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Personalized Context-Aware System for Chronic Low Back Pain

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만성 요통에 대한 맞춤형 상황 인지 시스템

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Treatment and management of chronic low back pain (CLBP) should be tailored to the patient's individual context. However, there are limited resources available in which to find and manage the causes and mechanisms for each patient. In this study, we designed and developed a personalized context awareness system that uses machine learning techniques to understand the relationship between a patient's lower back pain and the surrounding environment. A pilot study was conducted to verify the context awareness model. The performance of the lower back pain prediction model was successful enough to be practically usable. It was possible to use the information from the model to understand how the variables influence the occurrence of lower back pain.

Keywords : Chronic Low Back Pain, Context-Aware Model, Personalized Healthcare, Machine Learning, Mobile Health

1. Introduction

Relief of pain is the goal in the management and treatment of chronic lower back pain (CLBP). About 80% of the population suffers LBP, and these numbers are constantly increasing [1, 7, 10, 15]. After an initial episode, 44 to 78% of LBP patients experience reoccurrence, and 5 to 7% of those progress to CLBP [1, 7, 10, 15]. There are variety of approaches for the management and treatment of CLBP, such as exercise therapy, manual therapy, physical therapy, medication or pharmacological treatment, and education [1, 2, 10].

Treatment and management of CLBP should be tailored to the patient's individual characteristics. Specific causes of LBP are identified in only 15% of patients or less [1, 2, 10]. In addition, the causes of LBP vary according to disease, work, age, and gender of the patient [1,4,10]. For this reason, clear advice and management are required depending on the specific characteristics of the patient. This tailored treatment and management has shown an improved outcome in various studies [5,6,13].

However, there are limited resources available in which to find and manage the causes and mechanisms for each patient. In primary care, the patient's face-to-face time is about 15 minutes, which is often not sufficient to obtain proper understanding of the patient. In addition, various clinical evaluations are being performed within these 15 minutes. For this reason, previous studies have shown that patient-centered, targeted, multi-dimensional, behavioral approaches, called 'classification-based cognitive functional therapies,' are more effective than conventional manual therapy. In addition, these studies state that it is necessary to analyze and interpret behaviors that are highly correlated with pain and to develop techniques that can effectively communicate impairments and pain behavior.

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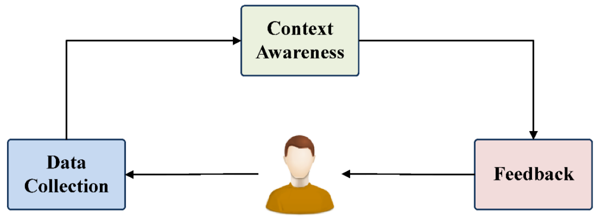
In this study, we try to solve this problem by developing a personalized context-awareness model to understand pain in individual situations and use it as a tool. This model provides feedback and information according to the patient's situation to help the patient manage the pain and make information available for help with treatment and diagnosis. The model can help the patient avoid LBP and understand the relationship between their current situation and back pain. This understanding will be helpful when the patient visits the hospital for diagnosis or treatment. In addition, by continuing to learn about how the pain evolves depending on the patient's changing situation, it is possible to be flexible in how to handle LBP management.

The purpose of this study was to verify whether the personalized context-awareness model for CLBP, as generated by machine learning techniques, has a significant effect on CLBP patient pain management. We designed and developed a personalized context-awareness system that determines the relationship between the patient's pain and her/his context. The system collects patient data, recognizes the context through machine learning techniques, and then provides feedback to the patient. We tested the performance of this model through a pilot study. The results showed that it was possible to control a CLBP patient's pain management through the personalized context awareness model.

2. Materials and Methods

The purpose of the context-awareness warning system is to reduce the pain experienced by CLBP patients in daily life. For this purpose, the system recognizes the situation surrounding the CLBP patient and warns patients who are in circumstances that can cause pain so the condition can be avoided. It also helps to reduce pain by adjusting the patient's own situation by visualizing the patient's low back pain pattern.

