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IoT-Based Unobtrusive Physical Activity Monitoring System for Predicting Dementia

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ABSTRACT Mental health-related disorders are common in elderly populations. Among the various mental health disorders, one most significant threat is dementia, and prediction of dementia has become an important issue related to well-being in old age, because the disease progression of dementia can be slowed by early diagnosis and disease control. In this paper, we propose an unobtrusive dementia-prediction system for monitoring physical activities of elderly persons either living alone or as a couple in different house structures, achieved through passive infrared (PIR) motion sensors combined with data processing. The proposed feature extraction algorithm extracts feature values related to physical activities from simple passive infrared sensors located in each room space. We then apply a variety of common popular classification models, including Deep Neural Networks (DNNs), to predict the risk of dementia in a sensor-enabled home. We implemented and validated algorithms on data collected for over a month from 18 participants who were engaged with a variety of living conditions. The proposed system was effective in predicting dementia risk, with up to an 0.99 area under the curve (AUC) using DNN with principal component analysis (PCA) and a quantile transformer scaler. In terms of the result based on leave-one-subject-out (LOSO) analysis, an accuracy of 63.38% was achieved using DNN with PCA and a standard scaler. The proposed methodology is non-invasive and cost-effective, and can be used for a variety of long-term monitoring and early symptom detection systems, helping caregivers provide optimal interventions to elderly individuals at risk for dementia.

INDEX TERMS Feature extraction, dementia prediction, Internet of Things, smart homes, unobtrusive monitoring, sensor technologies.

I. INTRODUCTION

Dementia is a complex neurocognitive disorder caused by Alzheimer's disease and various other conditions; it is a syndrome defined as an acquired decline from previously-attained cognition that impairs daily functioning. Dementia is a general term for progressive impairment of memory, language, problem-solving and other thinking abilities, severe enough to interfere with daily life and requiring considerable care [1]. There are seven modifiable risk factors (diabetes, midlife hypertension, midlife obesity, depression, physical inactivity, smoking, low education) that can have significant impact on dementia. If the prevalence of these seven factors can be reduced by 10% per decade, 8.8 million cases worldwide of Alzheimer's disease (AD) could potentially be prevented by 2050 [2].

Dementia results from several progressive neurodegenerative diseases such as Alzheimer's disease [3], and a 2005 Delphi Consensus Study on prevalence of dementia in the world estimated that 4.6 million new patients worldwide fall into dementia each year [4]. Depending on the disease's progression, dementia patients experience various degrees of decline

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in cognitive, memory, mental and other functions [5], with the socioeconomic burden of dementia estimated to be $1 trillion annually by the World Health Organization [6].

Because Korea has an aging society, its number of dementia patients has been increasing and is predicted to reach 1 million in 2030 and 2 million in 2050, potentially resulting in a significant increase in Korea's social and economic burden [7]. While no effective treatment has so far been discovered for dementia, early detection is important because early detection and drug treatment (symptom relief) can delay its onset. A previous study by Lopez *et al.* reported that rates of admission to nursing home after 5 years of dementia could be reduced by 55% when it was treated with drugs starting from its initial stage [8], and many recent analytic epidemiological studies have described dementia as a preventable disease [9], [10]. Developing a predictive model of dementia could assist with its early diagnosis and support active preventive management and treatment that could delay the deteriorative nature of the disease, possibly delaying its onset and reducing its prevalence; such a model could also help improve the quality of life of patients and their families and reduce social costs.

To solve dementia-related problems of high-risk elderly individuals and their caregivers, various attempts and solutions using new technologies have been proposed [11]–[14], and they can be broadly classified into four major types according to the technologies used: (1) Wearable Technology, (2) Non-wearable Motion-Sensor Technology, (3) Assistive/smart home technologies and (4) other technologies not falling into the first three categories [15]. Using such techniques, systems have been developed for monitoring dementia-related feature values, electrodermal activity (EDA), inertial measurement units (IMU), activities of daily living (ADL) and physical activities, and predicting dementia through various data-analysis techniques.

