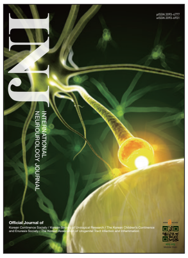

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Artificial Intelligence-Based Patient Monitoring System for Medical Support

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Purpose: In this paper, we present the development of a monitoring system designed to aid in the management and prevention of conditions related to urination. The system features an artificial intelligence (AI)-based recognition technology that automatically records a user's urination activity. Additionally, we developed a technology that analyzes movements to prevent neurogenic bladder.

Methods: Our approach included the creation of AI-based recognition technology that automatically logs users' urination activities, as well as the development of technology that analyzes movements to prevent neurogenic bladder. Initially, we employed a recurrent neural network model for the urination activity recognition technology. For predicting the risk of neurogenic bladder, we utilized convolutional neural network (CNN)-based AI technology.

Results: The performance of the proposed system was evaluated using a study population of 30 patients with urinary tract dysfunction, who collected data over a 60-day period. The results demonstrated an average accuracy of 94.2% in recognizing urinary tract activity, thereby confirming the effectiveness of the recognition technology. Furthermore, the motion analysis technology for preventing neurogenic bladder, which also employed CNN-based AI, showed promising results with an average accuracy of 83%.

Conclusions: In this study, we developed a urination disease monitoring system aimed at predicting and managing risks for patients with urination issues. The system is designed to support the entire care cycle of a patient by leveraging AI technology that processes various image and signal data. We anticipate that this system will evolve into digital treatment products, ultimately providing therapeutic benefits to patients.

Keywords: Urination recognition; Deep learning; Diagnosis support system; Patient monitoring system; Neurogenic bladder

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INTRODUCTION

Various tools, such as voiding diaries and monitoring systems, are utilized to manage patients with urination disorders. A voiding diary [1-3] is a method employed by physicians to objectively monitor the subjective symptoms of patients with urination dysfunction. It serves as the foundation for studying urination disorders and is a critical diagnostic tool, as the diagnosis and treatment plan are based on the physician's objective assessment of the patient's symptoms. An accurate diagnosis is paramount, and a voiding diary plays a significant role in achieving this. However, the reliability of the data in a voiding diary can be limited, as it requires patients to record daily information, which may lead to inaccuracies, even with well-instructed patients [4-6]. This is particularly true for children and the elderly, who may not be able to record all variables; therefore, they are often only asked to log urination times. While a voiding diary can monitor many variables, it is not clinically feasible to use this method with all patients due to varying levels of compliance. If a precise detection technology capable of monitoring urination could replicate the voiding diary's function and manage the patient's urination systematically and efficiently, it could potentially replace the diary. The integration of such technology with a smartphone and a wearable device, allowing automatic recording, would aid in the investigation of symptoms and mechanisms not typically observed in many patients. By collecting signal information, which includes patients' visual and motion data, this approach could improve patients' urinary health by improving the management of urination disorders and predicting risk.

In this study, we aimed to develop a system that applies artificial intelligence (AI) technology to support the monitoring of urination-related diseases. This system utilizes image and signal information from patients to record various activity data. The urination recognition technology introduced here extends existing pattern recognition techniques based on signal processing, similar to those used in smart home care services for recognizing specific behaviors. Our proposed technology identifies the signal pattern of urination and automatically records the frequency and duration of urination events. Motion recognition has been the focus of various methods and learning algorithms. Many studies have employed dynamic time warping [7] alongside traditional machine learning algorithms. However, time series algorithms are more suitable for predicting or classifying time series data that change dynamically. Common time series algorithms include the dynamic Bayesian network [8], hidden Markov model (HMM) [9], and recurrent neural network (RNN) [10]. For the urination patient monitoring system, we propose an algorithm that recognizes urination-related movements by analyzing acceleration and gyro signal data collected from a smart band. We employed the RNN-based long short-term memory (LSTM) [11] method for this purpose, with the goal of facilitating the monitoring of patients with urination issues and supporting disease management.

To predict the risk of urinary-related diseases, we have developed a technology that analyzes arm movement patterns, which is particularly useful for managing stroke-related neurogenic bladder. Neurogenic bladder is characterized by increased bladder sensitivity due to nerve damage in stroke patients, as diagnosed through hypersensitive bladder assessments and dynamic testing. Previous studies [12,13] have reported that stroke can influence the symptoms and disease progression of neurogenic bladder. Consequently, to facilitate comprehensive disease management in patients with complex conditions, a management module has been integrated into the system. This module utilizes technology to inform patients of their potential stroke risk based on their arm movement data. The aim of the proposed system is to create a monitoring platform designed to predict and manage patients' risk of urinary complications. To achieve this, the system is designed to support the entire patient care cycle by incorporating AI technologies that analyze a variety of imaging and signal data. We anticipate that such a system will evolve into digital therapeutic products, ultimately providing treatment options for patients.

