Personalized Stress Detection using a Lightweight Machine Learning Framework With Convenient Wrist-Worn Sensors

M. Hasan, M. Saha, M. Mahmud S. Baral, and K. Poudel

The 2024 IEEE Signal Processing in Medicine and Biology Symposium,
Temple University, Philadelphia, Pennsylvania, 19122, USA

MIDDLE TENNESSEE STATE UNIVERSITY

Outline

- Introduction and motivation
- Methods & materials
- Results & discussion
- Conclusion

MIDDLE TENNESSEE STATE UNIVERSITY

Introduction and motivation

- What is stress?
- Why this study is important?

Our main contributions:

- We empirically identified an optimal window size for best stress detection accuracy.
- We conducted stress detection at population level and individual level
- We conducted feature engineering to identify the important
- All participants registered a stress classification accuracy of 99% with one exception of 93%. The XGBoost achieved the best mean accuracy of 99.24% across subjects with a standard deviation of 1.77%

Methods & Materials

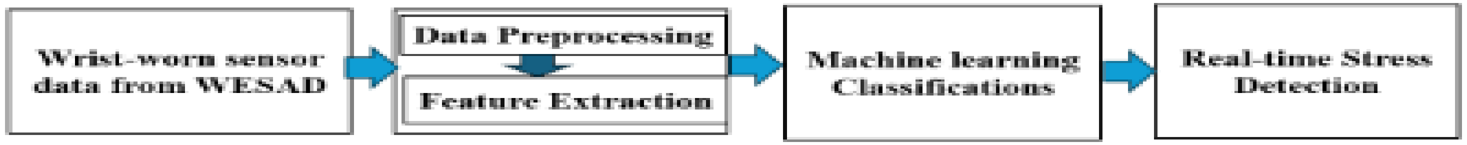

Figure 1. The process of stress detection from wrist-worn sensors.

Participants & Data Description

- 15 participants (12 males and 3 females) aged 18 to 44 years)
- All participants were English speakers, and none reported any neurological disease history.
- Sampling rate of 64, 4, and 4 Hz, respectively.
- Gave written consent for data release to the public.
- Participants wore a RepsiBAN Professional on the chest and an **Empatica E4 on wrist**
- Window sizes (e.g., 10 s, 20 s,…….and 30 s)

Methods & materials

Classifiers:

- KNN
- Decision Tree
- XGBoost
- LightGBM
- Random Forest
- SVM

Hyperparameter optimization:

- Grid search approach
- Five-fold cross-validation
- Select the best model parameters

Feature Selection:

- Shapley Additive Explanations (SHAP)

Methods & materials

Performance metrics formulas:

- Accuracy: (TN+TP)/(TN+TP+FN+FP)
- Precision: TP/(TP+FP)
- Recall: TP/(TP+FN)
- F1 score: Harmonic mean of precision and recall

		Predicted	
		Negative **(N)** **-**	Positive **(P)** **+**
Actual	Negative **-**	True Negative **(TN)**	**False Positive (FP)** **Type I Error**
	Positive **+**	**False Negative (FN)** **Type II Error**	True Positive **(TP)**

Fig.6: Confusion matrix [3].

Results & discussion

POPULATION LEVEL ANALYSIS

Table 1. Population level stress detection performance metrics (%) for KNN, DT, XGBoost, LigghtGBM, RF, and SVM classifiers.

Classifiers name	Average mea-sure(%)	window size stress (10 s)	window size stress (20 s)	window size stress (30 s)
KNN	Accuracy	83.49	82.03	83.48
	AUC	78.98	79.10	78.51
	Precision	74.48	65.21	71.92
	Recall	69.19	71.42	67.21
	F1-score	71.74	68.18	69.49
DT	Accuracy	91.15	89.82	89.88
	AUC	90.01	89.13	86.79
	Precision	85.58	80.89	85.23
	Recall	87.20	85.71	78.68
	F1-score	86.38	82.75	81.64
XGBoost	Accuracy	96.39	92.53	93.11
	AUC	95.82	91.15	90.21
	Precision	93.45	84.09	91.07
	Recall	95.26	88.09	83.60
	F1-score	94.58	86.04	87.17
LighGBM	Accuracy	96.18	92.63	93.57
	AUC	95.57	92.32	90.02
	Precision	94.28	81.91	94.33
	Recall	93.83	91.66	81.96
	F1-score	94.06	86.51	87.71
RF	Accuracy	96.03	93.86	95.87
	AUC	95.58	92.75	93.12
	Precision	93.42	86.36	98.14
	Recall	94.31	90.47	86.88
	F1-score	93.86	88.37	92.17
SVM	Accuracy	88.34	86.50	88.13
	AUC	85.06	83.91	84.01
	Precision	81.37	71.17	83.33
	Recall	78.67	78.57	73.77
	F1-score	80.00	75.00	78.26

