Estimation of Record Contents for Automatic Generation of Care Records

Haru Kaneko, Tahera Hossain, Sozo Inoue

Abstract Elderly person are increasing all over the world. Smart nursing facilities are required to support them for their good health.Especially in Japan, it is essential to have automated nursing facilities center to support the relentlessly increasing elderly person all over the country.As long as elderly people are increasing, the demand for nursing care services are also increasing day by day.There is a shortage of nurse to support this vast elderly people.In order to resolve the shortage of nurse, it is important to reduce the work load for nurse.There are some research to simplify the care recording process.The main approach is activity recognition or the development of new apps. However, we aimed for automatic generation of the care records of near future. So in this paper, we evaluate the accuracy of the automatic generation of care records using care record data from real nursing facility to simplify the task of making care records.We made two machine learning models to estimate the "target patient" and the "recorded value" of care records.And we evaluated the classification result from the data collected by the care record app.We used two months of data we collected from Japanese nursing facility for the evaluation.We can achieve, average F1-score of 'target patient' estimation is 74% and the average F1-score of 'detail of record' estimation is 58%. We believe that using these results in care records app will simplify the task of making care records.

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1 Introduction

Understanding the regular [28] and complex human activity [27] is important to support elderly person all over the world. By using IoT (Internet of Things) and ML (Machine Learning) technology, it is possible to monitor elderly peoples regular activity [9] [7] [23]. Sensor-based [8] and vision-based [3] activity recognition platform are offering promising techniques to support elderly people all over the world. Japan is experiencing a "super-aging" society [2]. In Japan, monitoring the daily activities of the elderly person is now a issue for healthcare center or nursing facility [13]. One of the main reasons is the increase of elderly person and healthcare issues, surveillance, fall detection, etc. [1] [22]. Movements of the body such as falling[14] can be recognized by advanced technology [24]. In this regard, smartphone get lots of attention because of its easy accessibility. By using mobile phone accelerometers, it is possible to detect human body movement. But Data annotation is a big challenge in this field. In this context, several mobile apps are suggested for human activity recognition [18]. Researchers are also conscious of the necessity of real time applications for hospitals and nursing homes [20]. Our laboratory has developed a care record mobile application. It is an Android app. Before do care action, the nurse uses this app to record the type of care action and its details. We did experiment of activity recognition in nursing care center by using this mobile application [12][26].

The purpose of this study is to be easier the work of creating care records. In nursing facility center, it is essential to have patient activity data and care records data. Care records data have details information of patient daily activities. Each activity can have multiple care details. Care details record has various information for target patients. A care record can be either single choice, multiple choice, integer, number, short text, and long text. It helps to evaluate elderly peoples day to day health status as it contains details care information which they need regularly. Caregivers and doctors can evaluate health status by evaluating care record details. For that purpose, we aimed to automatically generate care records. By using our proposed system, the staff enters nursing care records and activity labels to the application on the smartphone. By using Wi-Fi router in the nursing facility center, the data from smartphone placed to the cloud server. Following this smartphone apps, we have collected different types of activity data from number of different patients. In this specific activity data there are different types of records under one activity. In our this work, we use machine learning classifier to estimate "target patient" and "detailed record" from the specific activity what they performed.

We evaluate the estimation of record using the collected data. Our evaluation result shows the average F1-score of "target patient" estimation is 74 %., and the average F1-score of "detailed record" estimation is 58 %.

We organize the paper as follows: Section 1 covers the introduction of the paper. In Section 2, we present some related works on nursing activity recognition and uses of mobile apps for activity data collection. Section 3 presents data review and explanation of care record app. In Section 4, we present the methodology of our entire work and details of how we can predict specific target patients. Section 5 present the evaluation we conducted for the problem setting. In Section 6, we present the discussion and motivation behind this work. Finally, we conclude the paper with some future work points in Section 7.

2 Background

Elderly people are increasing day by day [2]. The demand of working staff at the healthcare center/nursing center/nursing care center are also increasing to help and support elderly person good health. To use IoT (Internet of Things) applications is expected to improve the shortage of caregivers [17]. It has evident that technological support can reduce work load of staffs as well as can increase the frequency of care record [12]. In conventional way, nurse record patient information by using handwriting recording system. Mobile application in smartphone can play a vital role here to make the recording system automated. It helps to get large amount of annotated data from real world nursing care staffs.

In nursing facilities, it is essential to have patient activity data and care records data. Care records data have details information of patient daily activities such as amount of food intake, medical assistance details, bathing method and different assistance demands which they need from care staff. Care staff or doctor need these care records information of patient to monitor their health condition or predict the need of future assistance for a particular patient. Sometimes care record details are also important to evaluate the care quality too.