MATERIALS AND METHODS

In this paper, we propose a monitoring system composed of 2 modules. The first module utilizes technology to recognize urination activity by analyzing data from the patient's accelerometer and gyro sensor. The second module employs technology to predict the risk of neurogenic bladder through analysis of arm movement. Together, these modules form a comprehensive monitoring system designed to support the complete care of patients with urinary concerns. Fig. 1 illustrates the concept of the proposed system.

Urination Activity Recognition-Based on a RNN

In this study, we developed an algorithm [14] that recognizes urination activity by analyzing the patient's posture and changes in posture. We collected motion data using a smart band worn on the wrist, which collected information from a three-axis accelerometer and a gyro sensor to measure tilt angles. Our algorithm identifies a three-step behavior pattern (approach, urination, withdrawal) associated with urination. We found that acceleration data played a more significant role in recognition than tilt angle data. Therefore, we primarily used acceleration data in our final algorithm to automatically calculate both the frequency and duration of urination events. This study introduces an advanced algorithm that not only measures the frequency of urination but also its timing, an improvement over previous studies [15] that only automated the measurement of frequency. To create this enhanced algorithm for recognizing urination, we employed an RNN with a LSTM architecture. The LSTM algorithm addresses the vanishing gradient problem, which can hinder the learning process in neural networks. The LSTM's architecture, featuring a series of cells with multiple gates, is specifically designed to maintain the gradient throughout the backpropagation process. Each LSTM unit can store, access, and preserve information within its cells, overcoming the gradient loss issue commonly seen in traditional RNNs and enhancing the network's ability to retain older information. Fig. 2 presents a flow diagram of the proposed algorithm.

Guidelines for urination management analysis were implemented under the supervision of a clinician. The necessary variables for the analysis were determined using data from the electronic voiding diary and the patient's urination pattern records. These variables included the daily frequency of urination, the maximum volume of a single void, and the average total daily urine output. Utilizing these variables, the previously mentioned urination recognition algorithm was employed to facilitate integrated urination management for patients. This approach enabled the establishment of quantitative and behavioral biomarkers. The proposed technique for urination analysis was validated by a urologist to ensure its accuracy and consis-

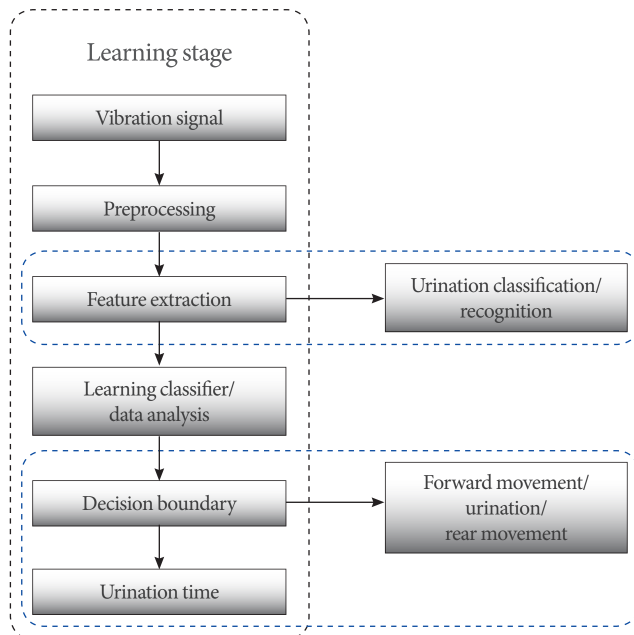

Fig. 2. The flow of artificial intelligence recognition algorithm.

