Abstract
Currently, the shortage of care workers for the elderly has become a big problem, and more streamlined care operations are needed. In care facilities, care workers are required to use their subjective experience to detect anomalies in physical condition of care receivers, including serious or insignificant deterioration or behavioral and psychological symptoms of dementia, which can decrease the work efficiency. Therefore, we aim to create a model using objective data for detecting anomalies in physical condition. In this study, data from 13 subjects in a care facility were collected, and isolation forest models were constructed for each subject. The subject’s anomalies in physical condition were documented in a care record by a nurse and used as reference for model evaluation. Recall and specificity were used to evaluate the model, expressed as the percentage of detection success for abnormal or normal conditions. Data collected for 1 to 60 days were used to train the isolation models, and the relationship between the amount of training data and model performance was simulated. Heart rate, respiratory rate, and time of getting out of bed were collected from a sensor placed on the subject’s bed and used as the model features. In addition, dietary intake information was collected from the care record. Analysis of the evaluation results showed recall and specificity of 45.6 ± 46.7% and 83.88 ± 6.06%, respectively, for the model constructed using training data of 60 days. For future studies, we will continue to collect data and increase the number of participants to improve the robustness and accuracy of the proposed anomaly detection system.

Keywords: anomaly detection, care facility, IoT.

1. Introduction
Currently, the shortage of care workers for the elderly has emerged as a big problem; thus, more streamlined care operations are necessary. In care facilities, workers are required to detect anomalies in physical condition of residents, including serious or insignificant deterioration or behavioral and psychological symptoms of dementia (BPSD), based on their own subjective experience or through self-reporting by the persons being cared. However, as elderly people in care facilities are frequently affected by dementia, they may find it difficult to self-report their physical condition. In addition, subjective judgement mainly using visual information may cause variability between caregivers, leading to decreased work efficiency. Therefore, a quantitative and objective judgement system can be an effective solution for streamlining care operations and shortage of care workers.

In previous studies, Internet-of-Things (IoT) or multiple sensors have been used to collect data on daily activities or risk of deterioration [1–8]. In these studies, various kinds of sensors were used and the usefulness of the collected data for monitoring changes of daily activities or detecting risk for elderly peoples were demonstrated [7]. For example, the study that collected data of daily TV use by an elderly woman for 10 years suggested a trend of correlation between television usage and social activities [8]. Meanwhile, some researchers used wearable sensors to estimate lower limb muscle strength [9] or evaluated the extent of frailty [10]. In addition, models for detecting danger pose [11] and anomalies of health data [12] were constructed in previous studies.

However, care facilities may find it difficult to intro-
duc multiple sensor systems, wearable sensors, or video cameras for long durations in the operation system. Multiple sensor systems entail high costs, and complex data gathering system can be a burden for care facilities. Wearable sensors may carry a risk of accidental ingestion or breakage for dementia patients, and video cameras may cause privacy problems. Therefore, we decided to use a single sensor placed in the bed, which does not require wearing or video data.

In addition, several models constructed in previous studies tried to detect whether subjects have illness by comparing the values collected in two periods [5, 10]. However, for facility use, a daily anomaly detection system that alerts abnormal condition for each day and for each subject is needed. Therefore, we conducted a four-month demonstration experiment in a real-world care facility and try to output whether the subject were in abnormal or normal condition every day. Then, the accuracy of the anomaly detection model was evaluated from the output result for every subject.

In our study, we constructed an anomaly detection model to detect change in condition for each day, using a single pressure sensor to be used in bed. The pressure sensor can collect the heart rate, respiratory rate, and the status of whether the subject was in bed or out of bed. Then, using the collected data, we constructed an isolation forest model [13] that can detect any change in the subject’s physical condition. Throughout the experiment, the model was updated with gathered data three times. Changes in physical condition were recorded by a facility nurse and used as the correct answers for accuracy evaluation.