Ubiquitous computing communities have been working on the improvement of care recording system [19][4]. Hossain et al. proposed an activity recognition platform [11][10] which would be reliable and could be possible to incorporate to real life healthcare application for elderly people [16] [29]. The main challenges for this area is to get real world nursing facility data to evaluate the performance of the activity [15]. As well as it is simple to detect normal regular activity for example walk, run, stay etc [21] [6]. But the situation is different in real nursing facility where staff need to record data of everyday life support activity as well as details of those activity.

By taking this issue as a challenge we developed a care record mobile application, "GtoLog". GtoLog is an Android application. Here it is possible to enters nursing care records and activity labels to the application on the smartphone. GtoLog has a function that the staff member inputs the care record details during their work time.This application can make the care records and collect acceleration data during care activity with a smartphone. While the system relay all data to the cloud server (after the recording) it sends data with proper annotation. It is important to have proper annotated data for activity recognition system by using supervised machine learning. By using this system we can have the type of activity data and the details of each activity record. Also all recording are done based on the specific patient ID. For evaluating our work, we did two months experiment in a nursing care center Japan by using GtoLog [12] [26]. By using our system, it is possible to print out in a format similar to traditional care records in a paper. In addition, we also did activity recognition of care action by collecting acceleration during care activity with a smartphone.

As I wrote above, there is research to simplify the care recording process.The main approach is activity recognition or the development of new apps.However, we are aiming for automatic generation of future care records.So in this paper uses care record data from real nursing facility to estimate value of care records and evaluate the results.We believe this is important for the goal of automatic generation of care records.

3 Data Review

This chapter, we introduce the data used for evaluation. For the evaluation, we used care record data collected by the experiment [12]. In the experiment, 23 caregivers entered care records using GtoLog. This paper use data collected that experiment from May 1, 2018 to July 1, 2018.

3.1 Care Record Application

By using GtoLog care recording application, the nursing care records are recorded which contains the daily state of the patient in the nursing facility center. Figure 1 shows the architecture of our application. In the main screen, the left most column is the details of care activity. We listed these care activity based on the suggestions from the nursing facility center staff. The middle column of the main screen contains the care target person information. By pressing the right most column after selecting the activity class and target users we can record the start and end of the each activity. Detail record input screen contains details of each activity record value. It includes, the patient's dietary intake amount, vitals information, daily status, bathing status etc. as per recording. These care records are used for health management, reporting to family members, and improving services. It is important to create a care record. Care records should include records of care activities performed by care staff on behalf of the patient. In this paper, we use machine learning to estimate the following two things. First, we estimate which patient is the target of the caring behavior. Second, we estimate the details of care giving behavior.

Figure 2 is an image diagram that uses the estimation function of the nursing record app. In this paper assume a system that displays an input screen with the estimated value as the initial value. First, the caregiver enters the care action to perform. Next, the app estimates the patient that is the target of that care action. The results are displayed as a list of recommended care recipients. The caregiver selects the target patient. Then start nursing care. During care activities, the app estimates detailed records. And create an input screen using the estimated values as initial values. After the care activity is completed, the caregiver input details of the care action. Then, the caregiver only needs to edit the incorrect estimate. We believe that a nursing record app with such an estimation function will lead to more efficient nursing record creation work.