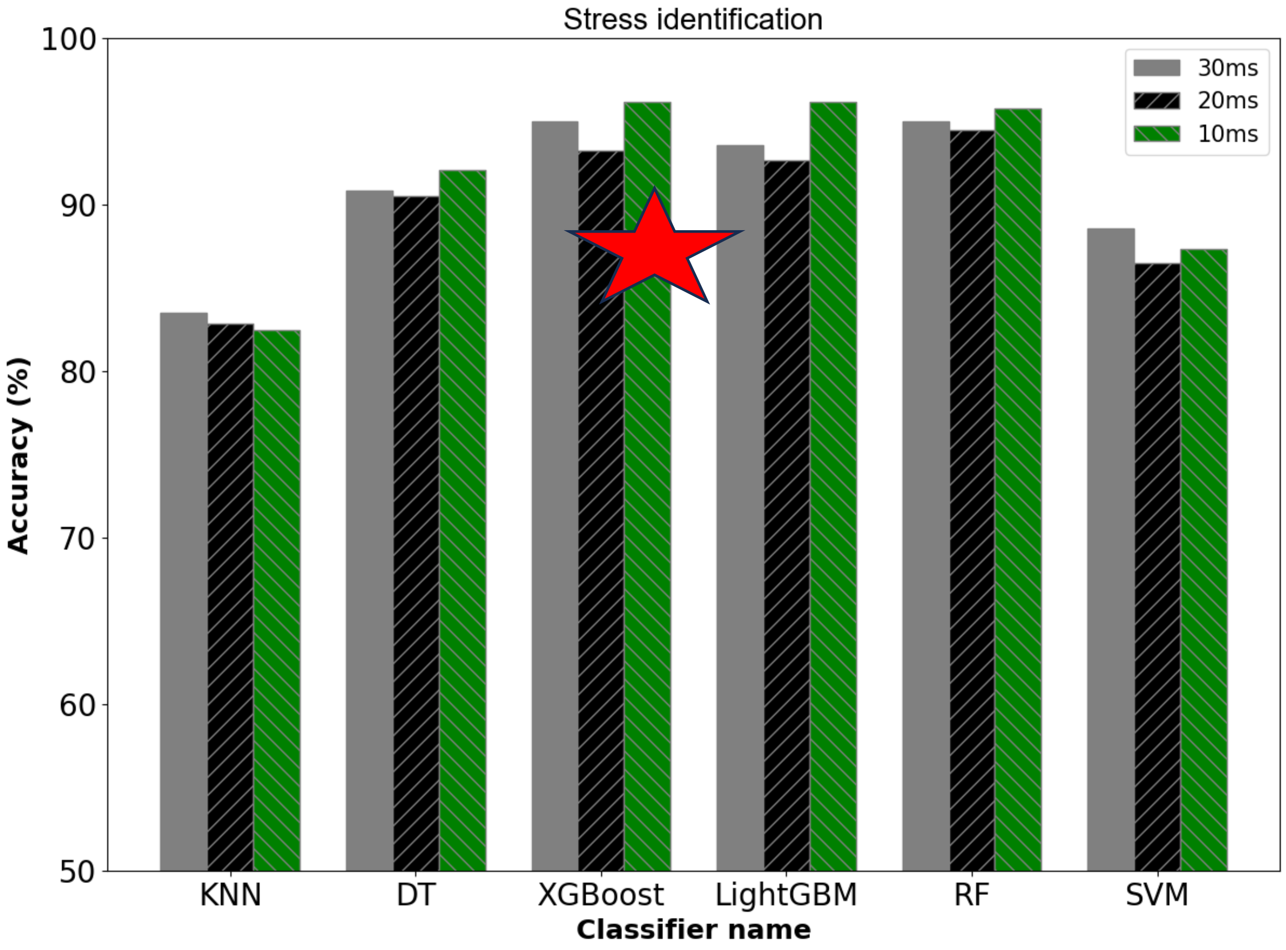

Figure 2. Detection of stress with 10 s time windows using KNN, DT, XGBoost, LightGBM, RF, and SVM classifiers.

Results & discussion

INDIVIDUAL SUBJECT LEVEL ANALYSIS

Table 2. Subject level stress detection accuracy for top 3 classifiers.

