Informatics in Medicine Unlocked 13 (2018) 92–100

Contents lists available at ScienceDirect

Informatics in Medicine Unlocked

journal homepage: www.elsevier.com/locate/imu

The open D1NAMO dataset: A multi-modal dataset for research on non-invasive type 1 diabetes management

Fabien Dubosson[a,*], Jean-Eudes Ranvier[b], Stefano Bromuri[c,d], Jean-Paul Calbimonte[a], Juan Ruiz[e], Michael Schumacher[a]

[a] University of Applied Sciences and Arts Western Switzerland, Sierre, Switzerland
[b] EPFL, Lausanne, Switzerland
[c] Open University of the Netherlands, Heerlen, Netherlands
[d] BISS Institute, Smart Service Campus, Heerlen, Netherlands
[e] Hôpital Riviera-Chablais, Vevey, Switzerland

ARTICLE INFO

Keywords:
Diabetes management
Wearable devices
Glucose
ECG
Accelerometers
Annotated food pictures

ABSTRACT

The usage of wearable devices has gained popularity in the latest years, especially for health-care and well being. Recently there has been an increasing interest in using these devices to improve the management of chronic diseases such as diabetes. The quality of data acquired through wearable sensors is generally lower than what medical-grade devices provide, and existing datasets have mainly been acquired in highly controlled clinical conditions. In the context of the *D1NAMO* project — aiming to detect glycemic events through non-invasive ECG pattern analysis — we elaborated a dataset that can be used to help developing health-care systems based on wearable devices in non-clinical conditions. This paper describes this dataset, which was acquired on 20 healthy subjects and 9 patients with type-1 diabetes. The acquisition has been made in real-life conditions with the *Zephyr BioHarness 3* wearable device. The dataset consists of *ECG*, *breathing*, and *accelerometer* signals, as well as *glucose* measurements and annotated *food pictures*. We open this dataset to the scientific community in order to allow the development and evaluation of diabetes management algorithms.

1. Introduction

Data science and data-driven algorithms are transforming the way health-care and chronic diseases are managed, including the use of monitoring, diagnosis and treatment technologies. This trend is supported by the increasing adoption of wearable devices with sensing capabilities, such as *Fitbit One*,[1] *Jawbone Up*[2] or *Garmin Vivofit*[3] [1]. Thanks to such devices, it is now possible to provide live analytics on personal health data, leveraging state-of-the-art research on quantified-self and health-tracking [2].

Diabetes management is a particularly interesting use-case in this context, given the importance of providing accurate and timely feedback, monitoring and diagnosis tools to both patient and health-care providers [3,4]. In fact, several research initiatives have addressed the challenges of managing the different aspects of diabetes, using wearable devices as sources of data [5,6]. However, the development of data-driven approaches depend on the existence of datasets that can be used for training, validation or automated learning. These datasets are needed not only in clinical and controlled environments (e.g. monitoring during a hospital stay), but also in everyday-life conditions, which are closer to what a patient with diabetes experiences in her daily routine.

The goal of this paper is to contribute to the development of data-centric algorithms and diabetes monitoring technologies, by providing an openly available multi-modal dataset acquired on real patients in non-clinical conditions. This dataset has been collected in the context of the *D1NAMO* project, and consists of a set of *Electrocardiogram ECG* signals, *Breathing* signals, *Accelerometers* outputs, information about *glucose levels* and *annotated food pictures*. The *D1NAMO* project aims at providing non-invasive diabetes management through machine learning data analytics performed on wearable sensor data signals [7,8]. This heterogeneous dataset was acquired on a study that included

* Corresponding author.
E-mail address: fabien.dubosson@hevs.ch (F. Dubosson).
[1] http://www.fitbit.com/.
[2] http://www.jawbone.com/.
[3] http://www.garmin.com/.

https://doi.org/10.1016/j.imu.2018.09.003
Received 16 May 2018; Received in revised form 19 September 2018; Accepted 26 September 2018
Available online 01 October 2018

29 patients — 20 healthy people and 9 patients with diabetes — in real-life conditions, using the *Zephyr BioHarness 3* wearable chest-belt device.

As explained in Section 5, the availability of datasets such as this, offers interesting possibilities for the development of healthcare monitoring systems, especially in the context of diabetes management through wearable devices. For example, one possible use case is for detection of hypoglycemic events, which can be potentially dangerous for the patient. Changes in glucose level in the blood have been shown to correlate with changes in the shape of the ECG signals, opening the door for non-intrusive detection. Nevertheless, this is not the only parameter to consider, given that the activity levels, or food intake, may have direct and indirect consequences on glycemic events on the patient. Added to the complexity of dealing with these different parameters, it is important to take into account the potentially noisy data that is commonly acquired under non-clinical conditions. Many algorithms that were originally developed using medical-grade signals require to be tested and adapted for everyday-life wearable devices signals, in order to be used effectively for health monitoring. Therefore, the purpose of this paper is to open this dataset to the scientific community, providing a valuable source of real patient information, which can be used for automated learning, training, experimentation and validation of algorithms and techniques in the realm of diabetes management. The publication of this dataset constitutes an important milestone and contribution in the context of the *D1NAMO* project, following our previous efforts regarding data analytics [8] and mobile health developments [7] for Type 1 diabetes management.

The remaining of this paper is structured as follows: Section 2 compares our dataset to relevant related works. Section 3 presents the methodology used for the data acquisition. Statistics of the dataset are described in Section 4. Different opportunities offered by this dataset are proposed in Section 5, and finally we provide final remarks in Section 6.

2. Related work

Research in diabetes has gathered considerable attention, especially regarding the development of techniques and algorithms relying on monitoring parameters using sensing devices. To support this research line, datasets have been released to allow researchers to advance the state of the art with respect to diabetes monitoring and treatment. While a lot of these publicly released datasets contain ECG waveforms, we have found only one that also contains glycemic data: the MIMIC II [9] dataset. This dataset is available on the PhysioNet platform [10] and provides data from patients who were in Intensive Care Unit ICU. The database has two parts: first, the clinical database containing information about the patients, their diseases, and other ICU-related data. The second part is the waveform database: it contains the signals that were recorded during the patients' stays at ICU using medical-grade devices, while patients were in a static position (i.e. lying in bed, with very limited movement). Despite the good signal quality and the additional type of data available, the dataset is not representative of everyday signals recorded with wearable devices, because of the ICU-related condition of the patients and of the quality of the sensing devices. Also, the glucose levels are not available for all patients but have only been acquired when the patient's condition required it.

The PhysioNet platform also provides a long list of physiological databases. Some of them are ECG databases, like for instance the MIT-BIH arrhythmia dataset [11] which offers 48 half-hour of ambulatory acquired ECG. Others are multi-parametric databases that include ECG along with other signals, but among all the databases listed on the webpage,[4] none of them includes glucose levels as time series. Another known resource for Machine Learning databases is the *UCI Machine Learning Repository* [12]. At least two of its datasets are related to this work. First, the *MHEALTH* dataset, which offers body motion data — including acceleration — as well as 2-leads ECG measurements [13]. Second, the *Diabetes* dataset that consists of glucose levels acquired both from a Continuous Glucose Monitoring CGM and from manual measurements.[5] These two datasets do not offer all the type of data needed for working on diabetes management through wearable devices, as they either lack glusoce information in the first dataset, and ECG in the second.