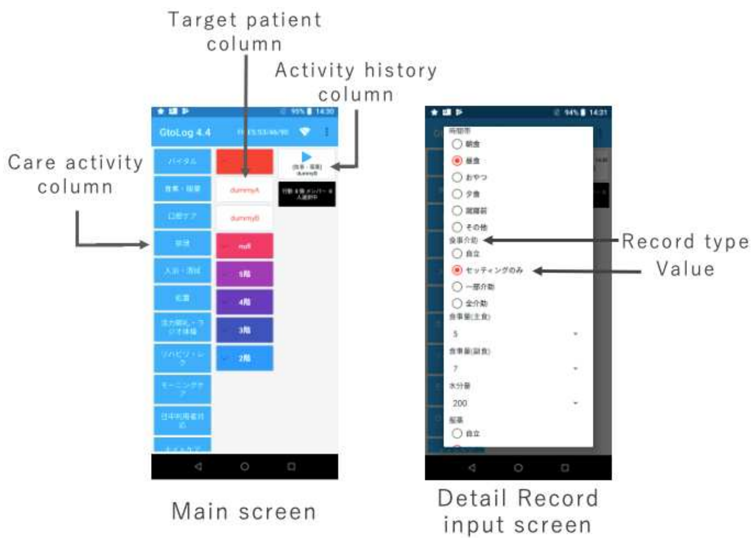

Fig. 1: Application screen of care record application GtoLog

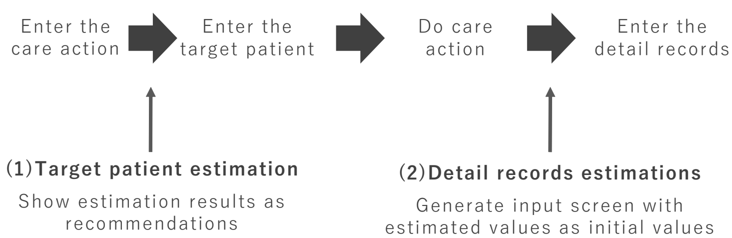

Fig. 2: Image of using the estimation system in the nursing record application

3.2 Data Overview

In this section, the structure of the care record data will be described. The data used this paper has 11 types of action class. It contains activity class of meal/medication, excretion, nighttime user support, daytime user support, morning greeting, bathing, support going out, treatment, oral care, meet family and visitor and changing assistance. Figure 3 illustrate the amount of data recording for each activity class.We can know that some classes have higher number of records than other classes.For example, meal/medication, excretion, nighttime user support, daytime user support have much higher records compare to other classes.We can understand the reason of this high record value of these classes is because of regular routine life.

Further, for each activity class, different types of care records are recorded. Under these care records,there are different values for each care record. The number of data of each detail record and its value summarized in figure 4.

For example, the "amount of meal eaten", "water intake", "dietary assistance" etc. Therefore, One care action has multiple detail records. Table 1 shows the correspondence between the detailed records and the values of the "meal / medicine" activity class. The caregiver enters the detail record in a selection format.

Here in this dataset, the total number of data is about 18,000 for the activity class and about 30,000 for the detail record. The amount of data in each action class and detail record summarized in Figure 3. From this figure, you can see that there is a bias in the number of data. You can also see that the there is a bias in values in the detail records. This is a data collected at a nursing facility. According to these figures, nursing record data collected at nursing facility is biased in behavior classes, detail records, and values. In this paper, the evaluation perform while paying attention to the bias in the number of data.

Table 1: Detailed records and values of the "Meal / Medicine" class

<table>
<tr><th>Activity class</th><th>Detail records</th><th>value</th></tr>
<tr><td rowspan="5">Meal / Medicine</td><td>Meal assistance</td><td>All support
Partial support
Setting only
self-reliance</td></tr>
<tr><td>Meal size(staple)</td><td>0, 1, 2 . . . , 10</td></tr>
<tr><td>Meal size(side meal)</td><td>0, 1, 2, . . . , 10</td></tr>
<tr><td>water intake</td><td>0, 50, 100, . . . , 500</td></tr>
<tr><td>medication</td><td>All support
self-reliance
Not taking medicine</td></tr>
</table>

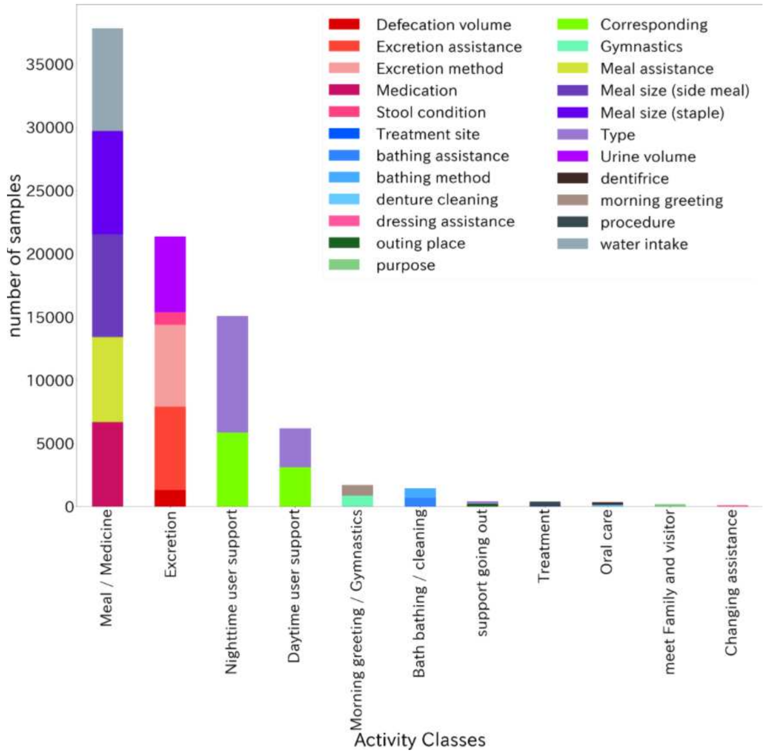

Fig. 3: Breakdown and number of data for each activity classes. The vertical axis is the number of data, and the horizontal axis is the activity classes. As shown in the legend, the color mean the type of each detailed record.

