# Integrating Activity Recognition and Nursing Care Records: the System, Experiment, and the Dataset

*Abstract*— **In this paper, we introduce a system of integrating activity recognition and collecting nursing care records at nursing care facilities as well as activity labels and sensors through smartphones, and describe experiments at a nursing facility for 4 months. A system designed to be used even by staff not familiar with smartphones has enhanced the content of nursing care records and shortened the recording time. In addition, we show a reference accuracy of recognition of nursing activity using the obtained data. The dataset collected is to be opened to the research community, and can be the utilized for activity recognition and data mining in care facilities. The dataset includes the sensor data from staffs' smartphones, activity labels, and care details input using the system.**

## I. Introduction

In an aging society, nursing care facilities increases, and thereby caregivers become in shortage. It is important to improve the efficiency of nursing care services using information technology.

In the field of ubiquitous computing, researches on human activity recognition technology using mobile sensors such as smartphones have been conducted [1]. If this technology is applied to recognition of nursing care activities, nursing care work and records can be created automatically, and work such as care record and work record can be done more efficient. Also, by visualizing the record and looking back, it can also be used as a material for care improvement.

In this paper, we conduct activity recognition while asking staff to record nursing care records through smartphones at nursing care facilities. We introduce a system to improve the efficiency of nursing care records and the result of an experiment at nursing facility for 4 months. A system designed to be used even by staff not familiar with smartphones has enhanced the content of nursing care records by 1.5 times compared with handwriting and shortened the recording time from an average of 57.6 minutes to 34.6 minutes.

In addition, we show a reference accuracy of recognition of nursing activity using the obtained data. We could achieve accuracy of more than 80% for 4 activities and more than 60% for 10 activities.

The dataset collected is to be opened to the research community, and can be the utilized for activity recognition and data mining in care facilities. The dataset includes the sensor data from staffs' smartphones, activity labels, and care details input using the system.

## II. Annotation Challenge in the Wild

There are many literature in activity recognition research[1], but there are few examples of actually conducting on complicated activities at work sites. Especially, cases used at hospitals and nursing care facilities are very limited [2], [3], [11].

As one of the difficulties, data with a training label is necessary for machine learning algorithms, but this part is extremely costly. Even giving a training label (*annotation*) is done in realtime by the person her/him self, the activity itself becomes strange, and if there is a possibility that the original duty may be affected if s/he does additional work. Therefore, we need often prepare observers and do manual work [6], [11]. Even if it is done later, it takes time to see all of the raw data and attach a label visually, and it often takes more than the actual activity time. Sensor data such as acceleration sensors are often more difficult to interpret than sensor data such as video cameras. When acting at a certain place or measuring in the laboratory, you can set up measuring instruments such as video cameras [7], [8]. However, in cases in the wild, it is often difficult.

As a way to alleviate the strictness required for such training labels, a method based on the person's memory [5], and a way to complement and complement experience based sampling [9], [10] have been proposed. We also proposed a method to improve accuracy even when the label time is inaccurate[13].

In this paper, we propose a system that integrates task records and activity label records routinely used by staff in nursing care field. Although this may cause inaccuracy due to self-labels, it aims to increase the number of label collection by easily recording.

## III. Care record / activity recognition system

We introduce the system that acquire sensors for activity recognition and activity labels for machine learning, accumulate them in the cloud server, and enable daily activity recognition, while asking staff to record nursing care records through smartphones at the nursing facility. The software of this system is an improvement of [12]. By using this system, the nurse care activities can be estimated automatically by giving activity labels for a few days.

The architecture of this system is shown in Figure 1. The staff enters nursing care records and activity labels to the application on the smartphone, and the smartphone sends the data to the cloud side via the Wi-Fi router placed in the care facility together with the sensor data on the smartphone. The cloud service provides authentication and Web user interface (UI), and at the same time, it trains the activity recognition model by machine learning from the data received regularly, and at the same time recognizes activity recognition for sensor data. The estimated activity can be confirmed and