An overview of the proposed context-aware system is illustrated in <Figure 1> It is divided into 3 main steps: (i) data collection; (ii) context awareness; and (iii) feedback. By collecting data about the patient, recognizing the situation, and providing feedback, the system can help patients to use this information to adjust their circumstances appropriately or improve their behavior. The results are then captured by the model's cyclical structure to provide iterative feedback on the improved situation.



<Figure 1> Design Conception for the Context-Aware System

2.1 Data Collection

2.1.1 Factors Used for the Personalized Context-Aware System (PCAS)

In order to provide feedback through context awareness, gathering the patient's situational information is essential. In this study, we used the International Classification of Functioning, Disability, and Health (ICF), which is useful for recording a profile of an individual's performance of function, disability, and health. According to the ICF, individual performance and disability are described through the dynamic interaction of health conditions and contextual (environmental and personal) factors. These can be divided into (a) health condition factors, (b) personal factors, and (c) environmental factors. Applying these factors to CLBP leads to the following three sets of data: (a) condition of low back pain; (b) patient actions; and (c) patient environment.

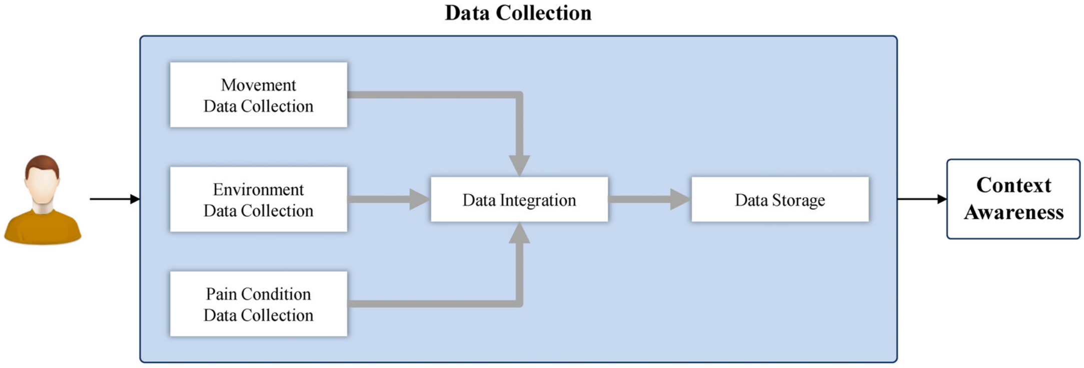
The first factor, health of the CLBP patient, can be used as a measure for lower back pain, such as pain intensity [9]. In this study, we asked the patients to record their level of lower back pain as a presence or absence of pain.

The second factor, patient actions, can include the time a patient spent sitting as well as overall physical inactivity [8], mobility [11], standing balance, physical load [12], and time in a neutral spine position [14]. In this study, we designed and developed a wearable belt with an acceleration sensor to measure the movement of the patient.

The third factor, patient environment, includes actions such as vehicle transfers, activity level, and work environment, all of which may affect the patient's movements. In this study, the environment was defined as space and action. The patients used a smart phone to input their current space and actions.

2.1.2 Data Collection Process

The data collection process is shown in <Figure 2>. Movement, environment, and pain condition data were col-



<Figure 2> Data Collection Process

lected from the patient's wearable device or smart phone, integrated, and stored.

