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SEAL: Sensing Efficient Active Learning on Wearables through Context-awareness

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***Abstract*—In this paper, we introduce SEAL, a co-optimization framework designed to enhance both sensing and querying strategies in wearable devices for mHealth applications. Employing Reinforcement Learning (RL), SEAL strategically utilizes user contextual information and the machine learning model's confidence levels to make efficient decisions. This innovative approach is particularly significant in addressing the challenge of battery drain due to continuous physiological signal sensing, such as Photoplethysmography (PPG). Our framework demonstrates its effectiveness in a stress monitoring application, achieving a substantial reduction of 76% in the volume of PPG signals collected, while only experiencing a minor 6% decrease in user-labeled data quality. This balance showcases SEAL's potential in optimizing data collection in a way that is considerate of both device constraints and data integrity.**

***Index Terms*—Efficient Machine Learning, Data Efficiency, Active Learning, Context-Aware Sensing, Reinforcement Learning.**

I. Introduction

In the realm of mHealth applications, such as affective computing for stress and emotion monitoring, the efficacy of supervised Machine Learning (ML) algorithms hinges on the availability of accurately labeled physiological signals like Photoplethysmography (PPG) and Electrodermal Activity [1], [2], alongside compute-optimization of mHealth applications running on edge devices [3]. The feasibility of training and eventual prediction accuracy of supervised learning methods in these applications depend on the availability of ground truth labels collected from end-users associated with features extracted from the raw signals [4]. Traditionally, this was performed by sending ecological momentary assessments (EMA) to end-users to provide self-reports (e.g., current stress level) to be used as ground-truth labels [5]. However, EMA often results in a low rate of useful labeled data acquisition. Recent advancements in active learning have sought to mitigate this by strategically soliciting user input, thereby increasing the utility and efficiency of the labeled data collected.

Despite these improvements, a persistent challenge remains: the substantial energy demands of continuous physiological sensing on wearable devices. This is exacerbated by the fact that the majority of the sensed data may not contribute meaningfully to model improvement, as Fig. 1 elucidates. Our framework offers a novel approach to this issue by incorporating a context-aware model that judiciously selects when to sense and when to query the user for labels. This model is informed by a variety of contextual parameters, including user behavior patterns and ML model confidence levels.

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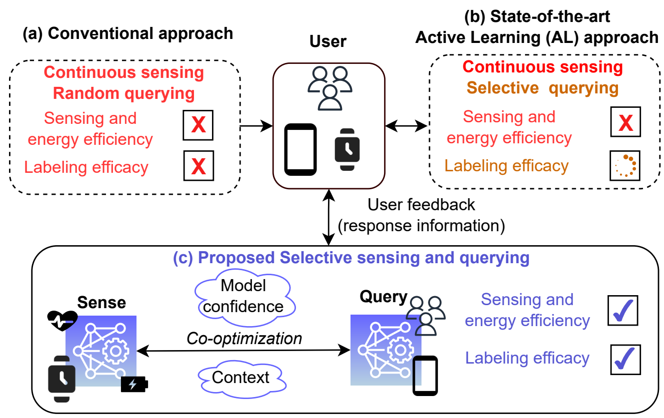

Fig. 1. Energy efficiency and improved labeling efficacy via selective sensing and querying (c) comparing to previous works (a and b).

The primary contributions of this work, as visualized in Fig. 1, are as follows:
(1) A comprehensive context-awareness model that effectively reduces unnecessary data sensing by leveraging user behavior data and ML model confidence, thereby preserving energy on wearable devices.
(2) Context-aware co-optimization of sensing and querying using reinforcement learning, to strike a balance between data collection sufficiency and energy efficiency.
(3) Evaluation of the proposed approach over stress monitoring case study with data collected from 35 participants in practical settings, demonstrating significant improvements over conventional active learning methods.

Overall, SEAL represents a significant step forward in the domain of efficient data collection for mHealth applications, promising to enhance the sustainability and scalability of wearable health monitoring technologies.