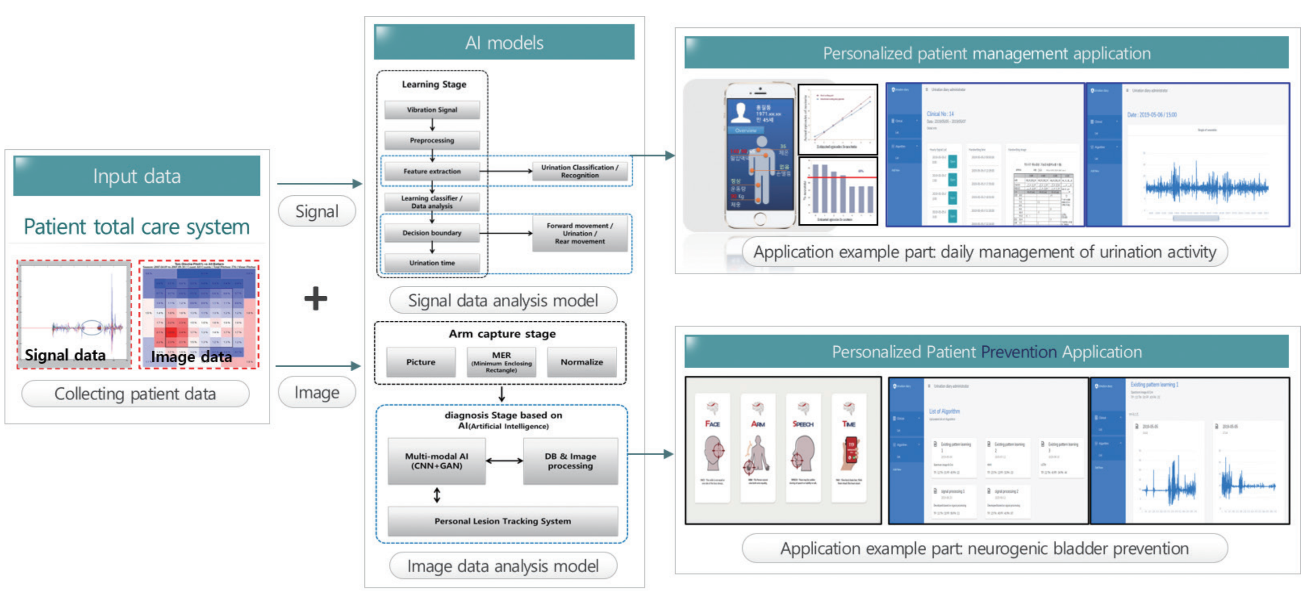

Fig. 1. The concept of personalized total care system. AI, artificial intelligence.

tency with traditional paper voiding diaries [16-19].

AI Monitoring Technology for Preventing Neurogenic Bladder

The AI diagnostic system [20-27] performs a lesion classification step using the convolutional neural network (CNN) algorithm, which relies primarily on the input data. Additionally, improvements are made using the generative adversarial network algorithm, allowing the tracking of personalized lesions. Fig. 3 below illustrates the processing configuration of the AI diagnostic system.

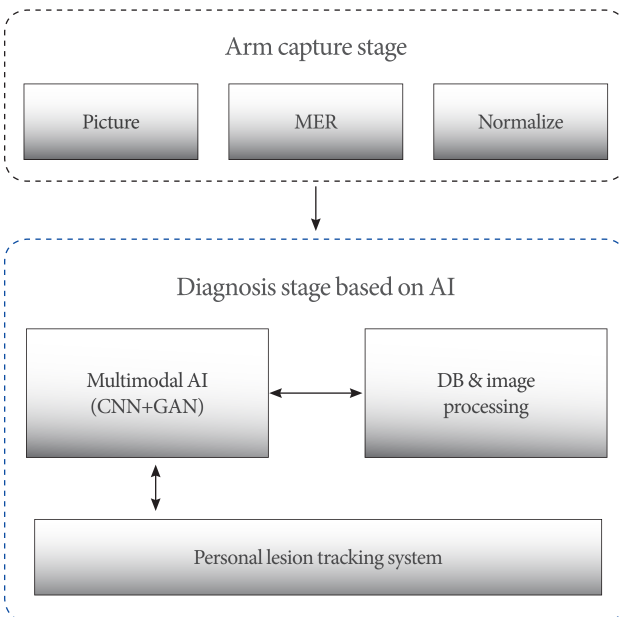

Fig. 3. The flow of artificial intelligence (AI) diagnosis method. MER, minimum enclosing rectangle; CNN, convolutional neural network; GAN, generative adversarial network; DB, database.

Using existing studies [28] on weighting factors for stroke assessment, the guidelines were updated to be appropriate for this task, and specific criteria for arm weakness were established. Following this, in collaboration with the AI diagnostic system, feedback functions were implemented to incorporate results, categorize and archive images, improve algorithms, and further learn from stroke patient data collected at Gachon Gil Hospital. This also included data processed by image processing technology and image sets designed to supplement the dataset where learning data were insufficient.