A dementia-prediction system using a wearable device is not easy to use in practice because of user inconvenience in having to wear and periodically charge such a device. Since this means requiring specific actions of possibly-impaired users for monitoring data, this approach tends to not be practically useful. Application of a system using ADL data in a smart home environment with several people in the house system is greatly restricted, with the associated large number of sensing devices increasing system complexity and making practical application difficult.

This study proposes a method for predicting dementia risk based on an IoT-based smart home system that combines a motion sensor-based sensing system integrated into each living space and using a machine-learning algorithm based on a new feature-extraction algorithm. The proposed system predicts a user's dementia risk level by using the feature extraction algorithm to classify the data from each battery-operated sensing node into data representing either the presence or the absence of a user in the space. Performance of the proposed system was evaluated by comparing the predicted data with the ground truth information labeled by the K-MMSE technique.

Contributions of this research are threefold:

1) The proposed system can predict potential risk of dementia both in a sensor-enabled home occupied by only one person as well as in a sensing environment where two people live as a couple. Although the proposed system cannot distinguish a specific person, it can predict that at least one person in a house has a high risk of dementia.
2) It predicts the potential risk of dementia in different house structures, such as those with different room sizes and positions, overall house size, number of room spaces, and house type.
3) The proposed feature extraction algorithm can convert raw sensor outputs with time stamps into meaningful feature variables that can be applied to predicting dementia risk.

The remaining parts of this paper are organized into five sections. In Section 2 we present related work divided into three subareas: diagnostic tools for dementia prediction, the relationship between dementia and physical activity, and current IoT-based systems for unobtrusively predicting dementia. In Section 3 we propose applicable sensing systems and data processing methodology. Results and discussion are presented in Sections 4 and 5, and Section 6 provides conclusions.

II. RELATED WORK

A. DIAGNOSTIC TOOLS FOR MEASURING DEMENTIA AND MILD COGNITIVE IMPAIRMENT (MCI)

Accurate evaluation of cognitive function is essential in the diagnosis of dementia, and the American Psychiatric Association's DSM-IV criteria for diagnosing dementia states that ''memory loss must be included and other cognitive decline in at least one other area must be accompanied'' [16]. While accurate diagnosis of dementia requires comprehensive and professional evaluation of various cognitive areas by specialists, time and environmental constraints and economic factors many result in failure to evaluate elderly people for dementia by appropriate specialists, often resulting in relatively untrained non-experts using cognitive-function screening tools to determine dementia risk. Such cognitive-function screening tests have the advantage of being easy to perform within a short period of time while providing quantified information related to the overall cognitive-function level [17].

The Mini-Mental State Examination (MMSE) is currently the most widely-used functional screening test within clinical settings and the community [18], [19]. The reliability and validity of the MMSE have been proven through many previous studies, and a variation, the Korean Mini-Mental State Examination (K-MMSE), has been developed and widely-used in Korea [17], [20]. The K-MMSE measures time orientation (5 points), place orientation (5 points), memory registration (3 points), attention and calculation (5 points), memory recall (3 points), language function (8 points) and spatiotemporal composition (1 point). The maximum total score is 30, and in Korea a score less than 24 is evaluated as suspected dementia [17]. While the MMSE has the advantage of making it relatively easy to perform screening, there are some cautions. Because the MMSE questions are relatively easy, a "false-negative" may be likely to occur in people with mild cognitive decline due to the so-called "ceiling effect". Prior research results in which the false-negative rate reaches 20-30% have also been reported [21], meaning that since the MMSE test is literally a screening test, even a MMSE score in the normal range reflects the possibility that dementia cannot be completely ruled out [22]. However, MMSE has long been actively used because of its accessibility and rapid implementation qualities, strengths of such screening tests.

The Montreal Cognitive Assessment (MoCA) is a tool developed to provide better screening than the MMSE for mild cognitive impairment, and although it has been less-used than the MMSE as a diagnostic tool for dementia, it has received added attention because it includes executive-function questions lacking in the MMSE. It awards 6 points for attention, 4 points for executive function, 4 points for construction ability, 5 points for memory, 5 points for language function, and 4 points for orientation [24]. While previous studies have reported the MoCA to be better than the MMSE for screening mild cognitive or vascular cognitive impairment [24], [25], before it can be trusted as an indicator of overall cognitive function at a very early stage, it seems that further research is needed [26].