4 Method

In this chapter, we describe how to use care record data to estimate detailed records. From this care record data, firstly we choose specific activity class and predict target patient for that specific care action. Afterwards, we choose target patient and their care action and identify details record value of those care action for specific patient. To do this we use Random Forest classifier as a classification algorithm. Random Forest is a type of ensemble learning algorithm that uses decision trees as weak learning machines [5].

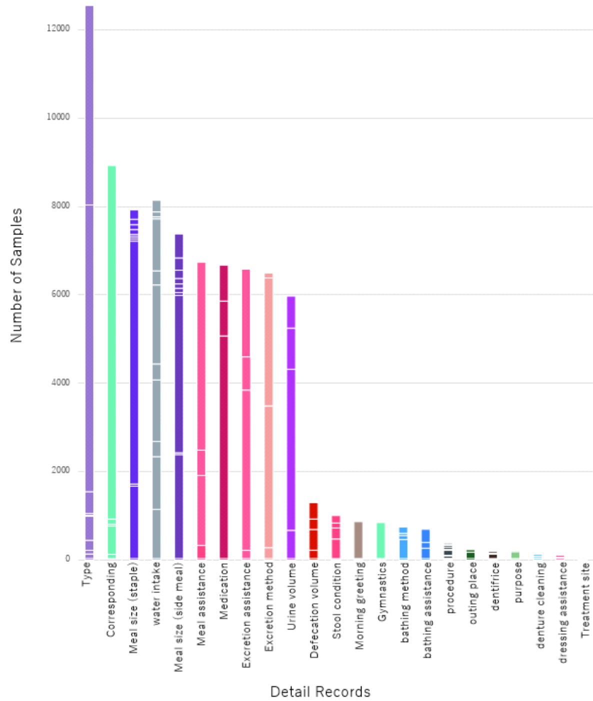

Fig. 4: The breakdown and number of data for each detail record. The vertical axis is the number of data and the horizontal axis is the detailed record. Each bar graph is separated by a white line. This white line mean difference the value of the detail record.

4.1 Predict Target Patient

In this section, we estimate the patient who are the target of the care record. We use the time, nurse, and type of activity class for the estimation. From this information, we create a machine learning model that estimates the patients who are the targets of that care record. However, some Activity classes, such as “meal / medication” and “excretion,” are often recorded for multiple patients by one nurse. Therefore, in this paper, we examined the problem of estimating the patient as a binary classification of whether the patient is included in the care record. Target variables are "included" or "not included" in the activity class. We estimate ’target patient’ for each activity.

We use time, nurse, and activity class as explanatory variables. This is because this paper assumes that the results will be used in a care records application. In The care record app, the patient is entered before entering the detail of records. For this reason, detailed records cannot be used as explanatory variables for caregiver estimates.

4.2 Predict Detail Records

In this section, we estimate the recorded value in the care records from past care records and type of that that activity class. This paper assumes that care record estimates are used on care record app.

The explanatory variable are the activity class, type of record, patient, nurse, times of day, previous recorded values of same type and patient, previous value of the “meal size(staple)" record of the “Meal / Medicine" class, previous value of the last “meal size(side meal)" record of the “Meal / Medicine" class, previous value of the "water intake" record of the “Meal / Medication" class, and previous value of the "Excretion" record of the "Excretion" class. The target variable is the recorded value in the care records.

5 Evaluation

In this chapter, we will evaluate the estimation methods described in section 4. This chapter has two sections that show the evaluation results for each estimation method. This paper uses care record data collected at the care facility, described in section 3 for evaluation. This data has a bias in the number of data. So we use accuracy rate and F1-score for evaluation [25]. F1 score is used to evaluate machine learning using biased data.

5.1 Evaluation of the Prediction of Target Patient

In this section, we estimate the ’target patient’ as described in the section 4.1. To predict ’target patient’, we evaluate the result of prediction accuracy, F1 Score, precision and recall in Fig. 5, Fig. 6, Fig. 7 and Fig. 8 respectively. These figures are accuracy, F1-score, precision, and recall for each activity class. We use random forest classifier to estimate whether the patient is included in the care record. The violin plot summarize the result of activity classes where more patient are included.

From Figure 6, it can be seen that there is a difference in the F1 value between patients. The overall average was 92% for average accuracy, 74% for average F1-score, 75% for average precision, and 74% for average recall. Looking at each activity class, the F1-score of the "Changing assistance" class is the highest at 94%. The lowest F1-score was 59% in the "excretion" class. This indicate that for the "Changing assistance" class it is easy to predict ’target patient’ from this activity class and it is difficult to predict ’target patient’ from "excretion" class.