2.2 Context Awareness

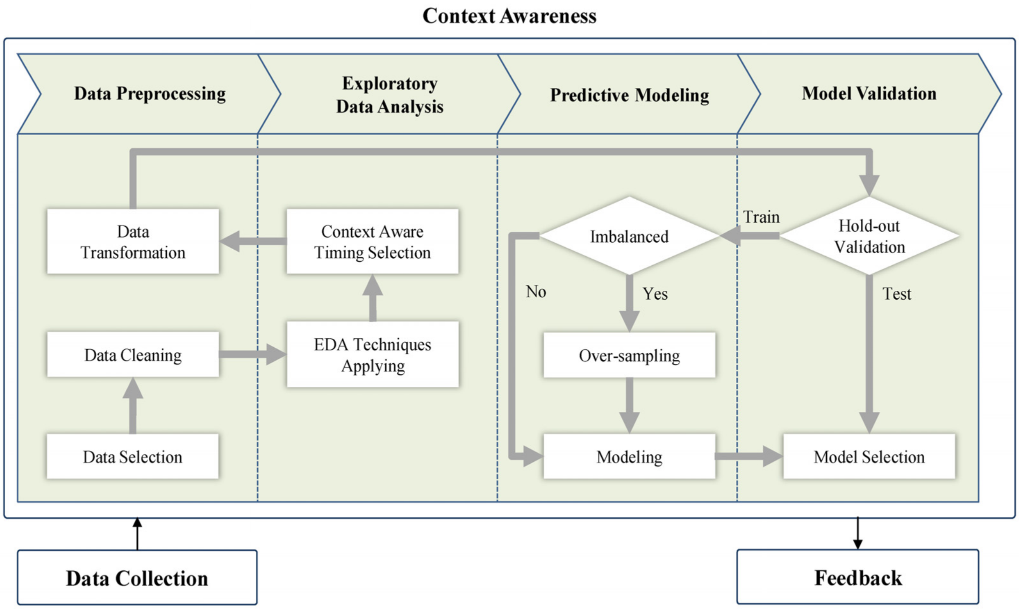
2.2.1 Machine Learning Techniques for Context Awareness Modeling

In order to understand the relationship between the patient's situation and lower back pain, a context awareness modeling process is needed. In this process, a machine learning technique is utilized. If the model can determine the relationship between lower back pain and the patient's situation, it can be used to predict the future state of the patient's lower back pain and be used as a predictive model. In addition, the model can be used to help understand the mechanisms of the patient's current lower back pain.

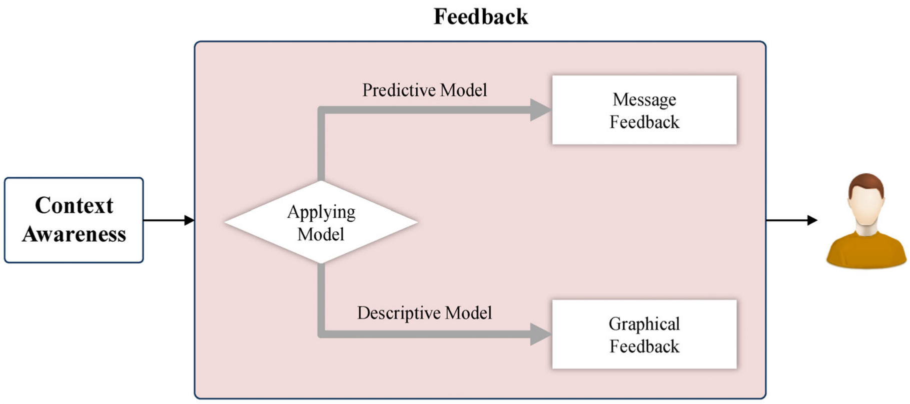
Based on the patient's movement and environmental data, the relationship with the pain condition corresponds to supervised learning. We used classification analysis for our context awareness modeling since it is an appropriate way to explain the relationships between target variables and explanatory variables. Classification analysis is performed using decision trees, the Bayes classification method, rule-based classification methods, or ensemble methods. In this study, we used the rule-based classification method and the ensemble method.

2.2.2 Context awareness Process

The context awareness process is illustrated in <Figure 3>. The patient's movement, environment, and pain condition data are used to generate a context awareness model. The collected information is transformed through data preprocess-



<Figure 3> Context Awareness Process



<Figure 4> Feedback Process

ing and exploratory data analysis (EDA) into a form suitable for modeling. First, the information is processed to remove missing values and noise. Cleaned data is then evaluated using an EDA technique to perform graphical and numerical summaries to understand the patients. At this point, the prediction time refers to a specific time in the future based on the context of the current patient's situation. For example, if the predicted time is 5 minutes, the model is predicting the pain the patient will experience after 5 minutes based on the current situation. After setting the prediction time, we construct the dataset to be used accordingly. The dataset is split into training data, to generate the model, and test data, to validate the model using hold-out validation. If the training data is imbalanced, an over-sampling technique such as Synthetic Minority Over-sampling Technique (SMOTE) is used to solve the problem. Models derived using training data are validated with test data, and the model with the highest performance is selected for further analysis. Further details have been given by [16].