The Clinical Dementia Rating (CDR) scale and the Global Deterioration Scale (GDS) are representative grading scales for evaluating the severity of dementia in patients [27], [28]. GDS and CDR are widely used both as criteria for determining the severity of dementia in clinical studies and as criteria for evaluating the efficacy of dementia drugs in clinical trials [29]. While GDS is a tool that includes both cognitive function and activities related to daily living and abnormal behavior, and it can be used as a useful test tool for early diagnosis of dementia by classifying early cognitive impairment into various stages in detail. Both GDS and CDR tools are time-consuming and for use only by experienced professionals [30].

This study therefore used the Korean version of the MMSE, K-MMSE, widely used as a screening tool with verified reliability and validity that can be quickly implemented by non-specialists.

B. DEMENTIA AND PHYSICAL ACTIVITY

While dementia is a common disease closely related to age and with a high social cost, little attention has been paid to identifying lifestyle habits that might be modified in seeking its prevention [31]. It is known that physical activity is associated with lower incidence of mild cognitive impairment and dementia [32], and exercise or general physical activity has been associated with lower risk of cognitive impairment, Alzheimer's disease, and dementia of any type [31].

Physical activity is defined as movement of skeletal muscles resulting in energy expenditure exceeding that of the resting state [33]. Many previous studies have shown that physical-fitness intervention can produce beneficial effects on memory and other aspects of cognition in elderly persons [34]–[39]. Cassilhas *et al.* assessed the impact of resistance training at two different intensities on cognitive functions in the elderly and showed that resistance exercise had a positive impact on cognitive function in the elderly. While such beneficial effects did not depend on resistance exercise being performed at moderate or high levels of intensity, from a psychological standpoint moderate intensity might be more appropriate for the elderly because it provides more significant improvement in their mood profiles and certain quality-of-life aspects along with cognitive benefits [40].

Physical activity that encompasses exercise is different from physical fitness [34], i.e., one can be physically active without necessarily having high aerobic fitness [41]. Physical activity has been noted as being beneficial across many domains, including cardiovascular disease, cancer, and depression [42].

Significant trends in increased protection against dementia through greater physical activity have been observed, and high levels of physical activity have been associated with reduced risk of cognitive impairment. Regular physical activity could represent an important and potent protective factor against cognitive decline and dementia in elderly persons [43].

Peter *et al.* [44], focusing on whether physical activity could reduce age-related risk, studied the effects of physical activity on dementia risk in older adults with mild cognitive impairment, and performed a 17-year follow-up, They found that even low levels of physical activity (ie, moderate physical activity once a week) may weaken the link between aging and dementia. Their survival analyses also found a remarkable 78% decrease in the risk of dementia in older people who were moderately-to-highly active, compared to that for an inactive group.

Dementia is a neurodegenerative syndrome characterized by a decline in functional capacity and cognition [45]. With aging, some cognitive functions such as attention, memory, and concentration, along with some physical functions such as walking and balance, decline and become slower and less efficient. These manifestations are the result of neural-cell loss in the frontal, parietal and temporal lobes, and many such cognitive changes can be evident and even cause mild disability even if a state of dementia is not reached [46].

Colcombe and Kramer [47] showed that reduced loss of hippocampal brain tissue in the aging brain is related to the level of physical fitness, in agreement with animal studies also showing increased brain-cortical thickness with voluntary exercise [48] and other positive brain changes, ultimately leading to a preventive effect of physical activity on inflammatory pathways and disturbed growth-factor signaling. [49].

TABLE 1. Units for magnetic properties.