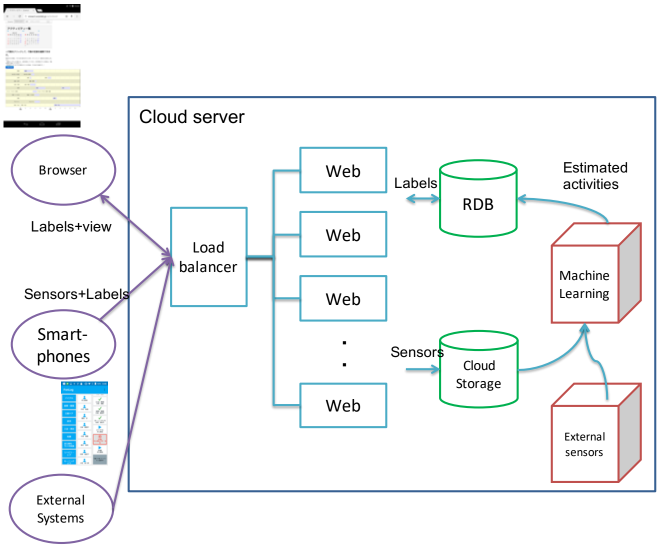



Fig. 1. Care record / activity recognition system configuration.

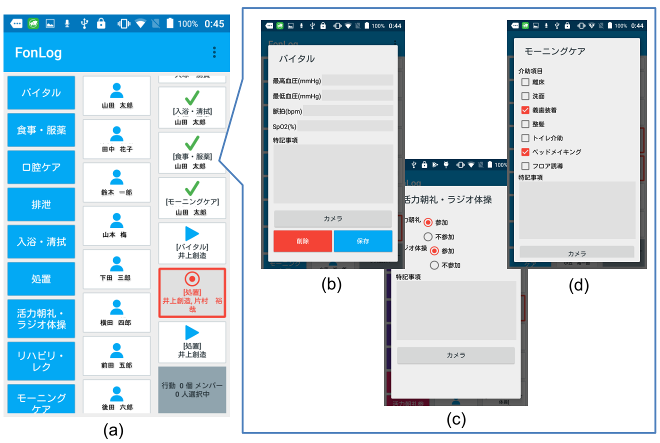



Fig. 2. FonLog: Care record / activity label input application screen.

modified on the Web, which is also used as learning data for the next learning.

### A. Smartphone Application

The developed Android smartphone application *FonLog* has a function that the staff member inputs the care record during work and relays it to the server on the cloud together with the sensor data in the smartphone. Nursing staff is not necessarily familiar with the use of smartphones, but also people who do not know what to do if the screen switches due to unintended swipe etc were seen in past experiments. For this reason, from the main screen as shown in Figure 2 (a), do not switch by tab, swipe, etc., and when you input details, you can use the Figure 2 (b) - (d) as shown in the dialog. This resulted in a better impression than past experiments.

The smartphone application FonLog has the following functions.

1) Activity label input function: In order to make activity recognition supervised and machine learning, it is necessary to collect correct answers (activity labels) of activities along with sensor data. The activity label is time-series data, and it is important to record the start time and end time. In FonLog, as shown in Figure 2 (a), the types of activity (activity class) are in the left column, the care target persons are in the middle row, and by pressing the gray button in the right column after selecting the activity class and target users, a box representing the activity label is generated in the right column. Each time you tap a activity label box, it will transition to before start (▶) → doing activity (⊙) → finish (■), you can record the start and end of the activity. These left, middle and right columns can be scrolled up and down like slot machines, and more contents can be displayed than the screen height. Moreover, the following operation is also possible.
   - Since another activity may be performed while performing one activity, multiple activity labels can be started and ended in parallel.
   - Since you may target multiple subjects with one activity like a meal, you can select multiple subjects for one activity class.
   - The target audience can also be grouped by floor etc. This setting can be set on the server side and can be acquired as metadata in 8).
2) Care detailed input function: by long-pressing the activity label in the right column of Figure 2 (a), a form appears, and you can input details such as Figure 2 (b) - (d). For this input form, data types such as single selection, multiple selection, numerical value, character string, long sentence can be set on the server side for each form, and it can be acquired with the metadata described in 7). For inputting, it is possible to use voice input which is the standard function of Android. Actually, in the experiment of the IV section, in many cases, voice input was actually used. In addition, as a reserve means, buttons for shooting information written on paper etc. from the camera on the smartphone and sending it are also provided.
3) The information entered in 1) and 2) is sent to the cloud server in Section III-B by the functions 6) and 7) below.
4) Function to acquire sensor data of smartphone: selectively acquire data from sensors such as acceleration, angular velocity, light / geomagnetism etc. in the smartphone and surrounding Bluetooth ID, and upload it to the server according to the following 5) – 7).
5) Automatic login function to cloud server: user authentication is done to the Web system of the Section III-B by the HTTPS protocol, and after logging in once, session information is saved in cookies and files of the application to make it possible to log in next time automatically.
6) Activity label / care detail – sensor data buffering function: even if the user is using another application, even if the user is using the different application,

since data collection is continued, the system enters into background execution state and continue to work. Moreover, it set through the API provided by the OS so that the application can be automatically started even if the application abruptly stopped or the terminal was restarted.