2.3 Feedback

2.3.1 Feedback Appropriate for Chronic Low Back Pain Patient

In order to apply the context awareness model to patients, it is necessary to incorporate appropriate feedback in the model. The context awareness model is divided into a predictive model and a descriptive model. Since each model has different characteristics, different feedback methods are required

The predictive model forecasts the patient's lower back pain condition at a certain point in the future based on the patient's current context and informs the patient when the pain condition will likely deteriorate. For this reason, it is important to provide information accurately and quickly. Accordingly, the feedback model is designed to provide patients with information in the form of a message to effectively communicate within existing coaching systems and the m-health system.

The descriptive model serves to explain the relationship between patient circumstances and lower back pain. The feedback should provide information in a way the patient understands. Accordingly, feedback is designed in the form of a graphic along with a brief written description. This feedback method has been verified and utilized in existing health and wellness systems.

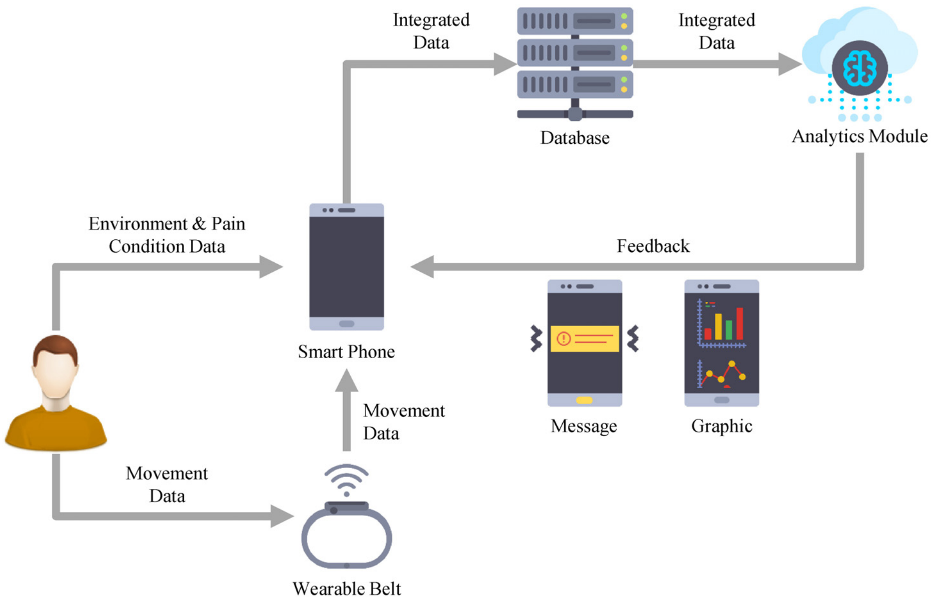
2.3.2 Feedback Process

The data collection process is shown in <Figure 4>. The derived context awareness model provides different feedback depending on the model. The predictive model provides information to the patient using message feedback, either via SMS or through an application on their smart phone. The descriptive model provides information to the patient through graphical feedback and a brief description through a smart phone application.

3. Results

3.1 Personalized Context Awareness System for Chronic Lower Back Pain

We developed the personalized context awareness system using the methodology described above. A smart phone and wearable belt were used for data collection. To acquire movement data, a wearable belt was used to measure the patient's



<Figure 5> Process of the Personalized Context Awareness System for Chronic Low Back Pain

waist motion. Environment and pain condition data were collected by the smart phone application. The information entered by the patient was integrated with the movement data transmitted from the wearable belt via Bluetooth communication and stored in the server. This integrated data contributes to the context awareness model through modeling in the analytics module of the application. In this study, Azure machine learning studio was used as an analytics module. Finally, the derived context awareness model provides feedback to the patient via a web service to the smart phone. The process for the PCAS for CLBP is shown in <Figure 5>.