Ref.	# of Subj	Domain Studied	Outcome measures	Technology
[55]	97	MCI	CDR, MMSE	PIR, door contact
[56]	265	MCI	CDR, Neuropsychiatric scales	PIR on the ceiling
[57]	5	Depression & Dementia	GDS, MMSE, SF-12	PIR
[58]	1	Dementia	Travel pattern with dementia detection	PIR

The encouraging results of these studies has prompted longitudinal and randomized trials that confirm the overall notion that physical exercise enhances cognitive function in older adults [50]–[54].

C. CURRENT IoT-BASED SYSTEMS FOR UNOBTRUSIVELY PREDICTING DEMENTIA

Although there are multiple technologies and methodologies for supporting clinical diagnosis and severity assessment of neurodegenerative diseases [55]–[57], we basically eliminated all wearable-type sensors and focused on fixed and ambient sensors, especially motion sensors. We did this because the sensing technologies for real elderly populations should be in feasible and convenient in-home environments and should minimize intrusiveness on privacy. Many technologies described in the literature [55]–[57], such as wristband wearables and video-based sensors, didn't meet those requirements, and force and pressure sensors tend to cover only a limited small space. Several studies in the literature propose the use of motion-sensor-based monitoring systems for dementia detection in home environments. Akl *et al.* [58] measured the walking speeds of elderly individuals using machine-learning and diverse sensors such as PIR sensors, door-contact switches, and motion-activated sensors. Dodge *et al.* [59] evaluated dementia using motion sensors mounted on the ceiling to examine features such as walking speed and home computer usage, although measurement of walking speed using the proposed sensors could not be applied to a home simultaneously occupied by two people. Galambos *et al.* [60] used PIR sensors for detecting depression and dementia, and Gochoo *et al.* [61] used PIR sensors and CNN for Elderly Travel Patterns that could be related to dementia, but the number of subjects in that study was small. An overall summary of these studies is given in Table 1.

III. THE PROPOSED SENSING ENVIRONMENT

A. PROPOSED OVERALL SYSTEM

Figure 1 depicts the overall system architecture of a proposed physical-activity-based dementia-prediction system using IoT devices. The system uses PIR sensing units as basic sensors that check whether participants are located in particular defined spaces. In their actual residence, experimental

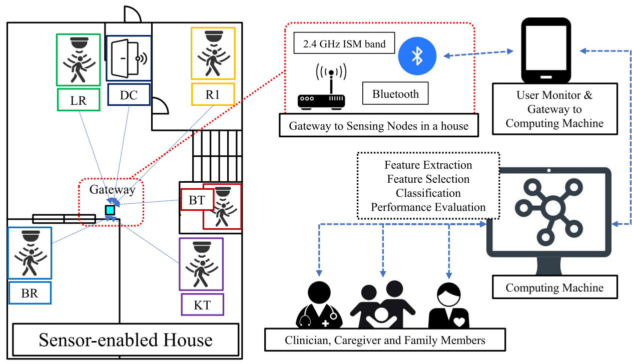


FIGURE 1. Overall system diagram and data flow of the physical activity monitoring system developed for dementia prediction.

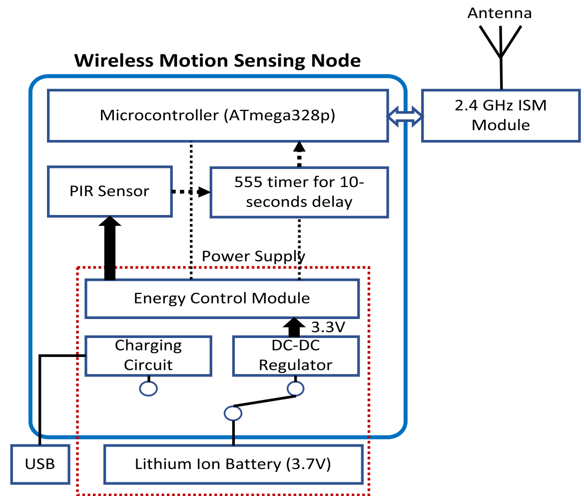


FIGURE 2. Overall system diagram and data flow of the physical activity monitoring system developed for prediction of dementia.

participants live freely both inside and outside the house, with their physical actions recognized through PIR sensors whose data is transmitted to a gateway installed at the center of the house using 2.4GHz ISM (Industrial, Scientific and Medical) band communication. The collected motion data, although possibly collected multiple times within 10 seconds, are organized as one event every 10 seconds transmitted to the User Monitor as a 2nd Gateway (UM2G) using Bluetooth communication. The data goes through a basic filtering processing and is then sent to the Computing Machine (CM) using Wi-Fi communication, where it is then subjected to data processing and machine-learning processing for calculation and prediction of dementia risk, with results sent to clinicians, family members, users, and caregivers.