The *Diabetic Cardiac Neuropathy Diagnostic and Modeling* dataset [14,15] (DICARDIA[6]) provides ECG from patients with diabetes, both with and without cardiac complications. Additional laboratory data such as glucose, hemoglobin or cholesterol are available, but only with a unique spot measurement per patient. Therefore, predictions of glucose levels or identification of glycemic events cannot be done with this dataset. Other research has also been made on topics requiring both glucose levels and ECG signals, but these datasets have not been made publicly available. Some examples of such works includes [16–19].

The D1NAMO dataset focuses on diabetes management through ECG, but the other types of data it provides have also been treated by the scientific community. The domain of activity recognition is mainly built upon Accelerometers and have released many datasets, for instance [20,21]. There exist picture databases that are oriented towards food recognition, such as *UEC FOOD-100* [22], *UEC FOOD-256* [23], *Food-101* [24] and *Food-pics* [25]. The D1NAMO dataset has less images in comparison, but the annotations by a dietitian are valuable in the context of calories estimation as it impacts glucose levels. Finally, up to our knowledge there is no other publicly accessible dataset offering a collection of signals coming from the *Zephyr BioHarness 3*. The Table 1 summarizes the differences between the datasets mentioned in this section.

3. Methodology

The D1NAMO dataset is composed of two distinct subsets: a first one that has been acquired on 20 healthy people, and a second one that has been acquired on 9 patients with diabetes. Having data from both populations offers possibilities in terms of comparison, exploration and impact of Type 1 diabetes with a reference group. The methodologies to acquire both subsets were quite similar, the same wearable device has been used, but a few differences exist though, notably concerning the acquisition of glucose levels.

Both subsets contain the following data:

- ECG signals
- Breathing signals
- Accelerometer outputs
- Glucose measurements (the method differs between subsets)
- Food pictures and annotations by a dietitian

Subsection 3.1 details the setup that has been used to acquire these signals and data and subsection 3.2 describes the protocol that has been followed for the acquisition in both groups.

3.1. Acquisition setup

The acquisition of physiological signals: ECG, Breathing and Accelerometers outputs has been made using the *Zephyr Bioharness 3* device for both subsets. This device looks like a sport chest belt as shown in Fig. 1. It has 3 electronic sensors: one measuring ECG with two electrodes; one measuring breathing through chest expansion; and one measuring accelerations in the three dimensions. These raw signals

[4] http://www.physionet.org/physiobank/database/- November 2017.

[5] http://archive.ics.uci.edu/ml/datasets/Diabetes.

[6] http://gbbanet.labc.usb.ve/DICARDIA.php.

Table 1
Existing research datasets related to Diabetes management, including ECG, and glucose measurements.).

Dataset	ECG	Glucose	Activity	Food Intake	Measurement conditions	Target
MIMIC II [9]	✓	limited	✗	✗	UCI conditions	Monitoring UCI patients
MIT-NIH [11]	✓	✗	✗	✗	Ambulatory	Monitoring ambulatory patients
ECG Physionet datasets	✓	✗	✗	✗	Heterogeneous conditions	Various
UCI MHEALTH [13]	✓	✗	✓	✗	Everyday life	Mobile healht
UCI Diabetes	✗	✓	✗	✗	Everyday life	diabetes management
DICARDIA [14]	✓	limited	✗	✗	Everyday life	Cardiac patients
D1NAMO	✓	✓	✓	✓	Everyday life	Diabetes management

Fig. 1. The Zephyr BioHarness 3 used for the data acquisition phase for the D1NAMO dataset [7].

can be used directly and the device also computes additional aggregated metrics such as Hearth Rate (HR), Breathing Rate BR, activity level, posture, etc.

The electrocardiogram of the *Zephyr BioHarness 3* is taken with a I-lead sensor, consisting of two silver-coated nylon electrodes working on skin contact. It measures the ECG at a rate of 250 Hz and up to 54.89 mV. The breathing is measured with an Ethylene-vinyl acetate EVA foam pressure sensor at 18 Hz. This measurement has no unit, it should be used as a relative value. Accelerometers measure the accelerations in vertical, lateral and sagittal directions at a rate of 100 Hz. These output values are given within the range of ±16 g.

The measurement of glucose levels for healthy people has been made 6 times per day using the *Bayer Contour XT* glucose meter with *Bayer Next strips*. To get a drop of blood, participants used the *Microlet 2 Lancing Device* with their related *Microlet Coloured Lancets*. Glucose levels of patients with diabetes have been recorded with an *iPro2 Professional CGM* sensor, allowing for a precision of 5 min between two glucose measurements.

For the food information, people were asked to take pictures of all their meals with their smartphone. We asked to put a 1 Swiss Franc coin on the picture in order to have a notion of scale (size of the coin: 23.20 mm). The pictures have then been annotated by a dietitian with a description of the food, an estimation of the number of calories, and an indication about the *Food Balance* and *Food Quality*. The later concepts are described by the dietitian as follows:

- **Food Balance** corresponds to the percentage distribution of macronutrients (carbohydrates, proteins and lipids) in a meal according to the Nutritional composition table from the Swiss Nutrition Society. A "Balanced meal" respects the optimal distribution of macronutrients according to this document and an "Unbalanced meal" does not.
- **Food Quality** is related to the amount of food items that should be ideally sporadically consumed in a meal: processed food, alcohol, saturated and trans fats, sweet or salty snacks. A "High food quality meal" contains mostly unprocessed food items and/or includes low quantities of the aforementioned food items. A "Low food quality meal" contains processed and/or the aforementioned food items.

3.2. Acquisition protocol

The protocol has been divided in two main arms, one for patients with diabetes and another for healthy ones. In the following we provide details about enrollment, inclusion and exclusion criteria, and the protocol description.

3.2.1. Data collection and equipment

Information collected at patient enrollment is anthropometrical (weight, height, sex, seated office blood pressure). Patients were provided with the following devices after enrollment: BioHarness sensor, BioHarness belt, BioHarness charger and cable. Healthy patients have been provided with a glucose meter. For patients with diabetes, glucose levels were measured using their continuous glucose monitoring (CGM) device. Participants were instructed to use their mobile phones for taking a picture of their meals.

3.2.2. Recruitment of patients with diabetes

Patients were recruited at routine clinic visits at the diabetes outpatient clinic of Hpital Riviera-Chablais, Vevey. All patients were screened for data acquisition enrollment. Exhaustive and detailed information about the data acquisition, its scope and objectives, its duration, its risks and benefits and its execution were provided to each and every patient. Patients willing to participate, signed a consent form. Eligibility for the diabetes arm was established according to the following inclusion criteria: patients should have a definite diagnosis of diabetes mellitus type 1, followed at the outpatient clinic. Patients must be able to speak French and be at least 18 years old. Furthermore, patients must provide written informed consent and be willing to participate in follow-up. Excluded from the study are patients who do not fulfill the diagnostic criteria for diabetes mellitus type 1. Patients that do not speak French and those not possessing the cognitive capacities to handle a smart phone are equally not eligible for study inclusion. All patients unwilling to provide written informed consent or to participate in follow-up were excluded from study enrollment. Furthermore, patients with significant psycho-social impairment that impedes on their ability to participate in follow-up such as homelessness, psychotic episodes, etc. were excluded.

All consent forms, information sheets, and the entire protocol was validated and approved by the ethcical committee of the Canton of Vaud in Switzerland (Commission cantonale d'éthique de la recherche sur l'être humain).

3.2.3. Protocol

Patients received instructions to start wearing the BioHarness after waking up in the morning, and shutting it down before going to sleep. For the first day they started to wear it directly after the instructions. People were asked to stop the data acquisition after the fourth day and to bring back the devices and forms the day after. The usage of the glucose meter was explained to healthy patients, and they were asked to do it once by themselves to be sure they understood correctly. The

Table 2
Statistics of the dataset.

