JoulesEye: Energy Expenditure Estimation and Respiration Sensing From Thermal Imagery while Exercising

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Background & Research Question

- Accurate monitoring of EE is critical given the increasing prevalence of obesity (More than 1 billion people worldwide are obese [1])
- Existing approach to monitor EE are either inconvenient (Indirect Calorimeter, Double Water Test) or inaccurate by over 30% (Fitness tracker, Smartphones) [2].
- **We set out to identify the sensor that promises to be practical and ubiquitous enough that it could be added to a consumer device and immediately unlock accurate energy expenditure (EE).**

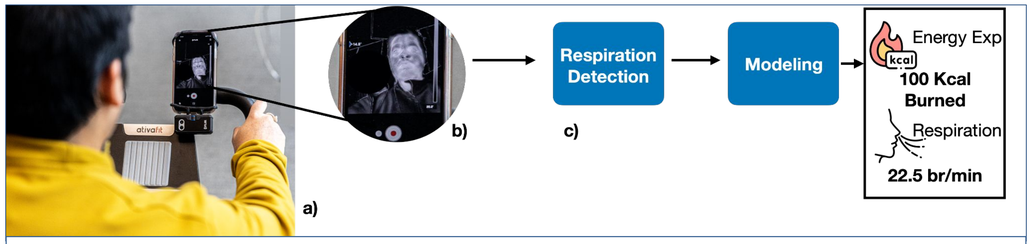


Fig 1: ***JoulesEye*** estimates Energy Expenditure (EE) from respiration rate. In a) the participant is riding a cycle with thermal camera and a phone is fixed on the handrail. b) shows a frame of the thermal video. c) shows the respiration rate detection pipeline during motion to predict energy expenditure.

Approach and Data Collection

- **Data Collection:** Figure 2 shows the JoulesEye system in **a** and **b.** The indirect calorimeter ground truth data collection system is shown in **e**.

Fig 2: *JoulesEye*'s is composed of a thermal camera retrofitted in an iPhone as shown in (**a**). JoulesEye can be used in a smartwatch as shown in b). The camera in b) is a low resolution (32x24) thermal camera. **(c)** and **(e)** show the ground truth data collection procedure with indirect calorimeter while running and biking. **(d)** shows a screen grab from the indirect calorimeter recording the energy expenditure during an exercise session.

Approach and Data Collection

- Respiratory rate is determined by tracking temperature fluctuations in the airways using thermal video to analyze pixel intensity changes around the nostrils.
- Channel and Spatial Reliability Tracker (CSRT) algorithm is used to track the nostrils during vigorous motion of participant.
- The respiration information is fed into a Temporal Convolution Network (TCN) to estimate EE
- Table on the right shows the participant demography of our study.

Total Participants	54
Participants who performed cycling on ergometer	41
Participants who performed running on treadmill	13
Female (n, %)	24, (44.4%)
Age (in years) (mean, range)	28.4 (25-54)

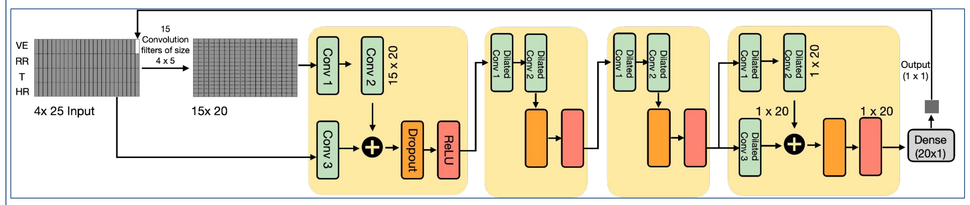
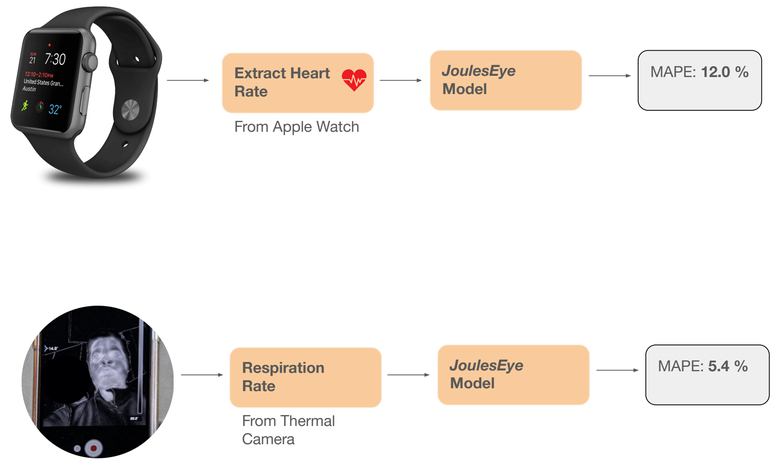


Fig 3: We build a deep learning network similar to the Temporal Convolution Network (TCN) with residuals to estimate volume as a function of respiration rate and volume i.e. $v_t = f_1(v_{(t-k:t-1)}, RR_{(t-k:t)})$. We also evaluated the performance of the model with additional covariates, namely heart rate (HR) and temperature (T) collected from forehead.

CSRT tracks the nostril even during vigorous motion. Scan the QR code to check the demo.

Evaluation and Result



	Participant With Normal BMI	Participant With Overweight BMI
Error (Apple Watch)	29.7%	51.8%
Error (*JoulesEye*)	5.2%	6.9%

Table 2: We found that the Energy Expenditure estimates by Apple Watch is higher for people with high Body Mass Index (BMI), whereas it is relatively better for people with normal BMI.

Selected references:

1. World Health Organisation. 2021. Obesity and overweight. https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight. [Online; accessed 13-January-2023].
2. Argent, Rob, et al. "Recommendations for determining the validity of consumer wearables and smartphones for the estimation of energy expenditure: Expert statement and checklist of the INTERLIVE network." *Sports Medicine* 52.8 (2022): 1817-1832.

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