Further, to analyze the relation between the amount of training data and accuracy, we constructed several simulation models with training data of different numbers of days (1, 3, 5, 7, 14, 30, and 60 days), and the accuracy was calculated.

The paper is structured as follows. In Section 2, we describe the participant groups, sensor, and method for processing the sensor signals as features. In Section 3.1, we present the evaluation of the accuracy of the proposed model in a facility environment. In Section 3.2, the results of the simulation model are presented, and the result of analysis of the relation between the amount of training data and accuracy is shown. Section 4 presents the discussion, and Section 5 states the conclusions.

2. Methods

2.1 Subjects and sensors

A total of 31 residents in an elderly care facility were recruited. Data from 13 subjects (aged 90.23 ± 4.82 years, 12 were female and 1 was male) whose changes in physical condition were recorded by the facility nurse were used in model evaluation. All subjects were affected by dementia, and two subjects had a history of stroke. This study was conducted in accordance with the ethical principles of the Helsinki Declaration. This study was approved by the Panasonic Healthcare Ethical Review Board. Informed consent was obtained from the subjects before the monitoring was started.

A pressure sensor (SleepAce RestOn Z400T, Shenzhen Medica Technology Development Co.) was placed on each bed to gather biological data when the subject was in bed. The collected data included the heart rate, respiratory rate, and whether the subject was in bed or out of bed.

2.2 Features and models for anomaly detection

Figure 1 shows the features calculated from the sensor data and from the care record. We used both sensor- and care record-related features. The features and models were processed for each subject individually. First, the heart rate and respiratory rate data and in or out of bed data were collected by the sensor at 1 Hz. Then, using the in or out of bed data, the absence time per hour was calculated. If the absence time was less than 10 min/h, the heart rate and respiratory rate features were processed from the corresponding 1-hour data. If the absence time was over 10 min/h, the 1-hour data was excluded. The absence time was also used as a feature.

Using the heart rate and respiratory rate data, the mean, maximum, minimum, standard deviation, kurtosis, skewness, and impulse factor were calculated as features. In addition, the differential value of sensor-based collected data was calculated for both heart rate and respiratory rate. Using differential value data, mean, maximum, minimum, standard deviation, kurtosis, skewness, and impulse factor were calculated as difference value-based features.

Dietary intake for each meal was recorded by a nurse or care staff using a scale of 1 to 10. The summary value of dietary intake for 1 day was used as a feature and was up sampled to 1-hour data. Recording of dietary intake is
one of the daily works in this facility. Therefore, the assessment method was shared between care workers and nurses.

The processed features were accumulated in a database and used as training data to construct an isolation forest model. The model can calculate anomaly scores for each hour even without correct labels.

**Figure 2** shows the method for calculating a 5-level anomaly score, which is the final output of our anomaly detection system. The features from the sensor or care record were first input into the constructed model, and the mean anomaly score for one day was calculated. Then, the moving average of 3-day value was processed. Moving average values were accumulated and used to calculate thresholds for scaled score, calculated using the amount of statistics as follows: average, average-0.5 sd, average-sd, and average-2 sd. Finally, the 5-level scaled scores were used as the output of our system. In our system, a score of 4 or 5 indicated an anomaly.

### 2.3 Verification test in a care facility

We started to collect sensor data in the facility from October 2020, and the anomaly detection system was in operation from January to April 2021. Initially, the anomaly detection model was trained with data collected from all the subjects from October 2020. From January 18, an individually trained model for each subject was introduced. The isolation forest model was updated on February 16 and March 10 using the collected features as training data. The nursing staff in the care facility performed verification by recording whether the subject’s physical condition was captured by the 5-level scaled score. Using the nursing record as reference, the recall and specificity of the individual models (starting from January 18) were evaluated. Recall and specificity were calculated from the number of cases of detected or recorded normal/abnormal conditions of participants, such as TP/TN/FP/FN shown in **Table 1**. Recall and specificity were shown in (1) and (2).

