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Few-Shot Personalized Stress Detection from ECG via Self-Supervised Learning

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Introduction

Physiological stress detection using wearable sensors is challenging due to inter-individual variability and limited availability of labeled data for personalization. Traditional supervised approaches often fail to generalize across users without extensive subject-specific calibration and memory overhead. Self-supervised learning (SSL) has recently emerged as a promising paradigm for leveraging large amounts of unlabeled physiological data to learn transferable representations. However, its effectiveness in enabling rapid few-shot personalization for ECG-based stress detection remains insufficiently explored. This study investigates whether SSL-based models can facilitate faster adaptation to individual users compared to conventional supervised and classical machine learning approaches.

Methods

We compare four approaches: a support vector classifier (SVC), a supervised convolutional neural network (SCNN), and two SSL-based CNN models pretrained via contrastive learning. All models are pretrained on the WESAD dataset and adapted to a target dataset (ADR) using transfer learning. Personalization is performed using a k -shot learning framework ($k = 0$ -7 samples per class) using leave-one-subject-out validation strategy. Model performance is assessed using accuracy and F1-score, with repeated experiments.

Results

During pretraining, SVC achieved the highest accuracy (0.814), while SSL-based models demonstrated competitive performance. Upon transfer learning on target dataset, SSL-CNN outperformed other approaches (accuracy 0.644). In few-shot personalization, SSL-CNN showed rapid adaptation, achieving substantial performance gains with as few as 1-3 samples, whereas SVC improved slowly. At higher k , both models converged to similar performance.

Conclusion

Compared to classical and supervised approaches, SSL facilitates faster adaptation with minimal labeled samples, making it well-suited for real-world wearable applications where rapid personalization and limited annotation are critical.