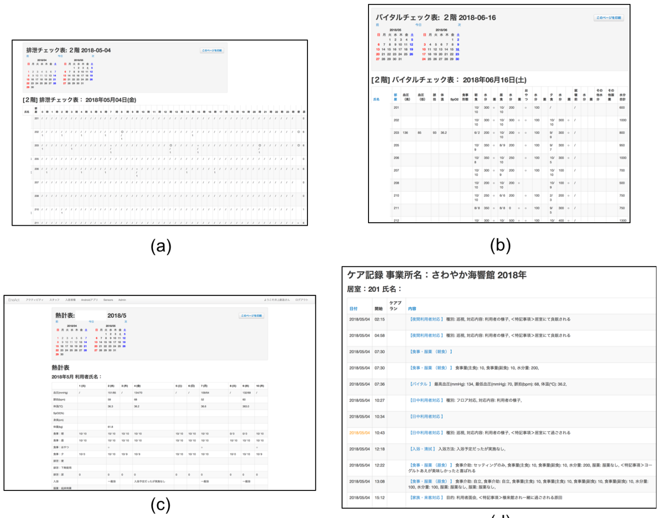
7) Function to upload buffered data to the cloud server: sensor data is uploaded to the server every minute by the HTTPS protocol, but even if the network connection is interrupted, even if the application abruptly stops, the data is lost should not be done. Also, you should avoid uploading data repeatedly over and over again. For this reason, the execution thread is divided into two parallel threads: a sensing thread and a thread to send to the server. The former stores data in the terminal in a certain size while enqueuing the data, and the latter randomizes the file order and sends the file to the server, and deletes the file only when the transmission is successfully executed. In the former, threads were prepared for each sensor device and sensor type, and in the latter, threads were operated in parallel in the range of 1 to 10 in order to increase the throughput of transmission.
8) Metadata download function: Figure 2 (a) requires information on the activity class list, care recipients, and care details input form. FonLog downloads these pieces of information from the cloud server in JSON format at a frequency of once every two hours, and reflects it in the display.

### B. Nursing care record / activity recognition cloud service

The cloud service side holds data sent from smartphones, forms forms of nursing care records, performs counting and activity recognition. It has the following function 1)–8).

1) Smartphone application and user authentication function: user authentication is performed by e-mail address and password from smartphone application FonLog or UI by Web.
2) Activity Label / care detail / sensor data receiving function: receive and store activity labels, care details, sensor data from smartphone application FonLog for each user by POST method in HTTPS protocol. Data is sent in CSV format, and the system saves the activity labels and care details in a relational database for easy handling. Because the sensor data are large, they are saved in the cloud storage after adding the receipt times.
   However, with regard to activity labels, attention should be paid to long-term activity. If you send an activity label from FonLog after the activity is over, no data is sent to the cloud server until it ends, and if it happens to be offline at the end, it will be sent much later. For this reason, we decided to send and receive state transition information in CSV format for each event such as creation, start, end, and deletion of activity labels.
3) Activity recognition and visualization function: using past activity labels and sensor data as training data, machine learning is performed about once every hour, and the activity of the user of the day is estimated. We use activity recognition algorithms appropriate for the day's activity recognition introduced in the document [13].
4) Activity label / care detail editing function: activity label and care details entered on smartphone, and activity presumed in 3) can also be corrected from the server side through the Web. The corrected estimated activity is determined and used as the next training data.
5) Form output function: activity label and care details are output as a form normally used by nursing care facilities as shown in Figure 3. In particular, what is called a care record such as Figure 3 (d) is a form to be printed at a later date and submitted to the municipality.
   Discussion at the time of system design is a function to show these records to doctors and emergency personnel when a health emergency occurs in the care recipient. In the case of handwriting, it is only necessary to take out past files collectively, but when digitizing, it is necessary to acquire past care records for the principal and collect them from outside the facility. Therefore, we prepared buttons to print past records collectively for each caregiver to prepare for an emergency.
6) Staff aggregation function: it is also possible to set activity classes that encourage staff among others or convey feelings of gratitude among activity labels. This is because not only the carer but also the nursing staff are enumerated in the middle row of Figure 2 (a). It is possible for the cloud server side to aggregate the communication between these staff and use it for reviewing and improving the work.
7) Activity label / care detail / sensor data monitoring function: in operation, it is necessary to monitor whether data from the smartphone application is sent correctly. However, even if it is tried to check whether it is normal or not every day, staff may be a non-working day even if activity label / care details have not been sent for a while, sensor data may be just offline for a while. For this reason, we have developed a function to visually check daily checks by counting and displaying the number of received data for each staff member and each cared person, for each of these data.
8) Metadata editing function: supports data classes of activity classes, care recipients, and care details in response to requests from the smartphone application in the JSON format, corresponding to the function 8) (Metadata download function) of the smartphone application .