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\text{Recall} = \frac{TP}{TP + FN} \\
\text{Specificity} = \frac{TN}{FP + TN}
\]

### 2.4 Simulation test with changing amount of training data

In the facility test, we updated the isolation forest model three times using the collected features. In addition, IoT sensors were placed in the subjects’ rooms gradually, and the amount of collected data and training data for facility test models were different among subjects. Thus, the accuracy of the facility test can be affected by changes in the model and the amount of training data. For example, if the amount of training data was too small, data distribution became sparse, causing decreased accuracy. On the other hand, if the amount of training data was too large, masking of abnormal data may occur, and detection ability will decrease. To verify the relation between the amount of training data and model performance, we constructed seven simulation models using the data collected from the facility test. For the simulation test, data from January to April were used for training and testing. Features collected for 1, 3, 5, 7, 14, 30, and 60 days were used as training data, and then the recall and specificity were calculated as evaluation indices for each model.

**Table 1** Definition of types of reported or outputted result from nurses or the models constructed.

| participant’s condition reported by nurse | output result from constructed model |
|------------------------------------------|-------------------------------------|
| TP                                      | detected abnormal condition         |
| FP                                      | detected normal condition           |
| FN                                      |                                     |
| TN                                      |                                     |
3. Results

3.1 Model performance in the facility test
The recall and specificity in the facility test were 66.03 (± 46.46) and 80.44 (± 12.20), respectively. The values were calculated from the care record reported by nurses and 5-level scaled score, which was used from January 18, 2021 to April 14, 2021. Recall and specificity represent the detection abilities for abnormal and normal conditions, respectively. During the facility test period, the isolation forest model was updated three times: February 15, March 8, and April 14. In the facility model, the standard deviation of recall is larger than that of specificity, which indicates that the detection of physical anomaly had individual differences among subjects.

Figure 3 shows the time series variation of a subject affected by aspiration pneumonitis and success of the system to detect the change in condition. From February 19 to 20, anomaly scores could not be calculated because of sensor error. The subject had serious accidental swallowing on February 20. She developed fever after the incident, and was admitted to hospital on February 24 with aspiration pneumonitis. Her body temperature or scaled anomaly score was normal before the accident occurred. Before the swallowing accident, the scaled anomaly score continued to show level 1 or 2 indicating normal condition. Then, after the accident, scaled score increased to level 5, which indicated large physical anomaly from the time aspiration occurred to before being admitted to the hospital, and coincided with the declining condition of the subject. In this case, drastic change of subject’s condition was detected by our model.

3.2 Relation between amount of training data and accuracy

Figure 4 shows the relation between the amount of training data and detection ability of a simulated model for anomaly or normal condition. The value of recall or specificity in Fig. 4 is the mean value of model evaluation index for each subject. When recall and specificity of the 1-day model were compared with those of other models by Dunnett’s test, p values showed no significant difference between models. In Fig. 4(a), when data of 60 days were used for training, the recall obtained was 45.56% (± 46.67). On the other hand, as seen in Fig. 4(b), specificity increased with an increase in amount of train-
ing data. The highest mean specificity was observed in the model that used training data of 60 days, with a value of 83.88% (± 6.06).

4. Discussion

In our research, we validated the efficacy of the anomaly detection model using an IoT sensor, which was used for collecting data and updating models in the facility test. Sensors were introduced gradually from October 2020, and the facility testing operation was started in January 2021. The test system was updated three times during the testing period.

