LARGE LANGUAGE MODELS FOR WEARABLE DATA ANALYSIS AND INTERPRETATION

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ABSTRACT

In this paper, we investigate the application of large language models (LLMs) to *zero-shot* and *few-shot* prediction and classification of multimodal wearable sensor data. Using data from the large-scale Homekit2020 dataset, we explore health tasks including cardiac activity monitoring, metabolic health prediction, and sleep detection. We demonstrate that LLMs perform feature extraction, prediction, and classification with comparable or higher performance than classical machine learning approaches even in the zero-shot scenario. Our findings show promising results in using LLMs for wearable data analysis and interpretation.

1 INTRODUCTION

Foundation large language models (LLMs) have recently demonstrated strong capabilities to solve a diverse range of tasks, including, diagnostic reasoning Wu et al. (2023); Moor et al. (2023), visual referring expression comprehension Sui et al. (2023), time series Sun et al. (2023), tabular Hegselmann et al. (2023), and other health data analysis Belyaeva et al. (2023). In this paper, we propose using LLMs to analyze and interpret wearable sensor data. The main advantages of LLMs in comparison to state-of-the-art techniques would be to ingest complex multimodal data to gain an understanding of individual health risks and to be able to do that from little amount of labeled data, which is challenging to obtain for passively sensed wearable sensor data. Only a few researchers investigated the use of LLMs for wearable sensor data Liu et al. (2023); Spathis & Kawsar (2023); Sooriya Patabandige et al. (2023). These approaches either employ self-curated toy datasets Liu et al. (2023), investigate zero-shot learning only, do not report baseline model accuracy making it difficult to interpret the results Sooriya Patabandige et al. (2023) or focus on identifying challenges related to the application of LLM to wearable data Spathis & Kawsar (2023). We build upon these studies and perform a systematic evaluation of the LLMs for feature extraction, prediction, and classification tasks on wearable data. We investigate for the first time the use of LLMs for sleep detection and the impact of varying window lengths of wearable sensor data collected in natural settings.

The objectives of the paper are: 1) investigate whether LLMs can be used out-of-the-box to predict health conditions from wearable sensor data, and 2) evaluate the number of samples needed by the LLMs to learn the task with sufficient accuracy. We formulate eight tasks related to cardiac activity, metabolic health, and sleep monitoring using wearable devices. We then use an off-the-shelf pretrained LLM, LLaMa 2 Touvron et al. (2023), and in context learning to show the feasibility of our approach. We compare the LLM score with supervised machine learning methods such as gradient-boosted decision trees. To this end, we use a large-scale, real-world dataset called Homekit2020 Merrill et al. (2023), which was collected from $5,034$ participants over four months in real-world settings. We evaluate different ways of prompting and passing data to the LLM.

2 LARGE LANGUAGE MODELS FOR WEARABLE SENSOR DATA ANALYSIS

Model. We use LlaMa 2 Touvron et al. (2023) as a pretrained LLM. In a recent study, it has been demonstrated that LLaMa 2 surpasses GPT-4 in arithmetic tasks by breaking down each digit into a separate token, ensuring a uniform tokenization of numbers Liu & Low (2023). We perform *zero-shot* – by using the LLM out-of-the-box to predict health outcomes from provided wearable sensor

Table 1: Comparison of performance between LLMs and baselines trained using few-shot learning across the health tasks explored in this work. The metric for sleep detection is accuracy and for the other tasks is mean absolute error (MAE). HR refers to heart rate. S refers to steps. C refers to context. Sle refers to sleep. Cal refers to calories.

Task	**XGB**		**LR/SVM**		**LlaMa 2**		
	3-shot	*10-shot*	*3-shot*	*10-shot*	*0-shot*	*3-shot*	*10-shot*
HR_{Avg}	9.38 (.4)	5.40 (.1)	2.62 (.3)	**0.08 (.0)**	0.77 (.1)	**0.75 (.1)**	0.93 (.1)
HR_{Max}	11.3 (.7)	7.18 (.5)	**6.08 (.9)**	12.0 (1.8)	0.82 (.1)	**0.43 (.0)**	0.73 (.1)
HR_{Min}	8.86 (.4)	5.19 (.1)	**4.76 (.4)**	9.23 (.6)	**0.38 (.0)**	0.56 (.1)	1.00 (.2)
HR_{Std}	2.68 (.3)	**2.48 (.2)**	2.90 (.3)	6.47 (.9)	11.6 (.6)	**1.11 (.1)**	2.17 (.1)
Cal_{HR}	875 (42)	830 (35)	**828 (44)**	958 (63)	**572 (35)**	1167 (116)	1047 (72)
Sle_{HR}	0.50 (.0)	**0.69 (.0)**	0.62 (.0)	0.64 (.0)	0.49 (.0)	**0.53 (.2)**	0.51 (.1)
Sle_{HR+S}	0.50 (.0)	0.75 (.0)	0.70 (.0)	**0.79 (.0)**	0.50 (.0)	0.59 (.0)	**0.60 (.0)**
Sle_{HR+S+C}	0.50 (.0)	0.75 (.0)	0.70 (.0)	**0.79 (.0)**	0.58 (.0)	**0.70 (.0)**	0.58 (.0)