The system is implemented by Web and HTTPS API except for 3), so implement it with the Ruby on Rails




(a) (b) (c) (d)

Fig. 3. Forms tabulated by cloud server. activity labels and care details are output in a form normally used by nursing care facilities as shown in Figure 2. In particular, what is called a care record as shown in Figure (d) is a form to be printed at a later date and submitted to the municipality.

framework and use Elastic Beanstalk which is Amazon's web load balancing PaaS to relational database system. We used RDS for storage and S3 for storage. Particularly with regard to 2), load balancing for receiving a large amount of sensor data is necessary, so load balancing function is used together with Web in Elastic Beanstalk. For 3), we installed EC2 server for activity recognition written in R language, received activity label from RDS, sensor data from S3, and write back the estimation result to RDS.

## IV. Experiment in a care facility

Between March and June 2017, we conducted verification tests on nursing care records and activity recognition with prior consent of staff and residents at a nursing facility.

In the experiment, we verify whether we can enhance the collection of nursing care records and activity labels by introducing the system, whether the recording time can be made more efficient. Moreover, we aimed at constructing a dataset for activity recognition described in the next section.

Nursing care records are usually recorded by handwriting at the target facility, but in the experiment, in the first two months in March and April, this system is also used in parallel in the usual way to keep handwritten recording, and in the latter half of May and June, the stability of this system also improved, so we asked the record of this system to stop recording the handwritten record.

The facility is a 6 floor building, the first floor part is the parking lot and the entrance, the second floor part is the administration office. There are 65 private rooms on the 2nd to 5th floors and residents live. On each floor there is a shared space in the dining room, dining halls, station, waste disposal room, waste laundry room, and there are bathrooms on the 2nd and 4th floors. We got the agreement of 27 people including 23 caregivers and 4 nurses and conducted experiments.

During the experiment, the staff carried the smartphone during the working hours and had them carried in an arbitrary position such as a pocket. Also, we asked our employees to record activity labels and care details using nursing care records. Especially for activity labels, we asked them to start and end respectively at the beginning and the end of the activity.

### A. Experimental Equipment

We used smartphones Priori 3 LTE from Plus One Marketing. As there were no network facilities such as wireless LAN in the facility, we set up mobile data routers and mobile routers that can be Wi-Fi base stations on each floor. Although it was not possible to cover all the areas, sensor data is stored on the smartphone even if it is not connected to the network, so that no data is lost by this. However, in order to increase the number of simultaneous connections with the smartphone and the bandwidth at the vicinity of the second floor where the smartphone is put at the end of the day, a dedicated wireless router was installed under the mobile router.

### B. Activity Classes

We predefined 28 activity classes after meetings with the staffs and manual documents such as nursing care facilities care records. The list is shown in Table 1.