	Total	Average per participant
Full dataset		
Participants	29	
Signals recording	~1550 h	~53 h
Glucose measurements	8884*	306.3*
Food annotations	473	16.3
Food pictures	352	12.1
Healthy people subset		
Participants	20	
Signals recording	~ 1100 h	~ 55 h
Glucose measurements	470	23.5
Food annotations	358	17.9
Food pictures	246	12.3
Subset of patients with diabetes		
Participants	9	
Signals recording	~ 450 h	~ 50 h
Glucose measurements	8414	934.9
Food annotations	115	12.8
Food pictures	106	11.8

* Not representative because of the difference in glucose measurements between the two subsets.

protocol defined 6 glucose measures per day, one before each meal — breakfast, lunch, diner — and one 2 h after the meal. Patients with diabetes were asked for participation in the study by their diabetologist, and upon agreement received instructions for the data acquisition directly from the nurses in diabetology, who had been trained beforehand. The protocol was almost identical to the healthy people subset: wearing the BioHarness during 4 days and taking pictures of their meals. However, and differently to the healthy group, the glucose levels have been acquired with CGM devices, which sample one glucose measurement every 5 min.

4. Statistics

This section first describes the statistics of the full dataset, then presents the statistics individually for each of the subsets in the following subsections.

The full dataset has been acquired for 29 participants. Table 2 presents the statistics of the full dataset and of both subsets. The full dataset contains around 1550 h of BioHarness measurements (for each kind of signals: 1550 h of ECG, 1550 h of Breathing and 1550 h of Accelerometers). The number of glucose measurements for the full dataset is not representative because of the difference in measurements methods between the two subsets. In addition, 352 food pictures and 473 food annotations complete the dataset.

Fig. 2 shows a sample of each kind of data available in the dataset, except for the glycemic levels that are presented later. The samples shown here are from clean parts of the signals, probably acquired when people where sitting. Due to the fact that time series have been acquired with a chest belt, every movement made by the people affects the measurements, whether it is of ECG or Breathing. This results in signals with both clean and noisy parts, and we also suspect that some people have worn the belt in a way that make the measurements mostly noisy. The dataset also has missing values: some people did not include pictures for all of their meals, or forgot to add a 1 Swiss Franc coin on some pictures. In other cases they forgot to write down measured glycemic values, or had problems with the belt. We decided to keep such signals in the dataset, because these problems naturally occur in every healthcare system including wearable devices and people, so these issues would have to be dealt with.

4.1. Healthy people subset

The participants agreed to share their data in an *anonymized* format with the scientific community. Therefore, we do not link their clinical information with the signals in the dataset in order to preserve their anonymity.

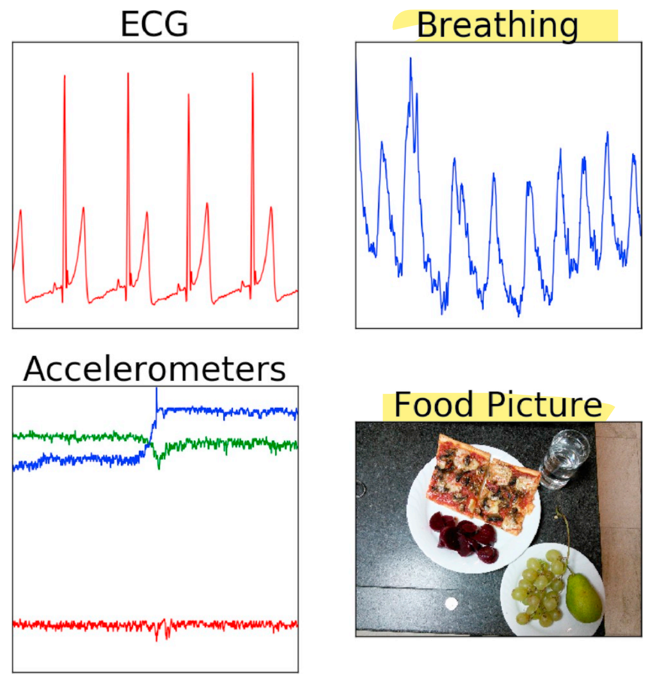

Fig. 2. Data samples.

Table 3
Population of the Healthy subset (sorted by age).

Age	Gender	Height (cm)	Weight (kg)
26	Woman	174	64
27	Man	184	75
28	Woman	170	54
29	Man	170	62
29	Man	190	83
31	Man	171	65
32	Woman	162	58
32	Man	170	72
32	Man	173	89
33	Man	170	78
33	Man	177	72
33	Man	185	90
33	Man	186	94
34	Woman	164	63
34	Man	185	87
34	Man	192	81
36	Man	170	73
36	Man	176	68
43	Man	176	74
45	Man	178	82

The population of the dataset consists of 20 healthy people from different countries: Switzerland(9), Italy(3), Spain(3), Russia(1), Austria(1), Mexico(1), Mauritius(1), and Britain(1). The participants clinical data are shown in Table 3. The dataset contains the following bias: All people are working in academic research, and are hence highly qualified people. We believe that this bias does not render the dataset less interesting, despite having a broader population would have been more valuable. Also, there is only 4 women for 16 men, and the ages range goes from 26 to 45. One person in this subset has diabetes type 1: he has been put in the healthy subset because he has not worn a CGM like other patients with diabetes, so the protocol he followed is the one of healthy subset. This person is not included in the glucose plots of this section, but his data are available in the dataset.

All measured glucose levels have timestamps indicating at which time of

Table 4
Individual glucose statistics of the Healthy Subset.

Patient ID	Mean	Std	Median	Count
001	5.39	0.73	5.70	18.00
002	5.45	0.38	5.40	24.00
003	5.24	0.48	5.30	21.00
004	6.21	0.86	5.90	24.00
005	5.42	0.70	5.20	20.00
006	5.97	0.72	5.95	24.00
007	5.80	0.93	5.60	31.00
008	4.93	0.76	4.80	23.00
009	5.35	0.63	5.30	24.00
010	6.11	0.60	5.90	23.00
011	4.86	0.70	4.80	23.00
012	12.31	4.40	11.75	30.00
013	5.37	0.70	5.20	22.00
014	5.47	1.04	5.00	23.00
015	5.32	0.43	5.30	23.00
016	5.30	0.57	5.20	24.00
017	6.03	1.11	5.40	24.00
018	5.63	0.57	5.60	24.00
019	5.53	0.66	5.55	22.00
020	5.63	0.73	5.50	23.00

the day they were taken. Table 4 shows the per-patient statistics of glucose measurements. Fig. 3 shows all the measures in one plot. In this plot the left-pointing green triangle represent the fasting glucose (just before eating) and the right-pointing blue triangle represent the 2 h postload glucose levels (2 h after eating). The dashed red lines represents the interpolated mean value of all measurements, and the blue area is the standard deviation around this mean. The dashed blue line represent a commonly used threshold for hypoglycemia [26,27], showing that a few hypoglycemia events appear in this subset. Figs. 4 and 5 show the same data with the respective thresholds of the American Diabetes Association for fasting glucose and 2 h postload glucose [28]. The green areas represent values that are considered as normal for fasting glucose, respectively for 2-h postload glucose. The orange area contains values that are considered as “impaired fasting glucose”, respectively “impaired glucose tolerance”, that are now referred as “pre-diabetes”. The red zones (not visible in Fig. 5) correspond to levels that are subject to provisional diagnosis of diabetes. Except for the patient with diabetes type 1 that is not shown in these plots, the other values are mostly in the normal range for the 2-h postload glucose. On the other side around 25% of fasting glucose are above the normal threshold. We suppose this is due to the fact that people are eating snacks in-between meals so it is not real fasting glucose.