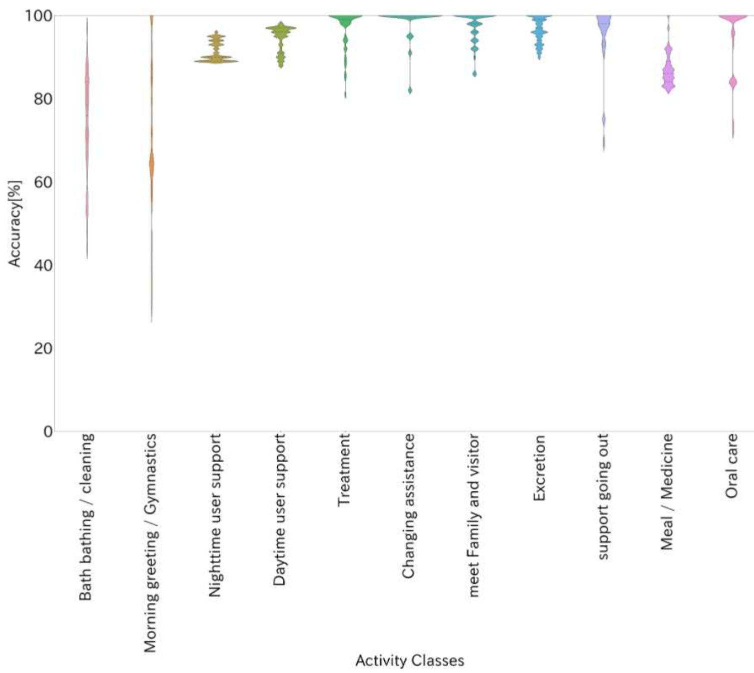

Fig. 5: Prediction accuracy when estimate target patient. Accuracy [%] in overlay and activity class on horizontal axis

5.2 Evaluation of Detailed Records

This section evaluates detailed estimates of care records described in the section 4.2. For details records estimation, we spited data and learning technique in three ways. We evaluate the result is this three approaches. In first approach, we choose data from multiple patients and we split data by period. In second approach, we choose data from multiple patients split data by period and patient. In third approach, we choose data from one patient split data by period. Then we classify the 'details records' for this three different approaches. The table 2 is the average accuracy and average F1 score for each learning method and split data method for learning and testing. In this paper, we evaluate the classification accuracy separately for these three different approaches.

In the first approach,we use data segmented by period for testing and training. The first 45 days of data were used for training, and the next 15 days of data were used for testing.

In the second approach,we use data segmented by patient for testing and training. Data from 45 patients for the first 45 days was used for training, and data from the other 17 patients for the next 15 days were used for testing. The first and second approach used data from multiple patients. In the third approach,we use data from

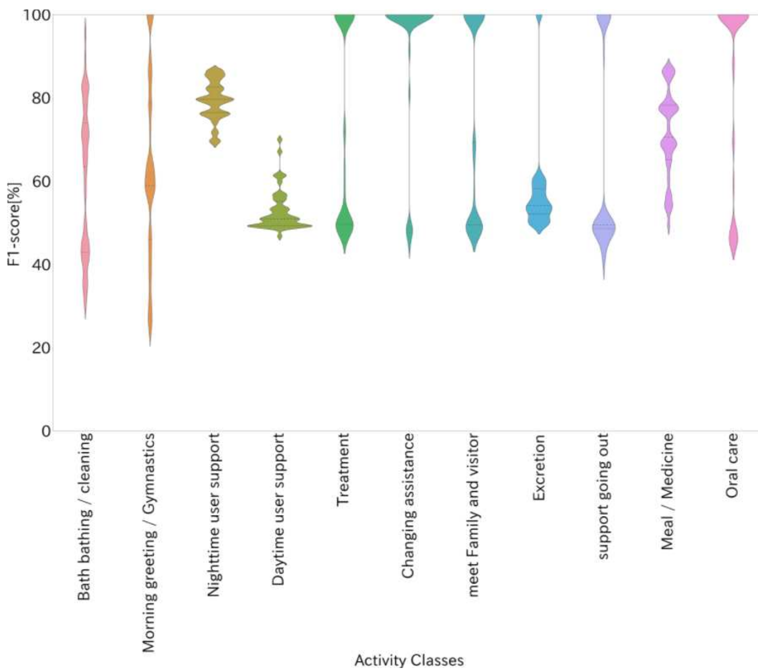

Fig. 6: F1-score when estimate target patient, F1-score [%] in overlay and activity class on horizontal axis

one patient. Also, data from one patient for the first 45 days was used for training, and data from the same patient for the next 15 days was used for testing. Result of each approaches has described in Fig. 9, Fig. 10 and Fig. 11.