B. SENSING DEVICES

The wireless-motion-sensing node (WMSN) is illustrated in Fig. 2. The PIR sensor (BS412), manufactured by Senba Sensing Technology, covers 120 degree angles and distances up to 8m. The Energy-control module (ECM) provides power to the PIR sensor during patient-idle status only as waiting status, and once human motion has been detected by the PIR sensor, the ECM activates the 555 timer module to delay for 10 seconds then activate the Microcontroller. The activated microcontroller then transmits detected human motion to the Gateway through a 2.4*GHz* ISM module. Once the sensing module has received an acknowledgment signal (ACK) from the gateway, to minimize battery power it will automatically change its status to sleep mode. After another 10 seconds, the ECM disables power to the microcontroller unit (MCU) and turns the timer modules off, returning them to waiting status with only the PIR sensor module active. This proposed hardware configuration minimizes energy consumption.

C. SUBJECT DATA & INSTALLATION

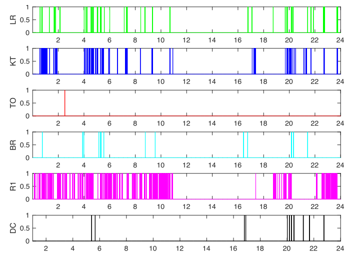
In the proposed system, space-to-space movements are significant factors. Since the experimental subject could occupy different house architectures and room spaces, we have defined generalized room spaces and front door referred to in the formal dictionary [Oxford English Dictionary] with added factors as follows:

4) Living room (*LR*): "A room in a house for general and informal everyday use (as opposed to a bedroom, dining room, etc.)."
5) Bedroom (*BR*): "A room used for sleeping or intended to contain a bed or beds; a sleeping apartment."
6) R*oom 1* (*R1*): "Capacity to accommodate a person or thing or allow a particular action; accommodation." R1 should not include a bed.
7) Kitchen (*KT*): "A room or area equipped with facilities for cooking and preparation of food."
8) Bathroom (*BT*): "A room containing a toilet or toilets, usually with facilities for handwashing, and sometimes also a bath or shower"
9) Door contact (*DC*) on front door: "the principal entrance-door of a house."

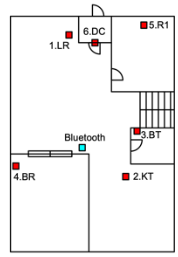
There were eighteen participants (5 male; 13 female; 65 ∼ 79 years old; 5 couples) in our experiments for collection of physical activity data in a real home. Among them, four scored fewer than 25 points on the K-MMSE that measures time orientation (5 points), place orientation (5 points), memory registration (3 points), attention and calculation (5 points), memory recall (3 points), language function (8 points) and spatiotemporal composition (1 point). The maximum total score is 30, and a score less than 24 in Korea is taken as an indication of suspected dementia [17].

This study was conducted between November 1, 2020 and February 28, 2021, targeting 18 elderly people older than 65 and living in the Busan and Ulsan areas in South Korea. The K-MMSE survey was conducted by a well-trained tester. The criteria for selection of study participants were:

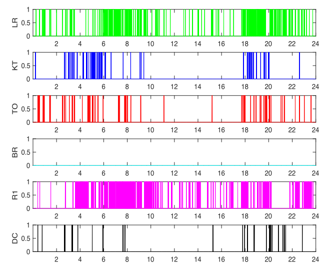
- People 65 years of age or older who could communicate
- Those with a K-MMSE score of 20 or more
- Those who understood the procedure and purpose of the research and who had signed the consent form
- Capability to conduct daily-living activities