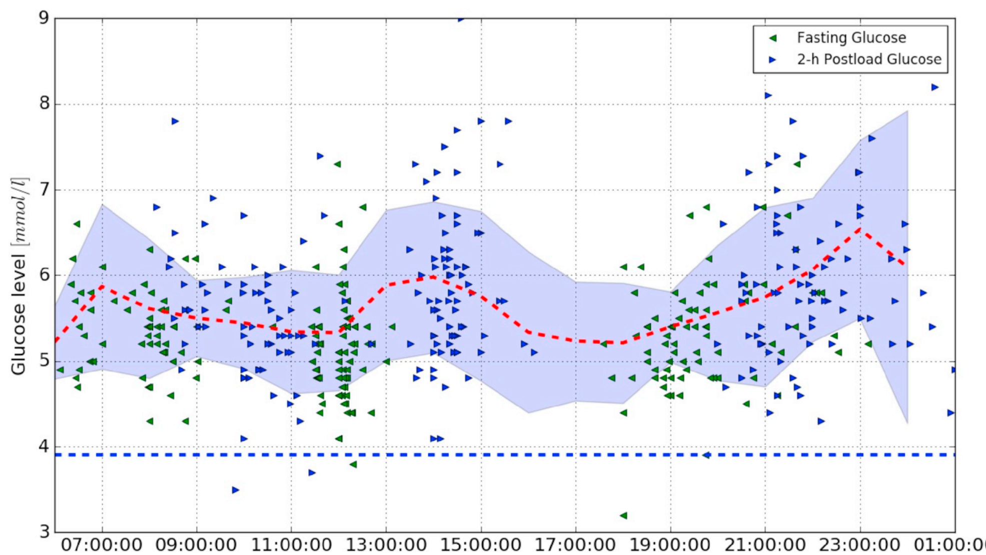

Fig. 3. Glucose measures of the Healthy subset.

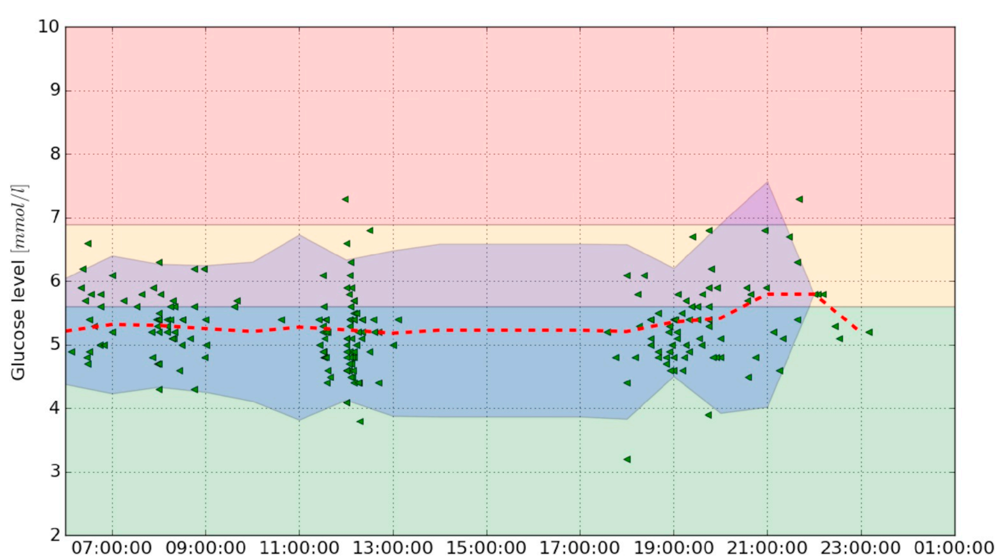

Fig. 4. Fasting glucose measures of the Healthy Subset.

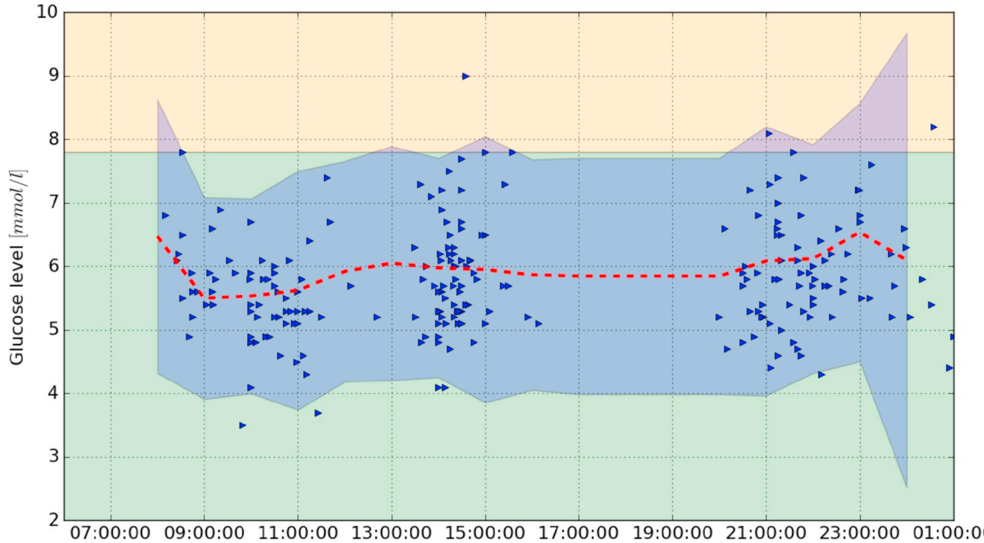

Fig. 5. 2-h postload glucose measures of the Healthy Subset.

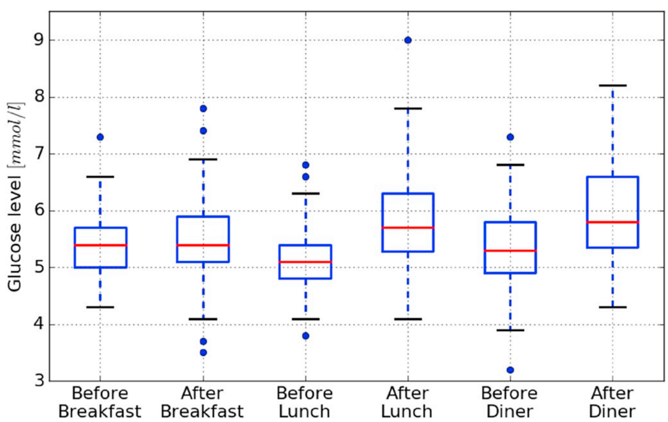

Fig. 6. Glucose measures of the Healthy subset grouped by categories.

Most of the glucose values are labelled with the moment they were taken: the 6 labels are: {Before, After} × {Breakfast, Lunch, Diner}. This has been done in order to compensate the fact that people have different eating timing habits. Fig. 6 shows the distribution of glucose level for each label.

4.2. Patients with diabetes subset

The patients agreed to share their data in an *anonymized* format with the scientific community. Therefore, we do not link their clinical information with the signals in the dataset in order to preserve their anonymity. Also, due to the relatively small size of this population, only the range of their clinical data are presented in Table 5.