Figure. 9 shows the results of the first approach (the data for the first 45 days were used for training and the data for the next 15 days were used for testing).This figure shows accuracy and F1-score for each detail record. The average accuracy is 70% and the average F1-score was 42%. In the "morning greetings" record, both accuracy and F1-score were 100%. The "morning greeting" record has a value of either participation or non-participation. But, no test data had a value of "do not participate". We attribute this to the reason that the "morning greetings" record had an F1-score of 100%. Excluding the "morning greeting" record, the next highest F1-score is 86% of the "excretion method" record. Conversely, the lowest F1-score is 8% of the "treatment site" record.

Next, the figure 10 shows the results of the second approach (data from 45 patients for the first 45 days was used for training, and the other 17 for the next 15 days for testing). This data shows the accuracy and F1 score of each detail record. The average accuracy was 62% and the average F1-score was 22%. The highest F1-score and accuracy is 100% (same as previous approach) for the "morning greeting" record. The lowest F1-score was 0% for both the "treatment site" record and the

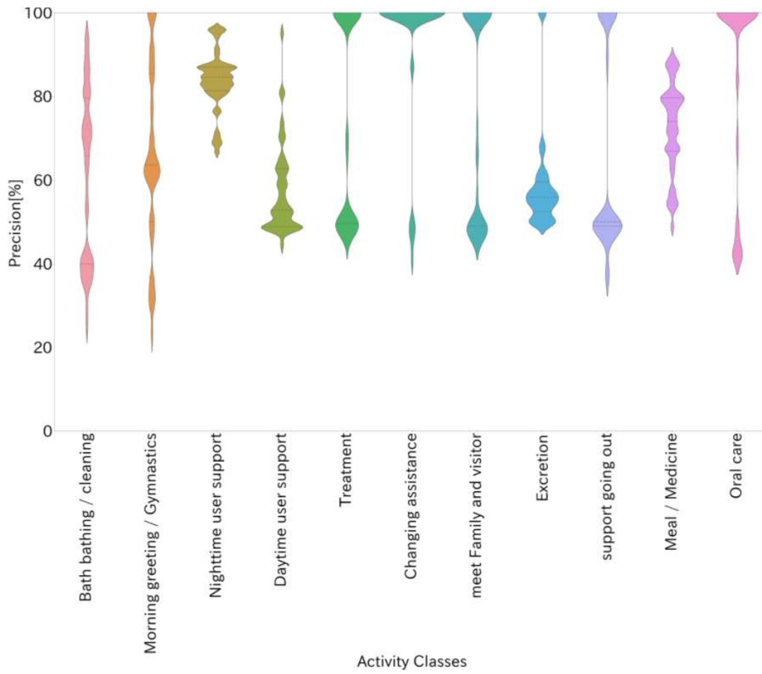

Fig. 7: Precision when estimate patient, Precision [%] for overlay, activity class on horizontal axis

"dental cleaning" record. We think that this reason is that the test data did not have any value of "no execution" for both "treatment site" and "dental cleaning" record. But the value "no execution" often found in the training data.

Finally, the figure 11 shows the results of the third approach (data from one patient for the first 45 days was used for training, and data from the same patient for the next 15 days was used for testing). This figure shows the accuracy and F1-score of each detail record. The average accuracy was 62% and the average F1-score was 58%. Classifier perform higher average F1-score for single patient data than multiple patient data. It is 58% average F1-score for single patient data but 42 and 22% for multiple patient data. In this case, the highest F1-score is 95% for the "morning greeting" record, and the second was 90% for the "gymnastic" record. The lowest F1-score is 7% of the "treatment site" record.

6 Discussion

In this section, we discuss the results described in section 5.

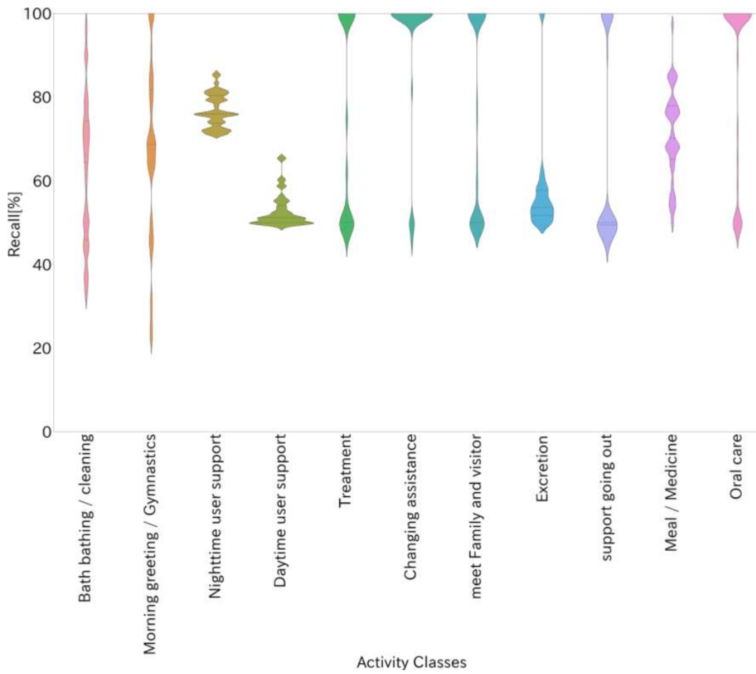

Fig. 8: Recall when estimate patient, recall [%] for overlay, activity class on horizontal axis

Table 2: The average accuracy and average F1-score for each learning method and method for split data for learning and testing.