TABLE I
ACTIVITY CLASSES

| |
|---|
| 1: Vital, 2: Meal / medication, 3: Oral care, 4: Excretion, 5: Bathing / wiping, 6: Treatment, 7: Morning gathering / exercises, 8: Rehabilitation / recreation, 9: Morning care, 10 : Daytime user response, 11: Night care, 12: Nighttime user response, 13: Family / guest response, 14: Outing response, 15: Linen exchange, 16: Cleaning, 17: Handwriting recording, 18: Delegating / meeting, 19: Get up assistance, 20: Change dressing assistance, 21: Washing assistance, 22: Medical doctor visit correspondence, 23: Preparation and inspection of goods, 24: Organization of medications, 25: Family / doctor contact, 26: Break , 27: Emergency response such as accident, 28: Special remarks / notes |

### C. Result

From the data obtained through the experiment, we analyze the effect of system introduction on the number of nursing care records and the recording time. In analyzing, we analyzed

a) whether or not the activity label collection and nursing care record input has been fulfilled by the system, and
b) whether the nursing care record input time has been shortened by the system.

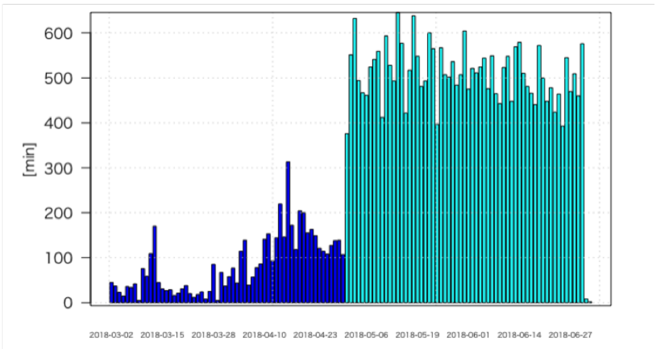



Fig. 4. Daily activity label number of document.
In the former term, the number was 101 labels / day, and in the latter the number has increased to 494.3 / day.

*1) Number of nursing care records:* Fig. 4 shows the total number of activity labels in the first half and latter half of this time. In the former term, the number was 101 labels / day, and in the latter the number has increased significantly to 494.3 / day.

As for the care record input of 1, whether or not the degree was increased was visually observed with the care record of Fighre 2 (d). The result was about 1.5 times input quantity by system use.

*2) Nursing care record time:* Next, we analyzed the activity record time of B). However, when examining the duration of the recorded activity label, many activities finished within one minute were found. Because of this, we gave additional inquiries to the staff again because there were doubts that the staff memorized "time of nursing care record" instead of recording "time of activity".

As a result, in the first half of the experiments, 18 of 12 respondents performed the handwritten records after the activity label was finished, and in the all term, 13 out of 22 performed the details input after the activity label was finished. Furthermore, 11 people out of 23 respondents performed the actual nursing care during the activity labels.

This highlights the negative aspect that the section of activity label is incorrectly recorded by unifying the care record and activity label collection. We need time correction technique as shown in document [13], but we decided to use this result to compare nursing care record time against this result as opposed to this result. Fig. 5 is a comparison of the activity labeling time before and after the handwritten record in the first half experiment and one person who was doing the care detailed input in the latter experiment within the time of the activity label.

According to Fig. 5, in addition to the fact that the number of recorded activity types in the latter experiment is increasing, the activity label time in the latter half also decreases in the activity classes existing both in the first half and the latter half . Total of all activity classes, on average 57.6 minutes per day, could be shortened to 34.6 minutes on average per day. From the results of this section, we found that

- the combination of nursing care records and activity label collections can improve the types and number of care records and activity label collection,
- however, inaccuracies remain in the start and end times of activity labels, and
- the record time can be shortened as compared with handwriting

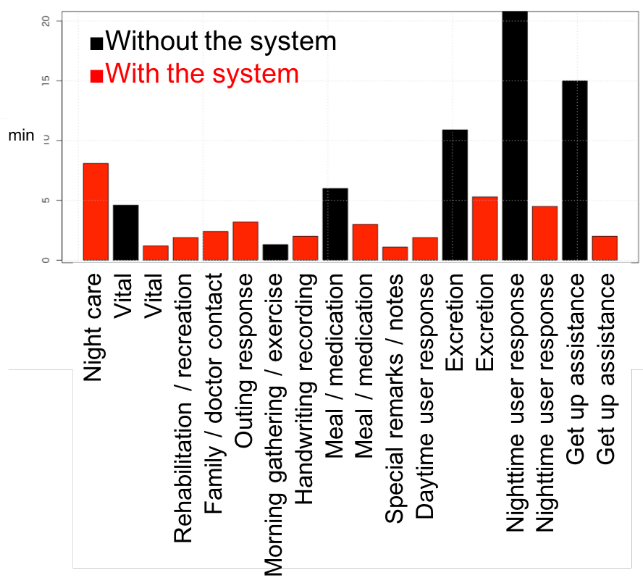



Fig. 5. Activity label time for handwriting and system usage. In addition to the fact that the number of recorded activity types in the latter experiment is increasing, the activity label time in both the first half and the second half is also lower in the latter half.