As shown in Table 2, the subset is composed of 9 patients with type 1 diabetes. 8414 measurements of glycemic levels have been made with the CGM, but this covers the 24 h of a day: only a part of these measurements can be mapped to the daytime-only signals acquired with the sensors. Table 6 shows the per-patient statistics of glucose measurements. Although the number of patients with diabetes is limited, we computed the required number of hypoglycemia episodes needed to get statistically relevant results. In order to do so, a calculation was made considering 3 main ECG parameters: ST-Segment changes, T-Wave amplitude changes, and length of the QT-interval. According to this calculation the recording of 18 hypoglycemic episodes would be sufficient to detect the differences published by Ref. [29] (with 80% statistical power).

Not all the patients have taken pictures of their meals, but people who have not done this have instead annotated what they have eaten. This is what has been used by the dietitian to annotate the food intake in such cases.

Table 5
Patients of the Type-1 Diabetes subset (sorted by age).

Age	Gender	Height (cm)	Weight (kg)
NA	Man	180–189	80–89
20–29	Man	170–179	60–69
20–29	Man	180–189	70–79
20–29	Man	180–189	80–89
30–39	Man	180–189	80–89
30–39	Man	190–199	70–79
30–39	Woman	160–169	70–79
60–69	Woman	150–159	50–59
70–79	Woman	160–169	50–59

Table 6
Individual glucose statistics of the Type-1 Diabetes Subset.

Patient ID	Mean	Std	Median	Count
001	10.19	4.87	9.60	1438.00
002	10.16	5.56	9.80	1071.00
003	7.13	1.85	6.95	186.00
004	11.20	4.98	10.80	984.00
005	8.55	2.49	8.30	928.00
006	9.44	3.19	9.20	1298.00
007	8.29	2.50	8.20	1011.00
008	7.18	3.19	7.00	1175.00
009	4.86	2.35	4.80	306.00

Glucose measures acquired with the CGM are shown in Fig. 7. The same thresholds as for Figs. 4 and 5 are shown for comparison. The background on the half-left side corresponds to American Diabetes Association thresholds for fasting glucose, while the background on the half-right side correspond to 2-h postload glucose. The same blue dashed line as before shows that a few hypoglycemia also appear in this subset.

4.3. Food pictures

Food annotations are provided for pictures of the meals for both healthy and type-1 diabetes subsets. The pictures have been taken from patients' personal devices, meaning they have been taken from different devices in different places and conditions, as it can be expected in real-

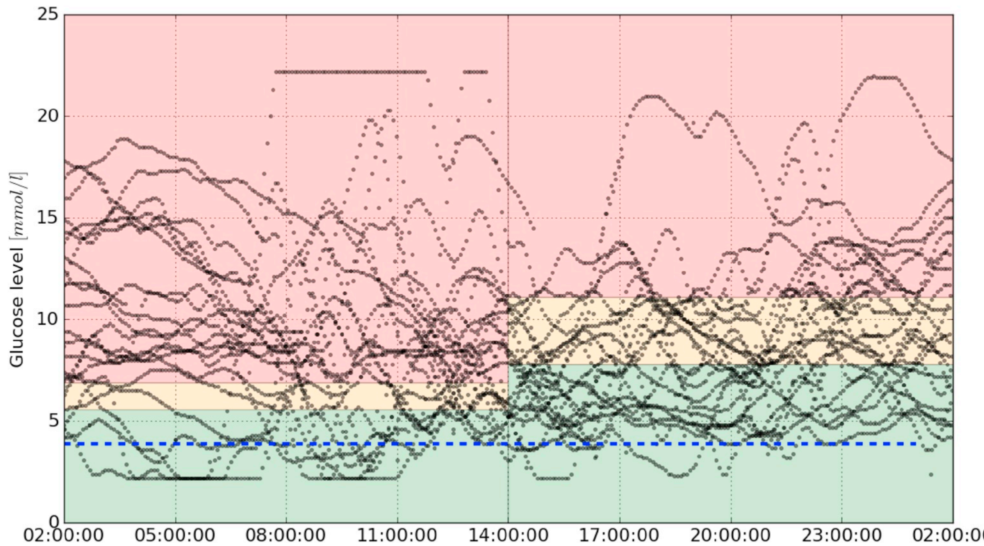

Fig. 7. Glucose measures of the Type-1 Diabetes subset.

life datasets. Fig. 8 shows a sample of food pictures and their related remarks, as annotated by a dietitian.

5. Discussion & opportunities

For the treatment of diabetes, glycemia is one of, if not the most important parameter to monitor. Therefore, in addition to tracking activities, gathering information about glycemic events is required in order to produce useful services for the patient. Signals acquired on the devices mentioned above, such as *Heart Rate*, *Skin Temperature* or *Steps Counter*, have already been addressed in the scientific literature. However, medical devices are still used for acquiring health-related signals such as ECG or glycemic levels. The design of these sensors, for instance glued patches ECG or subcutaneous sample acquisition for glucose, make their usage constraining as opposed to the ease-of-use of wearable devices. Technological progress makes now possible to capture some health-related signals such as ECG on embedded wearable devices. However, the gain in comfort has been made in detriment of the signals quality: wearable devices do not offer signals with quality as good as medical-grade devices. Therefore, it is important to count with relevant datasets that include this type of conditions, which are more representative of realistic scenarios of patients during their daily activities. Using these datasets, algorithms can be designed, developed, trained, validated, etc. in order to cope with uses related to diabetes monitoring and management.

The D1NAMO dataset provides interesting information that could be used in this context. Even if the data is reduced in terms of number of patients, it contains a considerable number of hours of recordings, which can be used in different scenarios. Most of these scenarios can be set up focusing on the different relatiomships and interactions among different parameters: activity levels, breathing and heart activity, food intake, and particularly, glycemic events. Among glycemic events, hypoglycemia episodes are especially relevant and potentially dangerous, as they have been shown to predict sudden death [30] and have been linked to the dead-in-bed [31] syndrome. It has been shown than these hypoglycemic events can be detected from the shape of ECG beats [32–34], and despite the decrease in signals quality, some preliminary results show that it is possible to detect glycemic events from wearable devices (e.g. such such as the *Zephyr Bioharness3*[7] [8,35] in D1NAMO), opening a way to improve diabetes management through wearable devices without the need of medical sensors. The *D1NAMO* project has focused on studying this topic, relying on machine learning algorithms to infer hypoglycemic events from the sensor data signals [7,8].

Although nowadays new alternative technologies are developed for continuous and less invasive glycemic monitoring, there is still room for further developments and the adoption of these technologies by a wider public. Examples of these devices include electrochemical impedance spectroscopy [36], Raman spectroscopy [37], transdermal monitoring [38], among others [39]. Even if these technologies are promising, direct glycemic measurements need to be combined with other information sources in order to provide a holistic approach to diabetes management. Food intake, activity levels, as well as heartbeat and breathing monitoring can substantially improve prevention and early detection of hypoglycemic situations, as well as enable personalized recommendations targeting behavioral change.

This dataset offers several opportunities for use in different scientific activities and research directions, and permits to develop applications in several domains. Next, we briefly mention some of these opportunities.