3.2 Pilot Study

3.2.1 Study Design and Participant

A pilot study was conducted to evaluate the performance of the context awareness model based on patient data. We performed an observational CLBP patient study. The IRB (Institutional Review Board) at Kyung Hee University approved this study (Protocol No: KHSIRB-16-021).

3.2.2 Data Collection

We conducted a pilot study for 24 days from 02.17.16 to 03.11.16. The daily data collection began when the patient put on the wearable belt in the morning and concluded when the wearable belt was removed. The data collection interval was one second. Movement information was collected buy an acceleration sensor installed in the wearable belt. The remaining data were input by the user using a smart phone application. <Figure 6A> is a picture of a patient wearing a the belt <Figure 6B> represents a prototype application based on the Android operating system.

3.2.3 Model Construction

The data used to derive the context awareness model was collected during the 24-day pilot study period. We used variables for time; the x-, y-, z-axes from the wearable belt's acceleration sensor; actions, space, and pain condition to build the models. These variables are described in <Table 1>. The prediction time of the model was set to 5, 10, and 15 minutes derived from EDA, and the best performance was selected

<Figure 6> Data Collection of Pilot Study. (A) Picture of a patient wearing the belt. (B) The main page of the prototype application for data collection

from these results. In the hold-out validation, the training dataset was set at 70%, and the test dataset was set at 30%. During the analysis, it was confirmed that the training dataset was imbalanced. Thus, modeling was performed after over-sampling using SMOTE. (REFERENCE) The random forest algorithm was used in the predictive model, while the C5.0 algorithm was used in the descriptive model. The predictive model was first generated through the random forest algorithm to determine the best prediction time. The descriptive model was derived using this prediction time.

<Table 1> Variables Used in Model Construction

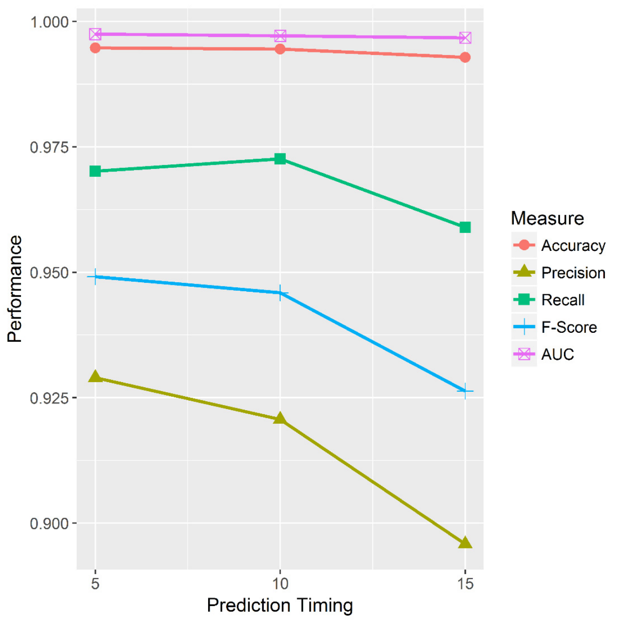
Variable	Explanation
Time	Time indicates how many hours have passed based on a 24:00 clock
X-axis	The x-axis value measured by the acceleration sensor in the wearable belt (Indicating the up and down movements of the patient)
Y-axis	The y-axis value measured by the acceleration sensor in the wearable belt (Indicating the left and right movements of the patient)
Z-axis	The z-axis value measured by the acceleration sensor in the wearable belt (Indicating the forward and backward movements of the patient)
Action	The current behavior of the patient (Walking, standing, sitting on the floor, sitting in a chair, lying down)
Space	The space in which the patient is currently located (Outside, inside, on public transportation (bus, subway), in an automobile)
Pain condition	Currently experiencing lower back pain or not

3.2.4 Predictive Model Validation

The performance of the predictive model is shown in <Figure 7> and <Table 2>. The best prediction time was 5 minutes, with accuracy = 0.9945, precision = 0.9280, recall = 0.9652, f-score = 0.9462, and AUC = 0.9981. Additionally, when the prediction time was set to 5 minutes, the best performance was achieved in accuracy, precision, recall, f-score, and AUC. As the predicted time increased, all the performance indices decreased steadily.