A. System Architecture

Fig. 2 shows the SEAL framework, integrating wearable devices, mobile phones, and cloud servers for efficient collection and labeling of physiological signals in mHealth applications. Equipped with sensors for selective sensing, the framework decides when to collect data and when to prompt the user for labeling via push notifications. Labeled data are stored locally and then uploaded to the cloud for machine learning model training, supporting both supervised and semi-supervised approaches. Model inference is performed on-device, utilizing model confidence in the querying decision process and incorporating time-aware user profiling and behavior from

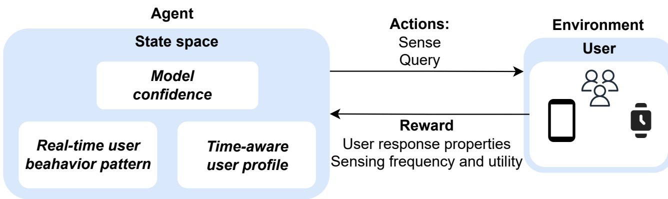

Fig. 2. Details of the RL agent designed for intelligent sensing and querying.

AWARE for context-awareness [6]. This synergy enhances the efficiency and efficacy of data collection and labeling. Further details on the implementation of the intelligent sensing and querying module will be discussed.

II. Sensing Efficient Active Learning Framework

A. RL agent based context-awareness model for selective sensing and querying

Building upon the established system architecture, the RL agent stands as the critical component driving the decision-making process. Using RL agent for the selective sensing and querying module aligns with its capability to encapsulate diverse input factors in its state space and make informed decisions through actions. This continuous interaction and adaptation to the environment ensures the system can respond effectively to varying conditions and user behaviors. Leveraging contextual data, and ensuing model confidence, the selective sensing and querying module, an RL agent in this framework, takes its actions. This RL agent operates in two distinct dimensions: sensing and querying. Subsequently, the pre-trained model labels a subset of the unlabeled data deemed significant for training. Depending on the volume of labeled data available, either a supervised or semi-supervised learning approach is employed to train the ML model tailored for applications (e.g., stress monitoring).

In our approach, we utilize RL combined with contextual data to optimize decision-making in adaptive systems. Specifically, we introduce an RL agent built on the Deep Q-Network (DQN) framework. This agent integrates real-time user behavior patterns from the AWARE framework [6] and time-aware user profiles to form a comprehensive state space for decision-making. By using this combined state representation, the agent can make informed decisions that optimize both system performance and user experience.

III. Experimental Results

Workload: Our study is built upon ZotCare [7], an efficient mHealth service platform. We evaluated SEAL in stress monitoring using PPG data from a Samsung Galaxy Gear Sport smartwatch [8] and AWARE mobile application data [6]. The research built upon ZotCare [7]. The IRB-approved study spans from March 2022 to May 2023, involving 35 participants aged 19-29, resulted in 23,012 samples after filtering. The specific PPG features were extracted using HeartPy [9].

Sensing Efficiency: Table I demonstrates enhanced sensing efficiency and labeling efficacy of our framework compared to: (i) continuous sensing with random querying, (ii) continuous sensing with selective querying, and (iii) a baseline selective sensing with a time-based random skipping approach. SEAL achieves a 76% reduction in sensing events compared to similar active learning approaches. It also outperforms our baseline selective sensing and querying strategy by generating 88% more labeled samples, demonstrating superior labeling efficacy. When compared to continuous sensing and selective querying, our method yields only 6% fewer labeled samples, despite a 76% reduction in total sample sensing. This efficiency in both sensing and labeling can be attributed to our framework's effective integration of context-awareness and sense-query co-optimization.

Stress Monitoring Model Performance: With the same sensing efficiency, the Random Forest model on the reduced dataset (with 100 estimators and the maximum depth of 5) scored an F1 of 0.67, higher than the 0.60 of the baseline approach, demonstrating the effectiveness of SEAL in maintaining model performance with less data.

TABLE I
Sensing efficiency and labeling efficacy

Strategies	Sensed samples		Efficient ratio
	Labeled	Unlabeled	
Cont. sensing, random query	1913	21098	0.08
Cont. sensing, select. query	3832	19179	0.17
Select. sensing & query (baseline)	1916	3421	0.36
Select. sensing & query (our)	3598	1739	**0.67**

IV. Conclusion

We presented SEAL, a context-aware sensing efficient active learning framework for wearable devices based on an RL agent. It both optimizes sensing and querying policies by combining contextual data and ML model confidence. Tested on stress monitoring using PPG signals from a Samsung Sport watch, SEAL reduced sensing data volume by 76% while missing just 6% of labeled data, outperforming the baseline. Future plans include expanding and evaluating SEAL across more applications and studies.

V. Acknowledgements

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