- The multimodal nature of the dataset allows to explore predictions of one of the signals from the other ones. For instance, trying to predict the HR from the *Breathing* signal or vice-versa. In the context of diabetes management it could be used to explore the prediction of glucose levels from ECG, Breathing and Accelerometers signals.
- The availability of multiple signals could permit to study relationships between them, for instance the ECG variations under different types of exercises or activities, or the impact of glucose level on breathing rate, if any. Different algorithms based on machine learning or pattern mining can be used for this purpose, leading to relevant correlations among the sensor observations.
- The fact that the dataset has been acquired in real-life conditions, with a wearable device, opens opportunities for the development and evaluation of pre-processing algorithms such as for cleaning or denoising signals. Different filtering and pre-processing techniques may be required, depending on the use-case. In some cases, excesive cleaning may lead to the elimination of apparently noisy signal features that may be relevant for further processing tasks.
- Another approach for working with noisy signals would be to discard parts that are not usable and to keep only the clean/usable portions. Such works can also be applied on this dataset, e.g. focusing only on time windows relevant to an activity, or a portion of the data where noise does not increase over a certain threshold.
- This dataset contains data from healthy people and patients with diabetes, therefore it permits to explore the differences between these two populations.

[7] http://www.zephyranywhere.com/.

(a) Sample from the type-1 diabetes subset (b) Sample from Healthy Subset

	Description	Calories	Balance*	Quality*
a	Pork potatoes salad and white bread	634	Not balanced	Medium quality
b	Greek salad, apple and chocolate cookie	677	Not balanced	Good quality

* as defined in Section 3.1

Fig. 8. Sample of the food pictures with the associated annotations.

- The large number of hours of signals in the dataset allows to imagine its usages in the world of Deep Learning. Possible ideas include the usage of these data to create a model to recognize healthy heart beat shape, to identify normal breathing behaviors, or to predicate heart rate and breathing rate from Accelerometers. Usages in unsupervised learning are also possible, such as building networks for learning features on one-dimensional time series.
- Having food information for each patient as well as their physiological signals — especially glucose — could be used for diet advice. Advice can either be in regard to the global health condition or in regard to glucose levels for decreasing risks for type 1 diabetes patients.
- Glucose together with food information may permit to explore the impact of Calories, Food Balance or Food Quality on the Glucose levels.
- The food annotations could also be used in conjunction with pictures in food recognition algorithms. The number of pictures is not sufficient on itself to fully train models but it can be used in context of transfer learning. It can also be used as a test set, or just used to increase the number of samples in an existing dataset. Since the pictures have been annotated by a dietitian, they offer a reliable ground truth for verification or calibration.

The availability of this dataset, inspired by the current trends on Open Science, also has limitations, related both to the acquisition process and the data itself. First, given that the goal is to have data measurements for everyday-life conditions, the dataset inevitably includes noise and data artifacts that make it more challenging to perform analytics on it. This is both a feature and a limitation, linked to both the sensing conditions (e.g. arbitrary movements, heterogeneous activities), as well as the device limitations (e.g. accuracy). Second, the recruitment process had a certain degree of complexity, considering the limited number of diabetes type 1 patients willing, or able to accept the study conditions. In many cases, the co-morbidities of patients would made them ineligible, given the complications of their health status. In other cases, physical and cognitive impairments would place certain patients clearly outside the inclusion group. Third, and related to the previous point, the dataset has a limited number of participants, although this is compensated by the diversity of the data, as well as the number of hours or registered observations. Finally, the dataset also has limitations considering the bias regarding age, background and geographical/socio-economic situation of the participants.

Another aspect that need to be considered is related to the usability, convenience and general feasibility of the approach, even beyond technical and algorithmic considerations. The fact of wearing the equipment, or using a mobile application that supports the data collection, monitoring and recommendations, needs to be explored from the point of view of the potential users. To that end, and in order to evaluate and improve these aspects, we conducted a qualitative evaluation on the ease of use of the Android Application developed for the *D1NAMO* project, with 18 participants. The study main goal was to evaluate the ease of use of the Android application, but we were also interested in getting general feedback and comments about all aspects of the approach. This study provided us precious knowledge on what the application should look like, an how the application should behave from the user's perspective. Although this study is out of the scope of this dataset paper, it provided positive evidence on the feasibility of non-invasive hypoglicemic detection.

6. Conclusions

This work presents the *D1NAMO* dataset that focuses on monitoring health, activity and food intake measurements in patients with and without diabetes type 1, under everyday-life conditions. This dataset been acquired in the context of the *D1NAMO* project, which studied the feasibility of non-invasive monitoring of hypoglycemic events. The dataset consists of *ECG*, *Breathing* and *Accelerometers* signals, as well as *glucose* measurements and annotated *food pictures*. These signals have been acquired with the *Zephyr BioHarness 3* wearable device in real-life conditions. The dataset is composed of two distinct subsets that have been acquired on different populations: one on healthy people and one on patients with diabetes. The full dataset is composed of roughly 1550 h of both ECG, Breathing and Accelerometers signals. The data acquisition took place on everyday-life conditions with a chest belt, meaning the dataset has noisy parts as well as missing data. This makes the dataset ideal for the development and evaluation of algorithms for wearable healthcare systems.

The emergence of datasets of this kind is expected to help and facilitate the development of technologies and algorithms that are able to pre-process, filter, clean, analyze, and extract information, mine, and exploit raw data measurements resulting from continuous monitoring of health related information, typically acquired through wearable sensing devices. Although, as noted in Section 5, other alternative methods for glycemic monitoring are currently under development, the inclusion of multi-modal data for diabetes management is still necessary, considering the possibility of taking into account food intake or activity levels for prediction or personalized recommendation tasks.

Data acquired in real-life conditions as in this dataset, offers interesting opportunities in different directions. First, in the context of diabetes management with wearable devices: there is not any other publicly accessible dataset offering *ECG* and *glucose* time series acquired both on wearable devices and in real-life conditions. Second, for the improvement of healthcare management algorithms through better processing of signals coming from wearable devices. Other potential use-cases of this dataset are also proposed in Section 5, even if reuse in other contexts is not excluded.

The dataset can be obtained through the Zenodo[8] platform. The platform provides a permanent URL and address for the dataset, as well as a DOI and versioning. The access to the data will be granted free of

[8] https://zenodo.org/record/1421616.

charge, subject to certain conditions specified by a data license distributed with the dataset. The main conditions refer to attribution and non-commercial use, as well as the provision of: a short description of the context in which the dataset will be used, and a signed form assessing that the dataset will only be used for scientific research and that no attempt will be made to identify patients. The license also includes other terms, such as the deletion of data upon owner request.

The authors would like to thank

- The Nano-Tera initiative[10] that financed the *D1NAMO* research project in which this data acquisition took place,
- Alejandra Ruiz Torres, the dietitian who annotated the pictures,
- The Hôpital-Riviera Chablais, in particular the nurses, for the valuable collaboration,
- Sandrine Ding and Karl Aberer for their work on the D1NAMO project.

Acknowledgment

This research project *D1NAMO* and the data collection protocol has been approved by the ”Commission cantonale d'éthique de la recherche sur l'être humain”[9] of canton de Vaud in Switzerland, under the number CER-VD 53/15.

References

[1] Clawson J, Pater JA, Miller AD, Mynatt ED, Mamykina L. No longer wearing: investigating the abandonment of personal health-tracking technologies on craigslist. Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing. ACM; 2015. p. 647–58.

[2] Calvaresi D, Cesarini D, Sernani P, Marinoni M, Dragoni AF, Sturm A. Exploring the ambient assisted living domain: a systematic review. J. Ambient Intel. Humanized Comput. 2017;8(2):239–57.

[3] Connelly J, Kirk A, Masthoff J, MacRury S. The use of technology to promote physical activity in type 2 diabetes management: a systematic review. Diabet Med 2013;30(12):1420–32.