data – and *few-shot learning* – by providing tuples of wearable sensor data and health conditions to the network similar to a supervised learning setting. Few-shot learning, also known as *in context learning* Brown et al. (2020), removes the need to further train the LLM, which might be challenging in the wearable data domain without suitable samples. We test the pipeline on unseen, test samples for *feature extraction*, *classification*, and *regression* tasks. Feature extraction refers to the prediction of the mean, maximum, minimum, and standard deviation of heart rate (HR). Regression task predicts the amount of calories burned during an activity from HR. Classification refers to inferring whether the user is asleep or awake from HR and the number of steps. To the best of our knowledge, we are the first to explore LLMs for sleep detection, which is a common wearable-based task.

Dataset. To evaluate our approach, we use Homekit2020 dataset Merrill et al. (2023), which is a large-scale, high-resolution, and publicly available dataset. It consists of minute-level HR, number of steps, and sleep measurements collected using Fitbit devices from $5,034$ participants over 4 months in real-world settings. We randomly sampled 3 and 10 examples for the few-shot experiments and 200 samples as the test sets. We repeat these experiments five times and each time pick a different set of samples to evaluate the performance. We report the average results (and standard deviation) over all the runs of an experiment. Table 2 shows the tasks and prompts used in this work.

Baselines. We compare LLM's performance to gradient boosting, (`XGB`), linear regression (`LR`), and support vector machine (`SVM`) for regression and classification tasks respectively.

Results. Table 1 shows a summary of the results we achieved. Our findings show that LLMs extract HR features with lower or comparable errors to baseline methods for both the zero-shot and few-shot learning scenarios. The LLM predicts calories burned during a day with a significantly lower error than classical machine learning algorithms. The performance of LLM for sleep detection is overall lower than that of baseline classifiers. In particular, with only 3 samples the LLM achieves an accuracy of 70% for sleep detection, which is the same as SVM in the 3-shot learning scenario. We further find that including more information, such as the number of steps and offering hints concerning HR changes during sleep and wake stages, as shown in the last query in Table 2, contributes to further improving the LLM's results. These findings demonstrate LLMs' potential beyond text processing and show their capability for analyzing and interpreting wearable sensor data.

3 Conclusion

This paper contributes to the application of LLMs for wearable health monitoring. We demonstrate LLM's potential to perform tasks related to cardiac activity, metabolic health, and sleep activity with comparable or higher performance to traditional methods. Our results warrant further investigation with a diverse set of LLMs and health tasks to enable personalized health recommendations and enhance user experience. Investigation of privacy and security risks as well as energy consumption are also needed to overcome the challenges of LLMs application to wearable health technology.

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A DATASET

This paper uses the Homekit2020 dataset (Merrill et al., 2023) collected as part of the Home Testing of Respiratory Illness Study by Evidation Health and described in Synapse. The study was conducted in partnership with the Biomedical Advanced Research and Development Authority (BARDA), an existing office of the U.S. Department of Health and Human Services, and Audere, a non-profit digital health technology corporation.

Homekit2020 consists of 14 million hours of minute-level Fitbit data, such as HR, number of steps, and sleep stage. The dataset is accessible through a request process to Synapse. The study that collected this dataset was approved by the Western Institutional Review Board (WIRB, Puyallup, WA, USA) and the University of Washington IRB (Study #1271380).

A.1 HEALTH TASKS

Heart rate metrics. This task derives the average, minimum, maximum, and standard deviation of heart rate (HR) from a series of instantaneous HR measurements. These tasks are framed as regression tasks to be able to compare the performance with conventional machine learning techniques.

Calorie prediction. Energy expenditure prediction refers to the estimation of calories burned during an activity. It is an essential aspect of health and well-being monitoring. The traditional techniques to estimate calories include direct calorimetry, indirect calorimetry, doubly labeled water, and the more recent wearable devices Gashi et al. (2022b). In this work, we investigate the challenging problem of estimating calories based on HR only and we frame the problem as a regression task.

Sleep detection. Sleep detection refers to the process of identifying whether an individual is asleep or not, which allows deriving metrics like sleep duration. It is crucial for understanding the overall health and well-being of an individual. Sleep is commonly measured through various methods such as polysomnography, actigraphy, and wearable devices Ibáñez et al. (2018). In this work, we use HR and the number of steps measured with wearable devices and predict whether the user is asleep or awake. We frame the problem of sleep detection as a binary classification task similar to Gashi et al. (2022a).

B RESULTS

In this section, we show graphical representations of the results presented in Table 1.

Table 2: Example of the tasks and prompts used to query the LLM. HR refers to heart rate, S refers to steps, C refers to context, Avg to average, Min to minimum, Max to maximum, Std to standard deviation, Sle refers to sleep, Cal to calories.