Method of learning	Method of split data for learning and testing	Average accuracy	Average F1-score
Data from multiple patients	split data by period	79	42
Data from multiple patients	split data by period and patient	62	22
Data from one patient	split data by period	75	58

In the target patient estimation result, F1-score of The "Support going out" class, the "Changing assistance" class, and the "oral care" class are biased to high or low. By visualizing test data, we found that some patients did not have some activity data ("Changing assistance" class, "oral care" class, etc.) in the test data. Therefore, some result each activity classes include patients with 100% accuracy, F1-score, precision, and recall. The average F1-score was 64%, excluding activity data that did not do include that patient. We found that the F1-score is different depending on patient. This is because some patients have a bias in the target value of the test data as described above.

The average recall is 74%. In patient estimation, recall is the ratio of how accurate the estimate is in the care activity for that patient. In other words, it is the ratio of

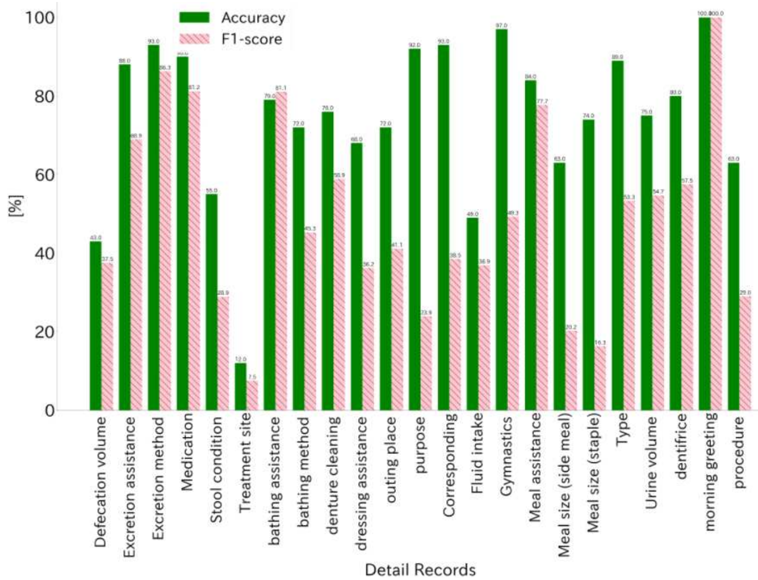

Fig. 9: Split data by period for testing and learning: The first 45 day's data was used for learning, Next 15 day's data was used for testing.In the figure, average the accuracy and F1score.The vertical axis is accuracy and F1- score [%], and the horizontal axis is detaile records.

how much was not missed. In the care record application, the estimation result of the patient is displayed at the top of the input options. Therefore, if there are many missed items, the care staff will have to search for the input buttons of the missed patients more frequently. So in patient estimation, it is most important not to miss. The average recall is 74%, so we believe that using this estimate in a nursing records app can streamline record entry.

Next, we discuss detail record value estimation. The average accuracy is 70% and the average F1-score was 42%. Detail record value estimation found that classifier perform higher average F1-score for single patient data than multiple patient data.

In particular, the gymnastics F1-score improved mostly with single patient data which improve from 49% (multiple patient data) to 88% (single patient data). In addition, the "Corresponding" record, the "meal size (staple)" record, and the "meal size (side meal)" record improved the F1-score by more than 15%. We attribute this to the fact that many patients take only the same value each time. The average highest F1-score is 58%, so we believe that using this estimate in a nursing records app can streamline record entry.