During the facility test, the anomaly detection models changed with each update, which can affect the accuracy. Therefore, to evaluate the relation between model accuracy and amount of training data, we constructed models using training data of different durations collected during the facility test and calculated recall and specificity as indices of the detection ability for abnormal or normal condition. The mean values of recall and specificity of the facility test system were calculated as 66.03% (± 46.46) and 80.44% (± 12.20), respectively, and the recall and specificity in the simulation test using data of 60 days for training were 45.56% (± 46.67) and 83.88% (± 6.06), respectively. In care facilities, body temperature is commonly used to detect changes in condition including infections. From the guideline for long-term care facilities developed by the infectious diseases society of America, the recall of detecting infections for elderly people in care facility was 70% [14]. Therefore, success detection rate of 70% may be one of the goal of accuracy for condition detecting system. In our system, there were individual difference in accuracy, especially recall in 60-day simulation models. Models for some subjects in the facility test or the simulation test were able to detect changes in condition with 100% recall or specificity, but some models from other subjects did not fulfill our goal of 70%. These differences in accuracy may be caused by the difference in the type of anomaly or attribution of participants. In future study, we will try to classify the type of change in condition and evaluate accuracy in various types of anomaly. In addition, in dementia patients, the type or severity of dementia may affect sleep behavior or night-time emotional behavior [15, 16]. In our anomaly detection system, sensors were installed on the bed. Therefore the change of sleep behavior or BPSD at night could change the trend of features in sensor data, and it might affect accuracy. We will analyze the relation of system accuracy with subject attributions that include sex, age, motor function, ADL, history of anamnesis, and severity of dementia.

The recall values were different between the facility test and simulation test. In addition, standard deviation was large in both tests, which indicated that the models constructed had different abilities in detecting abnormal condition in different subjects. Because the facility test and simulation models used data from October 2020 and January 2021, respectively, for training, the difference in the data collection periods may affect the recall value. In addition, although there were only a few cases of anomalies in physical condition, recall may be easily affected by even a small change in the model. Therefore, to evaluate recall, which represents the ability to detect an abnormal condition, a larger number of subjects with anomaly conditions are required. For future study, we will continue to collect sensor data in the same facility to evaluate the recall value accurately. Specificity increased to nearly 80% in both facility and simulation tests, and standard deviation was smaller than that of recall. Therefore, the system we developed was able to detect normal condition for each subject.

As shown in Fig. 4(a), recall and specificity did not change significantly among the various models. This result indicates that masking of data with anomaly, which is often caused by large amount of training data in isolation forest, is not a problem in the system we have developed. Therefore, longer training data might be needed to improve accuracy significantly. To improve our model, we are now collecting longer data for future study.

While the system was being tested in the facility, one subject was affected by aspiration pneumonitis and the model constructed was successful in detecting the change in condition. Subsequently, the scaled score continued to indicate an abnormal condition before the subject was admitted to the hospital. Therefore, it is evident that the scaled score output from the system accurately reflected the physical condition of the subject. Similar to this case, severe outcomes may be averted if the anomaly detection system can detect subjects with abnormal condition and alert the care staff or detect diseases in an early phase. In the future, we will continue to collect sensor and care record data in facility operations and confirm if our anomaly detection system contributes to improving the efficiency of care operations.

5. Conclusion

In this study, we constructed an anomaly detection model to detect changes in physical condition of care receivers using an IoT sensor, aiming to improve the efficiency of care operations. Using the system developed, a facility operation test was conducted for 4 months. We obtained recall of 66.03% (± 46.46) and specificity of 80.44% (± 12.20). In addition, our anomaly detection system succeeded in detecting the abnormal condition of a subject affected by aspiration pneumonitis. The novel system was able to warn about the change in the subject’s physi-
cal condition to the facility care staff with quantitative data.

In addition, simulation tests using training data of different durations were conducted. The recall and specificity of the simulation model using training data of 60 days were 45.56% (± 46.67) and 83.88% (± 6.06), respectively. There were no significant decreases in accuracy between models, which showed that there was no masking problem caused by excessive training data. In order to improve model, collection of more training data is needed for next study.

Owing to the availability of few records on abnormal condition of participants, more cases are required to accurately evaluate the ability of our system to detect abnormal conditions. On the other hand, in both the facility and simulation tests, the difference in specificity between subjects was small, which shows the stability of the system in detecting normal conditions. For future studies, we will continue to collect data and increase the number of participants to improve the robustness and accuracy of the proposed anomaly detection system.

Conflicts of interests

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