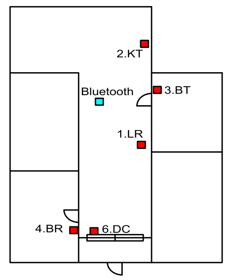
(a) Physical activity of subject #3 (High MMSE score, 30)



(b) Schematic Subject #3's house



(c) Physical activity of subject #16 (Low MMSE score, 24)



(d) Schematic Subject #16's house

FIGURE 3. The signal graph of the installed sensors' outputs with a human subject's movements and house layouts of the sensing environments: (a) physical activity of subject #3, (b) house layout of subject #3, (c) physical activity of subject #16 and house layout of subject #16.

After being briefed about the purpose of the study, all study subjects and their guardians voluntarily agreed to participate in it. The study was also approved by the University Institutional Review Board (YSUIRB-202004-HR-064-2). Participants 5 males and 13 females were ultimately selected, with an age distribution ranging from 65 to 79. The experiments were conducted for a month. For detecting the presence of a subject in a room, sensing devices communicating with the PIR sensor module were installed in each room space. The lens of each PIR sensor could provide infrared signals to the sensing module over a range of 120 degrees with a 12-foot detecting distance.

Figures 3 (b) and (d) show installations in the sensing environment for two different subjects, one with a low and the other a high K-MMSE score. To acquire data related to each subject's physical-motion status, sensing nodes were placed in common living areas. As can be seen, the data collected for physical activities during a day were quite different for subjects with different MMSE scores.

D. FEATURE EXTRACTION

The indices, constants and variables used by the system and proposed algorithms are listed below:

- h: packet identifier
- j: time slot
- r: placed sensor
- d: day slot

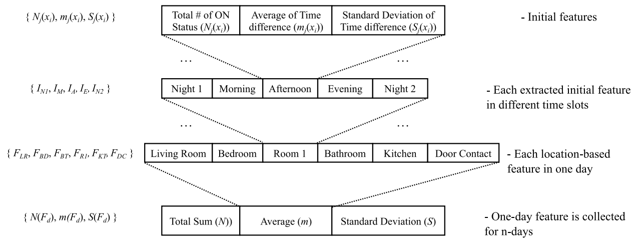


FIGURE 4. Conceptual framework for feature extraction.

- N_1: 1st night (00:00 AM – 5:59 AM)
- M: morning (06:00 AM – 11:59 AM)
- A: afternoon (12:00 PM – 04:59 PM)
- E: evening (05:00 PM – 7:59 PM)
- N_2: 2nd night (8:00 PM – 11:59 PM)
- $T_{s,j}$: start time at time slot j
- $T_{e,j}$: end time at time slot j
- *LR*: living room
- *BD*: bedroom
- *R1*: another room
- *KT*: kitchen
- *BT*: Bathroom
- *DC*: door contact
- $N_j(x_i)$: the number of sensor input, x_i, in time slot j
- $m_j(x_i)$: mean of sensor input, x_i, in time slot j
- $Sj(x_i)$: standard deviation of sensor input, x_i, in time slot j
- P: packet
- I: initial feature
- F: feature

We propose a time-slot-based feature for learning modules, each comprising five time slots (1st night, morning, afternoon, evening, and 2nd night), along with corresponding extraction algorithms used in detecting the ADLs of the elderly, as shown in Figure 4. The proposed time-slot-based feature extraction was used to distinguish among subjects living in the same house, because each subject generally has different living patterns, e.g., one might go out of the house while the other might mainly stay in the house. The proposed method will thus provide differentiated data for multiple people living in a given house.