Type	Task	Prompt	Output
Feature Extraction	HR_{Avg}	Answer only with the numerical average of the provided heart rate data. Exclude all other information or calculations. [HR]	`mean([HR])`
	HR_{Min}	Answer only with the numerical minimum of the provided heart rate data. Exclude all other information or calculations. [HR]	`min([HR])`
	HR_{Max}	Answer only with the numerical maximum of the provided heart rate data. Exclude all other information or calculations. [HR]	`max([HR])`
	HR_{Std}	Answer only with the standard deviation of the provided heart rate data. Exclude all other information or calculations. [HR]	`std([HR])`
Regression	Cal_{HR}	Your task is to provide a direct prediction of the total calories burned during a single day for an adult, based on heart rate collected by a Fitbit device. Use the given data for this calculation and respond with only the predicted calorie count. [HR]	`[Calories]`
Classification	Sle_{HR}	Predict sleep status (awake or asleep) based on these consecutive heart rates over a 30-minute interval. [HR]	`[Sleep]`
	Sle_{HR+S}	Predict sleep status (awake or asleep) based on these consecutive heart rates over a 30-minute interval and the total steps. [HR] and steps.	`[Sleep]`
	Sle_{HR+S+C}	You are a helpful assistant that analyzes heart rate data and total steps to predict sleep status. Consider that higher and more abruptly changing heart rates typically indicate the user is awake, while steadier and lower rates suggest the user is asleep. Very low step count indicates that the user is sleeping. Use this intuition to analyze the provided minute-level heart rate data from an adult, measured by a Fitbit, and predict whether the user is awake or asleep. [HR] and steps.	`[Sleep]`

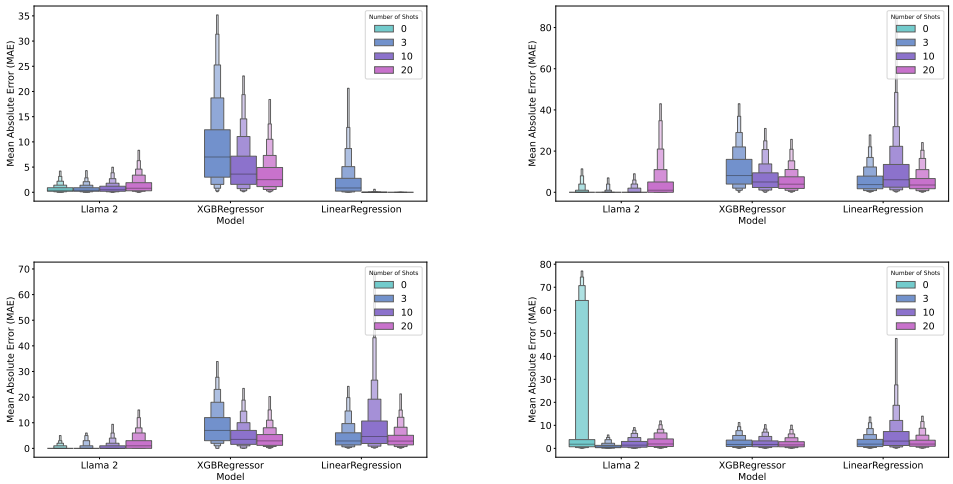

Figure 1: Mean absolute error (MAE) for the LLM and supervised baselines to predict HR average (top-left), maximum (top-right), minimum (bottom-left), and standard deviation (bottom-right).

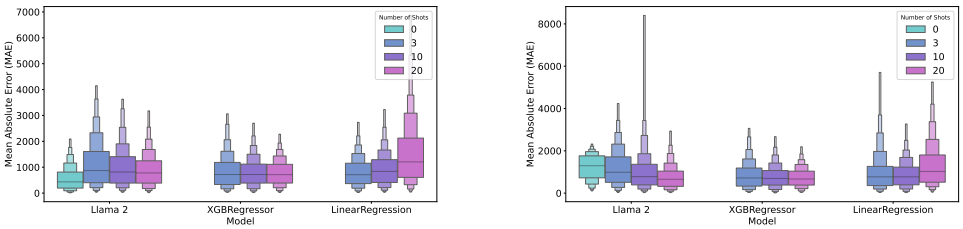

Figure 2: Mean absolute error (MAE) for the LLM and supervised baselines to predict calories burned during the day using HR (left) and HR combined with steps (right).

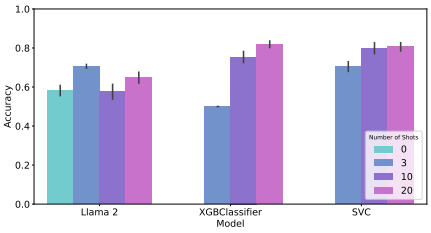

Figure 3: Accuracy for the LLM (Llama 2), gradient boosting (XGBClassifier), and support vector machine (SVC) classifiers to recognize sleep from HR data.

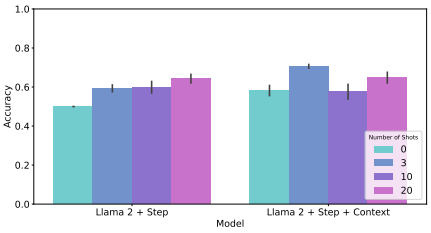

Figure 4: Accuracy for the LLM to recognize sleep from HR and steps (left) as well as HR and steps with more contextual information about the pattern of HR and steps during sleep.