In the next section, we further apply activity recognition and explore the possibility of shortening the recording time.

## V. Activity Recognition from Smartphone Sensors

Here we propose an algorithm to recognize the activity of the staff from the obtained sensor data. By activity recognition, there is a possibility that the time of nursing care record can be further shortened from the previous section.

We tried machine learning of activity recognition algorithm and its accuracy evaluation using the obtained sensor data and activity label. Details and results are shown below.

### *A. Preprocessing*

This time, only 3 axis acceleration on the smartphone was used. For each sensor, average, standard deviation, maximum value, minimum value for the time in the day and x, y, z axes were extracted as feature amounts every minute.

On the other hand, we also reformed the activity labels. As mentioned in Section IV, as it turned out that nearly half of the staff actually carried out nursing care activities outside the activity label section, we changed each activity label to a segment wider than the recorded, and extended 20 minutes before the recorded start time, and 17 minutes after the finish time by optimizing the activity label segments as an optimization parameter so as to maximize recognition accuracy.

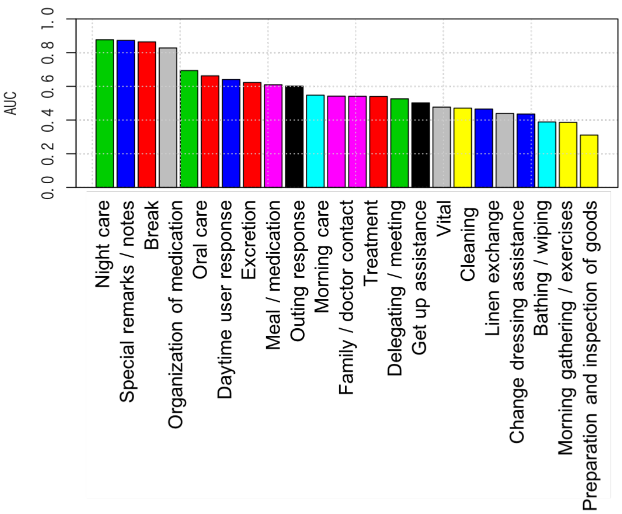



Fig. 6. Activity recognition accuracy. It shows that the precision of 80% or more for 4 activity and the accuracy of 60% or more for 10 activities are obtained.

### B. Evaluation method

As a machine learning algorithm for activity recognition, 1000 feature samples were sampled for each user, and machine learning and evaluation were performed for each user using Extremely Randomized Tree[4]. As for cross validation, assuming that training data of one day can be used the next day, dates were divided to odd days and even days, and trained and tested each other.

### C. Accuracy

Figure 6 shows activity recognition accuracy by AUC measure.

From the figure, it is understood that accuracy of 80% or more for 4 activities and accuracy of 60% or more for 10 activities are obtained.

### D. Discussion

It is expected that this level of precision was obtained from a simple sensor such as only the acceleration of the smartphone is due to specialized training for each individual and collection of a sufficient number of samples by the nursing care recording system.

From the result, it can be expected that the nursing care recording time can be further shortened from the previous section by increasing the estimation accuracy. With the current accuracy, if you missed by estimation the original recording time, the original recording time of about 50% if there was not missed, about 10 seconds to delete if there was a misjudgment Assuming that it takes time to estimate the nursing care recording time, it turned out that we could expect a reduction of 10.9 minutes per person per day.

## VI. Conclusion

In this paper, we introduced a system for collecting nursing care records, activity labels, and smartphone sensor data from nursing staffs, showed the result of experiments for 4 months at a nursing facility. The result could improve the number of records while decreasing record times, and we also showed the result of activity recognition.

The system can easily customize the forms for care details on the server side, so it is applicable for many fields not only to nursing care fields but also other business fields such as medical records, daily health activity records, and any activities on work.

In IoT application, not only data from sensors but also additional data such as business data are very effective for machine learning and service enhancement. This paper provides a dataset for such kinds of analysis and research.

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