The system is linked to the existing integrated urination management system to enhance patient care through a comprehensive approach. The newly proposed function for stroke diagnosis, which utilizes image analysis, is designed to prevent neurogenic bladder in patients. Patient feedback plays a crucial role in managing urinary tract activity. To facilitate this, a web-based system for urinary tract activity management has been developed, enabling systematic and ongoing prevention of conditions like neurogenic bladder. The development of the system was structured into 3 main phases: database development, backend development, and client development. The data managed by this integrated patient management system includes urinary tract information for monitoring the patient's urination patterns and arm image data for stroke diagnosis. A history viewer function is available for reviewing collected data. By incorporating a deep learning model, the system enables comprehensive management of the patient's urination activities. The system is designed as a total care patient management system, which includes a stroke diagnosis function to aid in the prevention of neurogenic bladder. This function improves upon the previously developed system for managing urination activities.

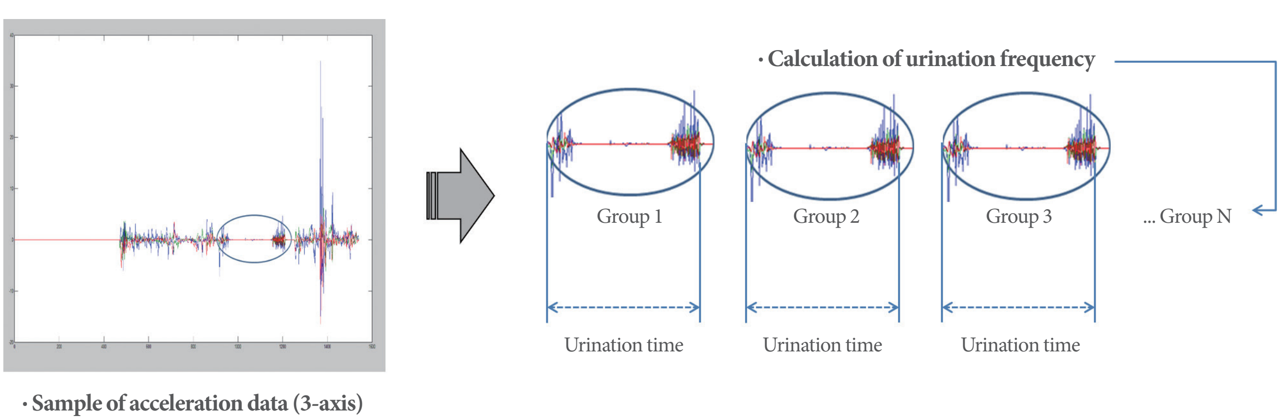

Fig. 4. The evaluation concept of algorithm.

RESULTS

The performance of the urination patient monitoring system proposed in this study was evaluated in 2 steps. Specifically, the accuracy was evaluated by dividing the system into (1) a urination activity recognition technology component and (2) a recognition technology component for preventing neurogenic bladder.

Accuracy of Urination Activity Recognition

Thirty patients were selected for the study, and the performance of the algorithm was evaluated using data (acceleration, tilt angle) gathered from the smart band over a period of 60 days. The algorithm's final accuracy was determined in accordance with the clinical guidelines employed by urologists. The evaluation workflow is illustrated in Fig. 4.

Acceleration and tilt angle data were collected at frequencies ranging from 12 to 13 Hz, and the coordinates along the *x*-axis, *y*-axis, and *z*-axis were recorded as time series data on the smartphone. This data was then reformatted into extensible markup language (XML) and split into training and test datasets at a 3:7 ratio. At this stage, the 24-hour cumulative signal data from patients with urinary dysfunction were analyzed to identify forward movement, urination, and rear movement as a single event, with the aim of determining the daily frequency of this combined activity. Essentially, this step involved recognizing the occurrence of urinary activity within the daily activity data. To evaluate the accuracy of urinary activity recognition, a comparative analysis was conducted against established recognition algorithms. The performance was benchmarked against traditional classification algorithms, specifically those based on HMMs [9] and support vector machines [29]. The proposed algorithm demonstrated an accuracy of 94.2%, confirming its robustness. The outcomes of the confusion matrix are presented in Table 1.

Table 1. Results of a comparison of the proposed method with other existing methods

Confusion matrix	Proposed method	HMM-based [9]	SVM-based [29]
True positive	56	45	39
False positive	4	15	21
True negative	57	52	46
False negative	3	8	14

Values are presented as number of test cases.
HMM, hidden Markov model; SVM, support vector machine.