<Table 2> Performance for Each Prediction Time in the Predictive Model

Prediction Time	Accuracy	Precision	Recall	F-Score	AUC
5 min	0.995	0.929	0.970	0.949	0.998
10 min	0.995	0.921	0.973	0.946	0.997
15 min	0.993	0.896	0.959	0.926	0.997



<Figure 7> Performance Comparison in Predictive Model

3.2.5 Descriptive Model Validation

We derived and verified the descriptive model using a 5-minute dataset selected from the predictive model. <Table 3> shows the measured performance of the descriptive model. This model showed similar performance to the predictive model, accuracy = 0.9940, precision = 0.9165, recall = 0.9703, f-score = 0.9426, and AUC = 0.9983.

<Table 3> Performance using a 5 Minute Prediction Time in the Descriptive Model

Accuracy	Precision	Recall	F-Score	AUC
0.994	0.914	0.980	0.946	0.999

We derived 517 rules using the C5.0 algorithm. We used count, number of training cases covered by the rule, and accuracy, measured by the Laplace ratio and rounded off to the fourth decimal place, to select the top four rules. We selected the rules with an accuracy higher than 0.95 and then those with high count.

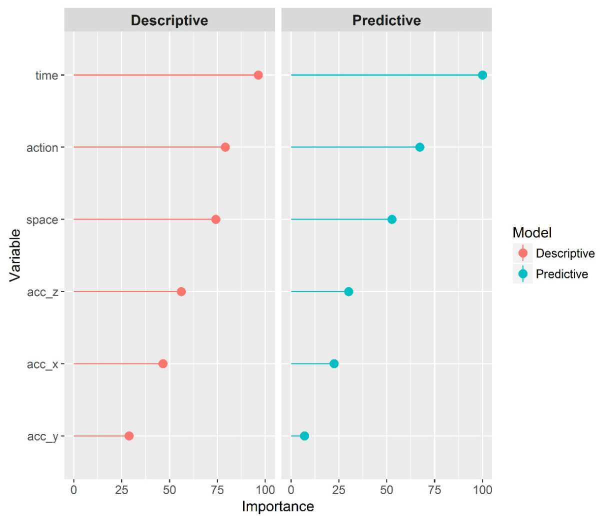
<Table 4> shows the top three rules attributed to the cause of lower back pain. The first rule, that LBP occurred when the patient was standing in the subway between 12:15 and 16:50, has accuracy = 1.000 and count = 24,088. The second rule concerns acceleration values. Since acceleration values are difficult to understand, we transformed them into pitch and roll. (REFRENCE) We calculated the pitch and roll using the average acceleration values of each axis in the correspond-

ing subset. LBP occurred when the patient tilted 68 degrees to the front and 15 degrees to the left when standing in the subway between 12:05 and 12:15. This rule has an accuracy = 1.000 and count = 11,955. The third rule showed that LBP occurred when the patient stood from 20:30 to 20:40. This rule has accuracy = 1.000 and count = 8,388.

We also assessed which variables are affected by the presence or absence of lower back pain. The importance of these variables in the generation of the predictive model and the descriptive model is shown in <Figure 8>. In the two models, the values are slightly different, but the order of importance is the same. Time variables were the most important, followed by action, space, accelerometer z-axis, accelerometer x-axis, and accelerometer y-axis.

<Table 4> Top Three Rules Demonstrating the Cause of Lower Back Pain

No.	Rules
1	time > 12.2408, time <= 16.845, action = Stand, space = Subway
2	time > 12.0917, time <= 12.2308, action = Stand, space = Subway, acc_x > 2.7921, acc_z > -0.4649
3	time > 20.5244, time <= 20.6406, action = Stand



<Figure 8> Variable Importance for Each Context Awareness Model

4. Discussion

In this study, we designed and developed a personalized context awareness system that uses machine learning techniques to understand the relationship between a patient's lower back pain and the surrounding environment. A pilot study was conducted to verify the context awareness model.

