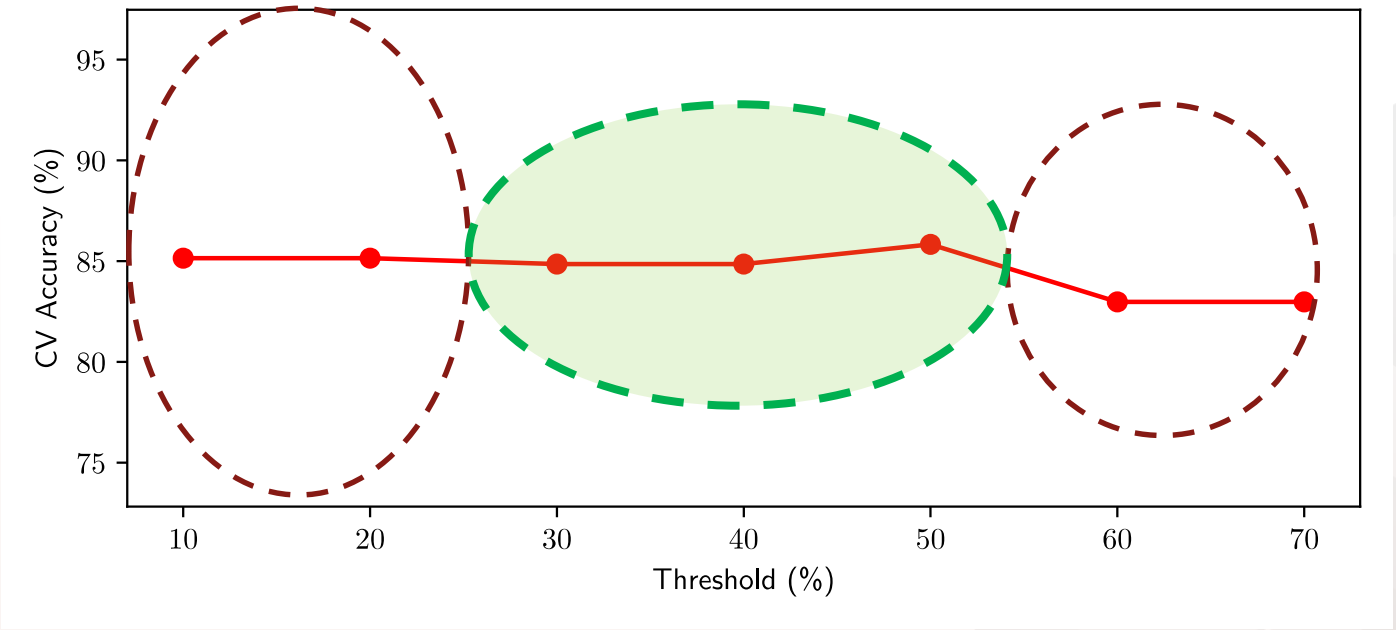
- Experimental Protocol:
  - 95 participant, male and female
  - Divided to two groups perfroming **stress** and **control** tasks

- Database:
  - ECG, PPG, EDA, RSP
  - 94 physiological features in the time and frequency domains extracted from time series in segmentation windows of 60s.





Results: Threshold Optimization



- With lower threshold, more features and samples are dropped: cleaner, but less data!
- With larger threshold, less features and samples are dropped: more unclean data!
- **Tradeoff required!**

Comparison with Conventional Methods

	CV (mean ± STD)	Inf. (All) (mean ± STD)	Inf. (Miss.)	#Feat
Drop NaN [13]	81.6 ± 12.0%	74.4 ± 30.0%	N/A	24
Mean Value [12]	53.9 ± 13.5%	50.2 ± 38.7%	51.1%	49
Last Value [12]	54.1 ± 12.4%	49.7 ± 38.2%	50.5%	36
ReLearn	**86.8 ± 6.4%**	**78.8 ± 25.4%**	**77.9%**	**38**

[13] Y. Bai, et al, “Fatigue assessment using ECG and actigraphy sensors,” International Symposium on Wearable Computers, 2020
[12] S. M. Jadhav, et al, “Artificial neural network based cardiac arrhythmia classification using ECG signal data,” International Conference on Electronics and Information Engineering, 2010.

Conclusion

- Machine learning algorithms require sufficiently large and clean data.
- Removing data with missing samples or using conventional imputation techniques lead to inaccurate prediction, especially for datasets with limited number of samples
- We proposed ReLearn, a machine learning framework for multimodal stress detection from physiological signals in presence of missing data and outliers
- Compared to conventional imputation techniques, ReLearn improved prediction accuracy by at least **26%** for missing samples.

Thank You!

For questions, please contact:
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