Evaluation of Techniques for Prevention of Neurogenic Bladder

This technology analyzes images obtained from arm motion and identifies potential stroke symptoms using AI. It serves as an auxiliary tool for stroke diagnosis by enabling the detection and identification of objects within the arm motion images. A common prognostic indicator in stroke patients is an asymmetrical arm position, with one arm appearing tilted compared to the other. To differentiate between patients and healthy individuals from the input images, we train the system to recognize the differences by extracting features from databases representing both groups. The data is then normalized and labeled before being trained using a CNN model. For image preprocessing, we isolate the arm region and plot the coordinates to generate a binary image with dimensions of 500×500 pixels. This image is then converted into a grayscale image with a resolution of 100×100 pixels for model training. The binary image is subsequently used in the convolution layer for further learning, with each image being assigned an appropriate label. The training was conducted using data from 605 patients and 725 individuals from the general population. Analysis of the training data revealed an average learning accuracy of 86% and a testing accuracy of 83%. The accuracy for both the control group and the patient group was also approximately 80%. Accuracy and loss metrics were tracked across the number of epochs, showing consistent performance for the training data. The results are presented in Tables 2 and 3.

The model was trained with data from 496 patients and 678 members of the general public, totaling 1,174 data points. We tracked the loss and accuracy values across epochs. As the number of epochs increased, we observed a decrease in loss and an improvement in accuracy. On average, the training accuracy reached 97%, while the validation accuracy was 86%. Specifically, the classification accuracy for patient data was 88%,

Table 2. Training result

Validation accuracy	Train accuracy
83%	86%

Table 3. Test result

Category	Normal	Abnormal
Dataset	205	201
Accuracy	76%	82%

Table 4. Training result

Validation accuracy	Train accuracy
86%	97%

Table 5. Test result

Category	Normal	Abnormal
Dataset	203	114
Accuracy	87%	88%

and for the control group, it was 87%, as detailed in Tables 4 and 5. Ultimately, our findings suggest that the application of AI to stroke diagnosis has an indirect yet positive impact on neurogenic bladder management.

DISCUSSION

The purpose of this study was to develop a monitoring system that supports the management and prevention of long-term disease in patients with urinary issues. Initially, we developed an AI-based recognition technology that automatically records a user's urination activity. Additionally, we created a technology that analyzes movements to prevent neurogenic bladder. To recognize urination activity, we employed the RNN model. RNNs are particularly effective for shape extraction and recognition as it can retain previous data for extended periods through the recurrent connections of the hidden layer, building upon the traditional multilayer perceptron neural network. However, RNNs have a limited capacity to maintain data in the hidden layer indefinitely. This issue, known as the vanishing gradient problem, leads to the gradual loss of data over time. To address this, we used the LSTM structure, which includes 3 gates, as part of our RNN-based classification algorithm to recognize urination activity. We also derived the result of feature similarity between accelerometer information and inclination angle information, optimizing the final recognition result by assigning different weights. The algorithm's performance was evaluated using data collected over 60 days from a study population of 30 real patients with urinary tract dysfunction. The results demonstrated an average accuracy of 94.2% in recognizing urinary tract activity, confirming the effectiveness of the technology. Furthermore, our motion analysis technology for preventing neurogenic bladder, which also employs CNN-based AI, showed promising results, with an average accuracy of 83%.

The proposed urination disease monitoring system is linked and integrated with the existing integrated urination management system to provide comprehensive support for patient urination management. The proposed image analysis-based stroke diagnosis function is intended to prevent neurogenic bladder. An important part of managing the urinary tract activity of the patient is the patient's feedback. To this end, a web-based urination activity management system was developed, and it can systematically and cumulatively manage the urinary tract activities of the patient, such as preventing neurogenic bladder. The development of the system was divided into 3 main phases: the creation of the database, the development of the backend, and the development of the client interface. The data managed by the integrated patient management system included urinary tract information for monitoring urination activity and arm image data for stroke diagnosis. The system features a history viewer for the collected data, and by incorporating a deep learning model, it enables comprehensive management of the patient's urination activity. The system was developed as AI analysis software, making it compatible with various hardware products. The implementation of such a total care system is anticipated to facilitate the overall management of urination disorders.

AUTHOR CONTRIBUTION STATEMENT

· Conceptualization: *ESK*
· Data curation: *ESK*
· Formal analysis: *SJE*
· Funding acquisition: *ESK*
· Methodology: *KHK*
· Project administration: *ESK*
· Visualization: *SJE*
· Writing - original draft: *ESK*
· Writing - review & editing: *ESK, ESK, KHK*

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