Subject	XGBoost (%)	LightGBM(%)	RF(%)
S2	92.85	92.70	92.80
S3	99.70	99.88	99.62
S4	99.75	99.88	99.93
S5	99.69	99.77	99.88
S6	99.77	99.88	99.55
S7	99.81	99.85	99.83
S8	99.77	99.66	99.78
S9	99.48	99.60	99.75
S10	99.73	99.19	99.43
S11	99.88	98.33	99.73
S13	99.69	99.49	99.78
S14	99.58	99.82	99.63
S15	99.51	99.89	99.70
S16	99.73	99.72	99.77
S17	99.71	99.81	99.90
Average	99.24	99.16	99.21
Std	**1.77**	**1.83**	**1.79**

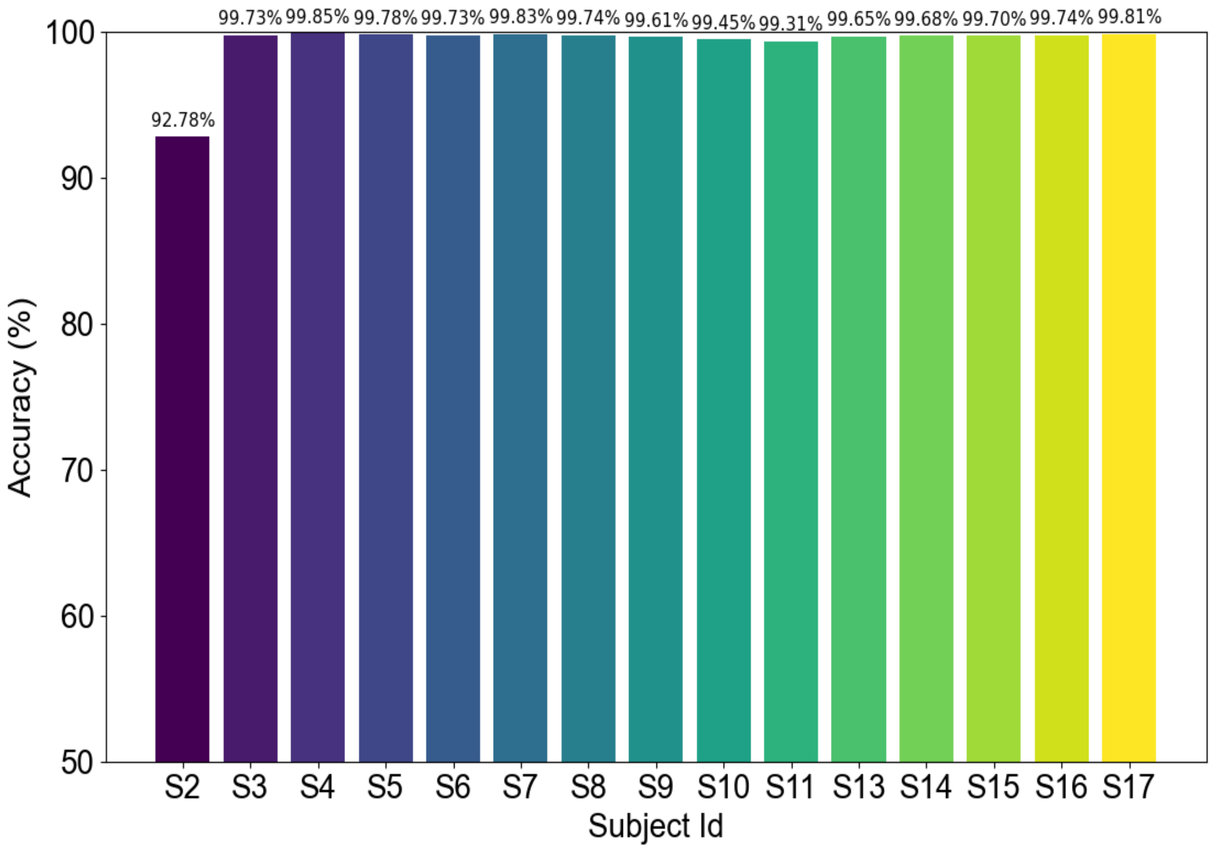

Figure 3: Best classification accuracy with individual subject.

Results & discussion

- We used SHAP over the XGBoost classifier to explain feature importance
- XGBoost demonstrated an improved accuracy of 97.53%, AUC of 97.20%, F1-score of 96.23%, precision 96.19%, and recall 96.02%.