In addition, I think there are two ways to improve F1-score. The first is to use acceleration data. In this paper, we did not use acceleration data to separate task of estimation of the care records and task of activity recognition. However, for example, the acceleration of "Excretion assistance activity" is very difference on whether it

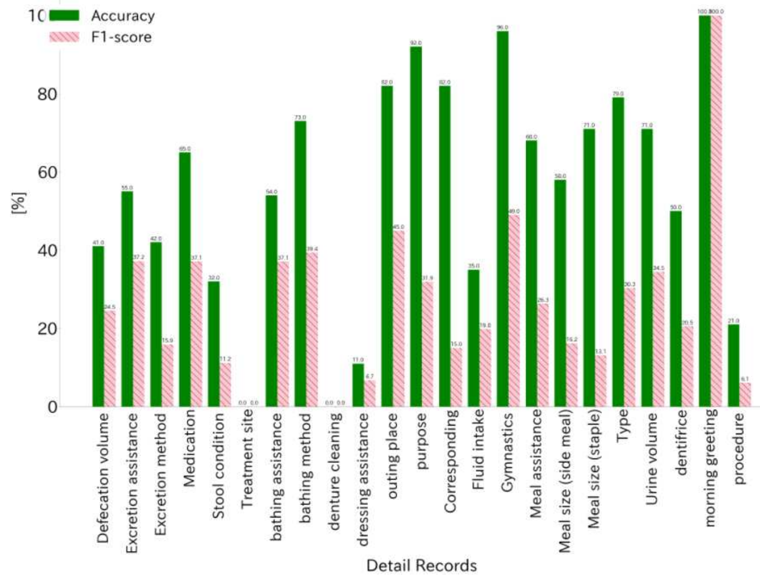

Fig. 10: Split data by patient for testing and learning: The first 45 days 45 patient's data was used for learning, Next 15 day 17 patient's data was used for testing.In the figure, average the accuracy and F1score.The vertical axis is accuracy and F1- score [%], and the horizontal axis is detaile records.

is "all support" or "partial support". In other words, we can use this acceleration to improve the F1-score of the machine learning model in this paper. The second is to increase the number of data. In this paper, the model with data from one patient is higher F1-score than model with data from multiple patients. But, We believe that increasing the number of data will change this result, and it will be higher F1-score to model with all patients data.

Finally, we discuss whether the F1-score of the estimated model in this paper is enough for nurses. It is essential to create a care recording app that uses the estimation model created in this paper. Without this, it is difficult to judge whether these F1-score of this estimated model is enough for nurses. However, We found some new knowledge in this paper. For example, it is possible to estimate detail of care records using care records data, how to create a model with a higher F1-score, and the bias of the data in care records. These knowledge are important for the automatic generation of care records and are the meaning of this paper.

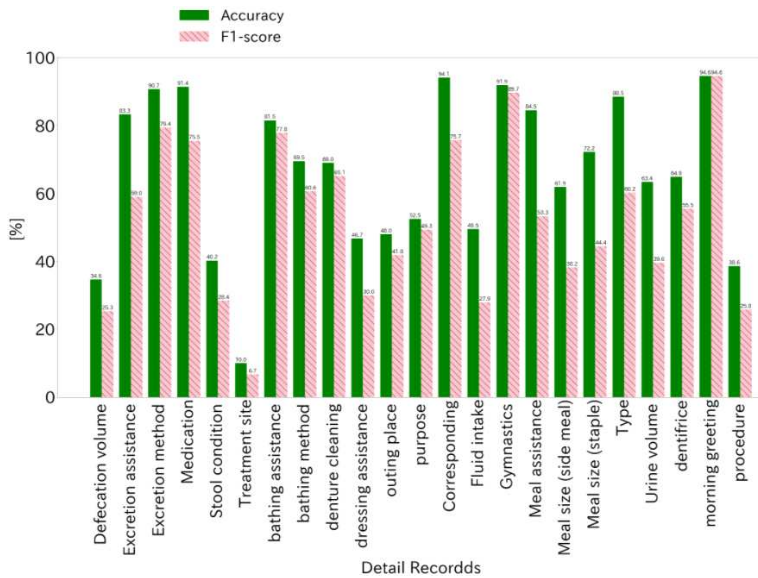

Fig. 11: Learn with data from one patient: The first 45 day's data was used for learning, Next 15 day's data was used for testing.The contents of the detail record for each patient were estimated as learning. In the figure, average the accuracy and F1score. The vertical axis is accuracy and F1-score [%], and the horizontal axis is detailed records.

7 Conclusion

In this paper, we aimed to automatically generate care records. For this purpose, machine learning was used to estimate the detailed records of the target patient and care records. We used Random Forest classifier for machine learning to estimate "target patient" and "detail record". In addition, we evaluated the estimation results using nursing record data collected at nursing facilities. The average F1-score of "target patient" estimation is 74% and the average recall of "target patient" estimation is 74%. "Detail record" estimation found that classifier performed with data from a single patient had average higher F1-score which is 58% than classifiers created with data from multiple patients.

We believe that using this estimation in a nursing records app will make entering records easier than with traditional recording apps. In this paper, "target patient" and "detail record" estimates were made to be a new feature in care applications. Therefore, it will be added to the function of the nursing record application "Gtolog" in the future. We always need to make sure that the estimated time does not interfere with the caregiver's job. In addition, in future we will consider UI (user interface) that makes entering care records the easiest.

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