[4] Vietri J, Witt E, Meyer T. Physical activity and health-related quality of life among adults with type 2 diabetes: results from wearable fitness trackers. Value Health 2016;19(7):A678.

[5] Lopez B, Herrero P, Martin C. Proceedings of the 1st ecai workshop on artificial intelligence for diabetes. 22nd European conference on artificial intelligence (ECAI). 2016http://www.pepper.eu.com/ApplicationFiles/Download/325.

[6] Falcionelli N, Sernani P, Brugués A, Mekuria DN, Calvaresi D, Schumacher M, Dragoni AF, Bromuri S. Event calculus agent minds applied to diabetes monitoring. International conference on autonomous agents and multiagent systems. Springer; 2017. p. 258–74.

[7] Dubosson F, Bromuri S, Ranvier J-E, Schumacher M. D1namo, a personal health system for glycemic events detection. Workshop artificial intelligence for diabetes, 22nd European conference on artificial intelligence (ECAI 2016). ECAI; 2016.

[8] Ranvier J-E, Calbimonte J-P, Dubosson F, Aberer K. Detection of hypoglycemic events through wearable sensors. Proceedings of the 1st workshop on semantic web technologies for mobile and pervasive environments co-located with the 13th extended semantic web conference (ESWC 2016), Heraklion, Greece, may 29, 2016. 2016. p. 21–6http://ceur-ws.org/Vol-1588/paper2.pdf.

[9] Saeed M, Villarroel M, Reisner AT, Clifford G, Lehman L-W, Moody G, Heldt T, Kyaw TH, Moody B, Mark RG. Multiparameter intelligent monitoring in intensive care ii: a public-access intensive care unit database*. Crit Care Med 2011;39(5):952960. https://doi.org/10.1097/ccm.0b013e31820a92c6https://doi.org/10.1097/CCM.0b013e31820a92c6.

[10] Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals. Circulation 2000;101(23). https://doi.org/10.1161/01.cir.101.23.e215. e215e220 https://doi.org/10.1161/01.CIR.101.23.e215.

[11] Moody G, Mark R. The impact of the mit-bih arrhythmia database. IEEE M EMB 2001;20(3):45–50. https://doi.org/10.1109/51.932724http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=932724.

[12] Lichman M. UCI machine learning repository. http://archive.ics.uci.edu/ml; 2013.

[13] Banos O, Garcia R, Holgado-Terriza JA, Damas M, Pomares H, Rojas I, Saez A, Villalonga C. mhealthdroid: a novel framework for agile development of mobile health applications. International workshop on ambient assisted living. Springer; 2014. p. 91–8.

[14] Quintero L. Desarrollo de una base de datos para la evaluación de la neuropatía autonómica cardíaca de origen diabético, Ph.D. thesis, Tesis de Maestría, Universidad Simón Bolívar. Coord. de Ing. Electrónica; 2007.

[15] Ledezma CA, Severeyn E, Perpinan G, Altuve M, Wong S. A new on-line electrocardiographic records database and computer routines for data analysis. 2014 36th annual international conference of the IEEE engineering in medicine and biology society. IEEE; 2014. p. 2738–41.

[16] Nyongesa H, Alexakis C, Saatchi R, Rodrigues M, Harris N, Heller S, Davies C, Emery C, Ireland R. Classification of saecg by autoregressive modelling and neural networks. AFRICON, 2004. 7th AFRICON conference in Africa, vol. 2. IEEE; 2004. p. 841–4.

[17] Christensen TF, Tarnow L, Randløv J, Kristensen L, Struijk J, Eldrup E, Hejlesen OK. Qt interval prolongation during spontaneous episodes of hypoglycaemia in type 1 diabetes: the impact of heart rate correction. Diabetologia 2010;53(9):2036–41.

[18] Alexakis C, Rodrigues M, Saatchi R, Nyongesa H, Davies C, Ireland R, Harris N, Heller S. A knowledge-based electrocardiogram-monitoring system for detection of the onset of nocturnal hypoglycaemia in type 1 diabetic patients. 2006 computers in cardiology. IEEE; 2006. p. 5–8.

[19] Nuryani N, Ling SS, Nguyen H. Electrocardiographic signals and swarm-based support vector machine for hypoglycemia detection. Ann Biomed Eng 2012;40(4):934–45.

[20] Anguita D, Ghio A, Oneto L, Parra X, Reyes-Ortiz JL. A public domain dataset for human activity recognition using smartphones. ESANN; 2013.

[21] Sherar LB, Griew P, Esliger DW, Cooper AR, Ekelund U, Judge K, Riddoch C. International children's accelerometry database (icad): design and methods. BMC Publ Health 2011;11(1):485.

[22] Matsuda Y, Hoashi H, Yanai K. Recognition of multiple-food images by detecting candidate regions. Proc. Of IEEE international conference on multimedia and expo. ICME); 2012.

[23] Kawano Y, Yanai K. Automatic expansion of a food image dataset leveraging existing categories with domain adaptation. Proc. Of ECCV workshop on transferring and adapting source knowledge in computer vision. TASK-CV); 2014.

[24] Bossard L, Guillaumin M, Van Gool L. Food-101 – mining discriminative components with random forests. European conference on computer vision. 2014.

[25] Blechert J, Meule A, Busch NA, Ohla K. Food-pics: an image database for experimental research on eating and appetite. Food cravings 2015;26:40.

[26] Pitzer KR, Desai S, Dunn T, Edelman S, Jayalakshmi Y, Kennedy J, Tamada JA, Potts RO. Detection of hypoglycemia with the glucowatch biographer. Diabetes Care 2001;24(5):881–5. https://doi.org/10.2337/diacare.24.5.881. arXiv http://care.diabetesjournals.org/content/24/5/881.full.pdfhttp://care.diabetesjournals.org/content/24/5/881.

[27] Reach G. Which threshold to detect hypoglycemia? Diabetes Care 2001;24(5):803–4. https://doi.org/10.2337/diacare.24.5.803. arXiv http://care.diabetesjournals.org/content/24/5/803.full.pdfhttp://care.diabetesjournals.org/content/24/5/803.

[28] Association AD. Diagnosis and classification of diabetes mellitus. Diabetes Care 2006;29(suppl 1):s43–8. arXiv http://care.diabetesjournals.org/content/29/suppl_1/s43.full.pdfhttp://care.diabetesjournals.org/content/29/suppl_1/s43.

[29] Laitinen T, Lyyra-Laitinen T, Huopio H, Vauhkonen I, Halonen T, Hartikainen J, Niskanen L, Laakso M. Electrocardiographic alterations during hyperinsulinemic hypoglycemia in healthy subjects. Ann Noninvasive Electrocardiol 2008;13(2):97–105.

[30] Lee SP, Yeoh L, Harris ND, Davies CM, Robinson RT, Leathard A, Newman C, Macdonald IA, Heller SR. Influence of autonomic neuropathy on qtc interval lengthening during hypoglycemia in type 1 diabetes. Diabetes 2004;53(6):1535–42.

[31] R. Tanenberg, C. Newton, I. Almond Drake, Confirmation of hypoglycemia in the” dead-in-bed” syndrome, as captured by a retrospective continuous glucose monitoring system, Endocrine practice.

[32] Eckert B, Agardh C-D. Hypoglycaemia leads to an increased qt interval in normal men. Clin Physiol 1998;18(6):570–5.

