



## Introduction

Traditional methods for health profiling are usually expensive and development of wearable devices have made it feasible to collect ambient sensor signals, providing us with new opportunities to profile children's health in a cost-effective and comprehensive manner.

Inspired by recent works in multimodal learning, we propose a health profiling framework for children. First, we extract context and motion patterns from their personal and family characteristics and acceleration signals. Then, context and motion embeddings are generated by two encoders and input into a lightweight neural network to profile children's health from the perspectives of physical activity intensity, physical functioning, health confidence, psychosocial functioning, resilience, and connectedness.

We evaluate the proposed method on real-world datasets, and the results show its outstanding performance. Specifically, the context pattern is effective in profiling children's health, while the motion pattern is significantly effective in assessing children's physical activity intensity.

## **Dataset Description**

**Participants** 



Figure 1. Gender distribution of participants.

### **Data Collected**

- Demographics
  - age, gender, BMI, body fat percentage, grade learning mode
- Tri-axial accelerometer data
  - Mean wear days: 13.85 days
  - Standard deviation: 6.94 days
- Questionnaires
  - Background characteristics
    - Socioeconomic status, electronic device usage patterns, financial satisfaction, academic performance, sleep pattern, exercise habits, and dietary patterns
- Clinical Scales
  - PedsQL: health-related quality of life
  - EQ5D: mobility, self-care, usual activities, pain/discomfort, and anxiety/depression
  - Connor-Davidson Resilience Scale: resilience
  - Resnick Social Connectedness Scale: connectedness

## Conclusion

We propose a health profiling framework for children leveraging multimodal learning based on ambient sensor signals. Although the motion pattern can significantly improve the performance on MVPA, it adversely influences performance on other indicators, thereby decreasing the average performance. **Future Work** 

- Explore better ways to fuse the information from two modalities.



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## A Health Profiling Framework for Children Leveraging Multimodal Learning Based on Ambient Sensor Signals

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• Prune the less important contextual features and motion channels to make the model more lightweight.

Model	Setting	MVPA	PHYF	<b>VVAS</b>	PSYF	RESI	CONN	Mean	Std.
(1) SVM	(a) C	0.706	0.649	0.714	0.697	0.873	0.596	0.706	0.085
	(b) M	0.780	0.518	0.451	0.545	0.533	0.555	0.564	0.102
	(c) CM	0.743	0.656	0.657	0.686	0.841	0.612	0.699	0.075
(2) XGB	(a) C	0.727	0.707	0.713	0.732	0.878	0.703	0.743	0.061
	(b) M	0.743	0.461	0.467	0.441	0.542	0.557	0.535	0.102
	(c) CM	0.786	0.706	0.619	0.618	0.847	0.650	0.704	0.086
(3) Ours	(a) C	0.695	0.730	0.749	0.730	0.913	0.702	0.753	0.074
	(b) M	0.861	0.647	0.507	0.638	0.609	0.553	0.636	0.112
	(c) CM	0.834	0.672	0.733	0.695	0.777	0.635	0.724	0.066

- under all settings and is more robust when dealing with both modalities