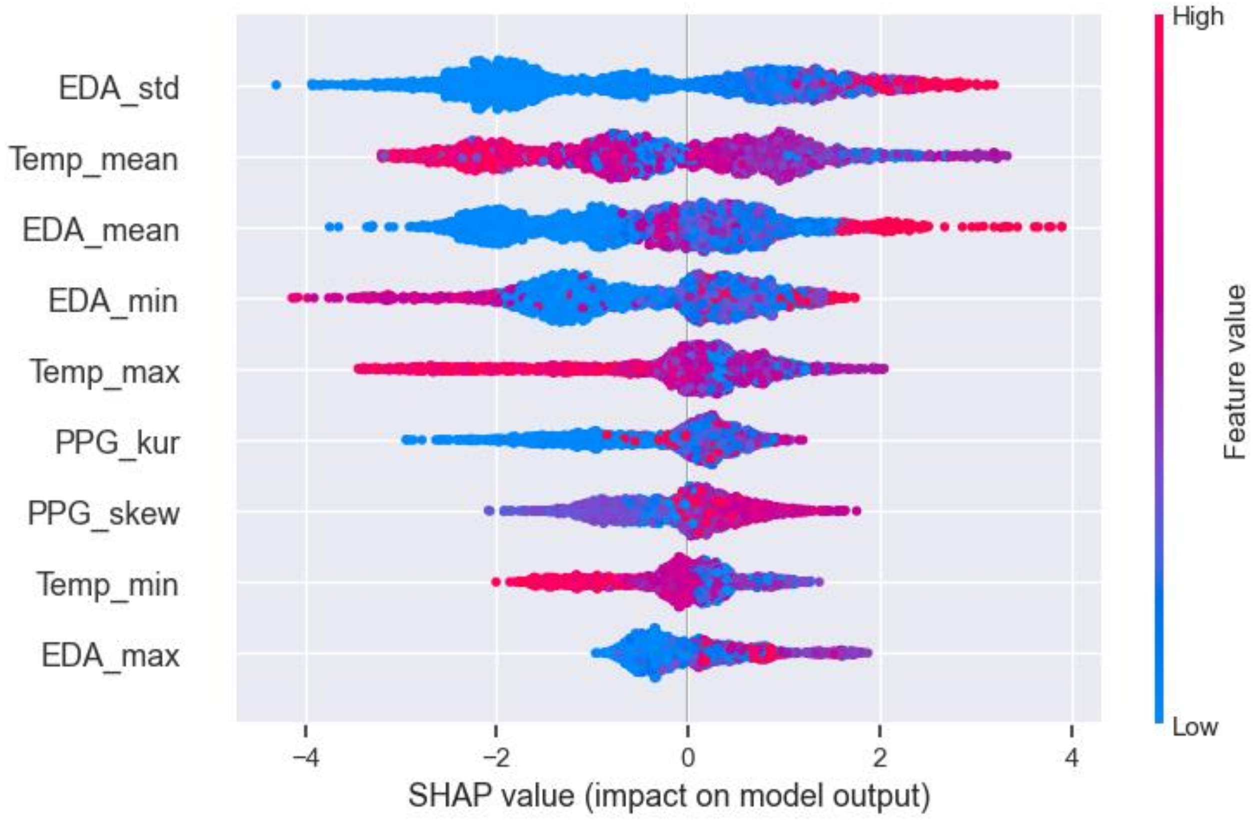

Figure 4: Density scatter plot of SHAP values obtained from XGBoost classifier. A higher value indicates the most importance

Conclusion

- We developed an efficient ML framework for stress detection from wrist sensor data. Our analysis shows that stress detection is more accurate **(at population level 96.39%)** based on 10s non-overlapping windows and **individual subject level 99.24 % with Std. 1.77.**
- Our feature selection analysis indicates that the model can predict most robustly from nine features only.
- Our work has a limitation: we could not determine why one subject showed approximately 5% lower performance than others. Further analysis is needed to investigate this.

MIDDLE TENNESSEE STATE UNIVERSITY

Acknowledgments

- This work was supported by the Computational Data Science program and the Department of Computer Science at the Middle Tennessee State University, Murfreesboro, Tennessee, USA.

MIDDLE TENNESSEE STATE UNIVERSITY

References

[1] B. S. McEwen, “Allostasis and allostatic load: implications for neuropsychopharmacology,” *Stress and the Brain*, pp. 2–18, 2013.

[2] R. M. Sapolsky, *Why zebras don’t get ulcers: The acclaimed guide to stress, stress-related diseases, and coping*. Holt paperbacks, 2004.

[3] M. F. Dallman, “Stress-induced obesity and the emotional nervous system,” *Trends in Endocrinology & Metabolism*, vol. 21, no. 3, pp. 159–165, 2010.

[4] M. R. Salleh, “Life event, stress and illness,” *The Malaysian journal of medical sciences: MJMS*, vol. 15, no. 4, p. 9, 2008.

[5] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. Van Laerhoven, “Introducing wesad, a multimodal dataset for wearable stress and affect detection,” in *Proceedings of the 20th ACM international conference on multimodal interaction*, 2018, pp. 400–408

Thank you!

MIDDLE TENNESSEE STATE UNIVERSITY

Questions?

MIDDLE TENNESSEE STATE UNIVERSITY