[33] Marques J, George E, Peacey S, Harris N, Macdonald I, Cochrane T, Heller S. Altered ventricular repolarization during hypoglycaemia in patients with diabetes. Diabet Med 1997;14(8):648–54.

[34] Meinhold J, Heise T, Rave K, Heinemann L. Electrocardiographic changes during insulin-induced hypoglycemia in healthy subjects. Hormone and metabolic research= Hormon-und Stoffwechselforschung= Hormones et metabolisme 1998;30(11):694–7.

[35] B. Cvetkovic, U. Pangerc, A. Gradišek, M. Luštrek, Monitoring patients with diabetes using wearable sensors: predicting glycaemias using ecg and respiration rate, 1st ECAI workshop on artificial intelligence for diabetes at the 22nd European conference on artificial intelligence (ECAI).

[36] Malkoc A, Probst D, Lin C, Khanwalker M, Beck C, Cook CB, La Belle JT. Enhancing glycemic control via detection of insulin using electrochemical impedance spectroscopy. J. Diabetes Sci. Technol. 2017;11(5):930–5.

[37] Lundsgaard-Nielsen SM, Pors A, Banke SO, Henriksen JE, Hepp DK, Weber A. Critical-depth Raman spectroscopy enables home-use non-invasive glucose monitoring. PloS One 2018;13(5):e0197134.

[38] Lipani L, Dupont BG, Doungmene F, Marken F, Tyrrell RM, Guy RH, Ilie A. Non-invasive, transdermal, path-selective and specific glucose monitoring via a graphene-based platform. Nat Nanotechnol 2018:1.

[39] Chen C, Zhao X-L, Li Z-H, Zhu Z-G, Qian S-H, Flewitt AJ. Current and emerging technology for continuous glucose monitoring. Sensors 2017;17(1):182.

[9] http://www.cer-vd.ch/.

[10] http://www.nano-tera.ch/index.php.

Update

Informatics in Medicine Unlocked

Volume 21, Issue , 2020, Page

DOI: https://doi.org/10.1016/j.imu.2020.100474

Informatics in Medicine Unlocked 21 (2020) 100474

Contents lists available at ScienceDirect

Informatics in Medicine Unlocked

journal homepage: http://www.elsevier.com/locate/imu

Erratum regarding missing Declaration of Competing Interest statements in previously published articles

Declaration of Competing Interest statements were not included in published version of the articles that appeared in previous volumes of Informatics in Medicine Unlocked. Hence, the authors of the below articles were contacted after publication to request a Declaration of Interest statement:

1. "Automated scraping of structured data records from health discussion forums using semantic analysis" [Informatics in Medicine Unlocked, 2018; 10C: Pages: 149–158] https://doi.org/10.1016/j.imu.2018.01.003
2. "Molecular dynamics simulation approach to explore atomistic molecular mechanism of peroxidase activity of apoptotic cytochrome c mutants" [Informatics in Medicine Unlocked, 2018; 11C; Pages: 51–60] https://doi.org/10.1016/j.imu.2018.04.003
3. "An efficient and secure remote user mutual authentication scheme using smart cards for Telecare medical information systems" [Informatics in Medicine Unlocked, 2018; 16C: Article Number: 100092] https://doi.org/10.1016/j.imu.2018.02.003
4. "A numerical modelling of an amperometric-enzymatic based uric acid biosensor for GOUT arthritis diseases" [Informatics in Medicine Unlocked, 2019; 12C: Pages: 143–147] https://doi.org/10.1016/j.imu.2018.03.001
5. "Automated heartbeat classification and detection of arrhythmia using optimal orthogonal wavelet filters" [Informatics in Medicine Unlocked, 2019, 16C; Article number: 100221] https://doi.org/10.1016/j.imu.2019.100221
6. "CHROMATOGRAPHIC ANALYSIS OF PHYTOCHEMICALS IN COSTUS IGNEUS AND COMPUTATIONAL STUDIES OF FLAVONOIDS" [Informatics in Medicine Unlocked, 2018; 13C: page range: 34–40] https://doi.org/10.1016/j.imu.2018.10.004
7. "Sperm motility analysis system implemented on a hybrid architecture to produce an intelligent analyzer" [Informatics in Medicine Unlocked, 2020; 19C; Article number: 100324] https://doi.org/10.1016/j.imu.2020.100324
8. "Medical video compression using bandelet based on lifting scheme and SPIHT coding: in search of high visual quality" [Informatics in Medicine Unlocked, 2019; 17C: Article number 100244] https://doi.org/10.1016/j.imu.2019.100244
9. "A histopathological image dataset for grading breast invasive ductal carcinomas" [Informatics in Medicine Unlocked, 2020; 19C: Article number 100341] https://doi.org/10.1016/j.imu.2020.100341
10. "Cancer diagnosis in histopathological image: CNN based approach" [Informatics in Medicine Unlocked, 2019; 16C: Article number 100231] https://doi.org/10.1016/j.imu.2019.100231
11. "The open D1NAMO dataset: A multi-modal dataset for research on non-invasive type 1 diabetes management" [Informatics in Medicine Unlocked, 2018; 13C: Pages: 92–100] https://doi.org/10.1016/j.imu.2018.09.003
12. "The prediction of good physicians for prospJective diagnosis using data mining" [Informatics in Medicine Unlocked, 2018; 12C: Pages 120–127] https://doi.org/10.1016/j.imu.2018.07.005
13. "Prediction of Pathological Complete Response after Neoadjuvant Chemotherapy for Breast Cancer using Ensemble Machine Learning" [Informatics in Medicine Unlocked, 2019; 16C: Article number: 100219] https://doi.org/10.1016/j.imu.2019.100219
14. "Classification of intra-genomic helitrons based on features extracted from different orders of FCGS" [Informatics in Medicine Unlocked, 2019; 18C: Article number: 100271] https://doi.org/10.1016/j.imu.2019.100271
15. "Visual feedback framework for rehabilitation of stroke patients" [Informatics in Medicine Unlocked, 2018; 13C: Pages: 41–50] https://doi.org/10.1016/j.imu.2018.10.002
16. "Performance of source imaging techniques of spatially extended generators of uterine activity" [Informatics in Medicine Unlocked, 2019; 16C Article number: 100167] https://doi.org/10.1016/j.imu.2019.100167
17. "Automated classification of benign and malignant cells from lung cytological images using deep convolutional neural network" [Informatics in Medicine Unlocked, 2019; Volume 16C: Article number: 100205] https://doi.org/10.1016/j.imu.2019.100205

DOIs of original article: https://doi.org/10.1016/j.imu.2019.100205, https://doi.org/10.1016/j.imu.2019.100221, https://doi.org/10.1016/j.imu.2019.100167, https://doi.org/10.1016/j.imu.2018.04.003, https://doi.org/10.1016/j.imu.2020.100341, https://doi.org/10.1016/j.imu.2018.01.003, https://doi.org/10.1016/j.imu.2018.03.001, https://doi.org/10.1016/j.imu.2018.10.002, https://doi.org/10.1016/j.imu.2020.100324, https://doi.org/10.1016/j.imu.2018.09.003, https://doi.org/10.1016/j.imu.2019.100219, https://doi.org/10.1016/j.imu.2018.02.003, https://doi.org/10.1016/j.imu.2019.100244, https://doi.org/10.1016/j.imu.2018.07.005, https://doi.org/10.1016/j.imu.2019.100271, https://doi.org/10.1016/j.imu.2018.10.004, https://doi.org/10.1016/j.imu.2019.100231.

https://doi.org/10.1016/j.imu.2020.100474

Available online 4 November 2020