First, the performance of the lower back pain prediction model was successful enough to be practically usable. The average of the performance value was 0.9664, indicating greater than 95% effectiveness, and accuracy and AUC were higher than 99%. Precision was higher than 90%, while recall was greater than 95%. The difference in these performance values suggests that the predictive model's detection of lower back pain is good and has good predictive ability with regard to lower back pain. The feature of this model is not a big problem in actual application. The patient reported that lower back pain could occur, but it did not actually happen. In addition, the problems of recall and precision can be solved naturally with increased collection of data on pain condition.

Second, it was possible to determine the rules that affected the occurrence of back pain in patients using the descriptive model. These rules can be provided to patients to help them understand the mechanisms causing their lower back pain, which in turn, can help them to control the pain. These rules can also be used for patient diagnosis and treatment.

Third, it is possible to understand patient characteristics through the rules derived from the descriptive model. The above rules showed that a patient who participated in the experiment suffered lower back pain in the standing posture and on the subway. The accelerometer measuring the movement of the waist can be used as an index to measure lower back pain even though the angle of motion to the left and right is smaller than the angle of motion back and forth. We were able to ascertain that the patient was suffering from pain during left and right movements. In addition, we confirmed that the patient sometimes experienced fatigue-stress type pain because the third rule explains that the patient suffered low back pain at night. Because the wearable device is not attached to the body of the patient, it is difficult to detect the exact movement of the waist, but this information can still be used as an aid in the treatment or diagnosis of the patient.

Fourth, it is possible to use the information from the model to understand how the variables influence the occurrence of lower back pain. This can be used to identify the cause of lower back pain in each patient. In this study, we assessed the importance of each variable by performing importance evaluations. In one patient, time was the most important variable, indicating that the patient felt lower back pain at certain times.

Finally, the data collection, context awareness, and feedback methods used for system development in this study can be applied to other chronic diseases as long as they satisfy the following conditions. First, the goal should be to perform real time predictions. In this study, we set a goal of reducing lower back pain. In order to reduce pain, it was necessary to predict the pain in real time and provide feedback. Second, it must be possible to measure the goal since these conditions are essential for data collection. In this study, patient lower back pain was measured using an application on a smart phone. Third, measurement of personal and environmental factors also should be possible. In this study, patient movements and environmental factors (space and action) were used as these variables. Fourth, data must be collected over a period of time. We constructed the model using data collected for 24 days.

5. Conclusions

In this study, we designed and developed a personalized context awareness system that uses machine learning techniques to understand the relationship between lower back pain and patient environment. The system requires collection of the patient's data through a wearable belt and use of a smart phone application to generate information for the context awareness model and to provide feedback to the patient. We also conducted a pilot study to verify the performance of the model. Results show that the model achieved high performance and suggest the possibility of practical use for chronic lower back pain patients.

The significance of this study is as follows. Through the system of this study, it is possible to analyze and predict the patient's condition using the patient's daily life data. Based on this, it is possible to provide timely warning and feedback on pain to the patient, making it possible to avoid situations and movements that are unfavorable for back pain. In addition, the movement and situation information in the patient's life is automatically recorded, so it can be used for diagnosis by doctors. Finally, the cause of low back pain can be identified based on data analysis, enabling effective low back pain treatment.

We suggest several follow-up studies. First, it will be necessary to verify the method used to derive the personalized context awareness model by applying various experimental groups. Because the pilot study was based on only one patient, additional validation of the methodology is needed. Second, automated patient data collection is required. The current system collects data based on patient input. This approach has great implications for individual efforts in collecting data. In order to solve these problems, it will be necessary to develop and utilize algorithms that can collect situational data automatically. Finally, it will be necessary to reduce the size of the wearable device. The current belt is bulky and not easy to wear with thin clothes or during times of high activity. In order to continuously collect patient data, it will be necessary to reduce the volume of the device so that it can be easily worn anywhere.

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