Each generated data packet was comprised of seven elements: packet identifier *h*, timestamp *Time* (in granularity of seconds), and `ON/OFF` status *LR, BD, R1, KT and DC* sensors. The h^{th} packet *Ph*, is denoted as:

$$P_h = \{ID, Time, LR, BD, R1, KT, DC\}_h. \tag{1}$$

Each data packet provided only the *ON/OFF* status of each of the five sensors in the home, together with a corresponding packet identifier *ID* and timestamp *Time*. We then derived the ADLs by defining the initial feature values based on a time slot representing sequential packets and home configurations. Time slots I are defined as the set of start and end times at time slot j, denoted as $T_{s,j}$ and $T_{e,j}$, respectively. We extracted two values, the total number of *ON* status values of the sensor, $N_j(x_i)$, and the collection of *Time* data as the *ON* status of the sensor. First-order time derivatives (delta features) were extracted from the entire collection of Time data by taking differences of adjacent pairs of values in the array, while original samples (static features) were not utilized in the following stages. The array of difference values is calculated as an average, $m_j(x_i)$, and standard deviation, $S_j(x_i)$, of all values in the array. All values representing initial feature vectors at j, I_j, are denoted as:

$$I_{j,p} = \{T_{s,j}, T_{e,j}, N_j(x_i), m_j(x_i), S_j(x_i)\}. \tag{2}$$

The extracted initial feature vectors are divided into 5 different time slots. Each extracted initial feature vector in different time slots was collected into a location-based feature vector, F_r, denoted as:

$$F_r = \{I_{N1}, I_M, I_A, I_E, I_{N2}\}. \tag{3}$$

Each location-based feature vector for a given day was collected into the one-day feature vector, F_d, that can be written as:

$$F_d = \{F_{LR}, F_{BD}, F_{BT}, F_{R1}, F_{KT}, F_{DC}\}. \tag{4}$$

The one-day feature values were collected for n days to calculate statistical feature values such as total sum, average, and standard deviation. All values of an n-day feature vector can be written as:

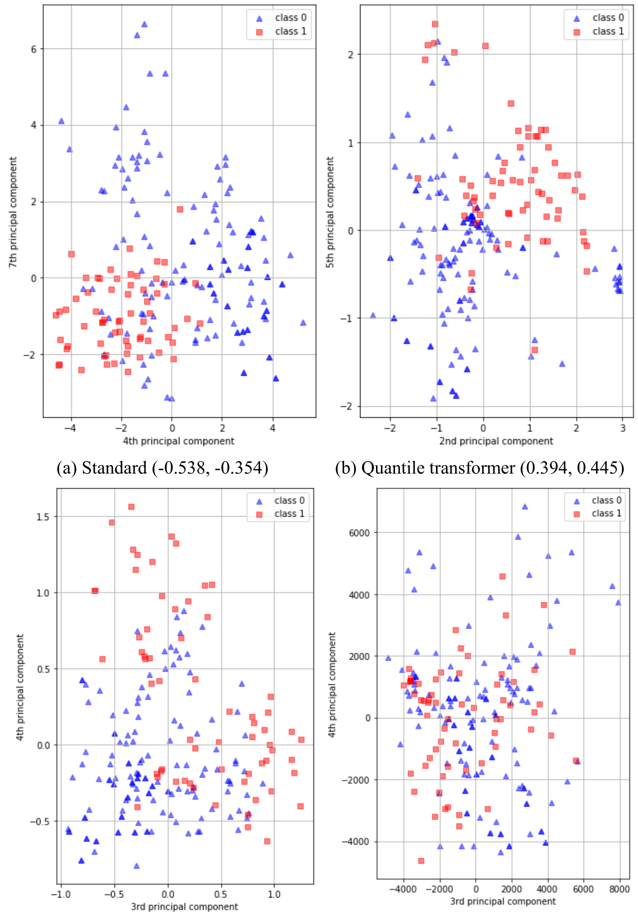
$$F_n = \{N(F_d), m(F_d), S(F_d)\}. \tag{5}$$

The F_n values, results of the proposed feature extraction algorithm, will become the input values for PCA processing. Based on the feature-extraction process, the extracted 90 features serve as inputs to the PCA process.

PCA is a transformation that projects initial input data into a new coordinate system for extracting meaningful information from high-dimension datasets [62]. In general, PCA is used to reduce the number of dimensions of the initial raw data and discern optimal hidden features that can generate inputs for the backend classification algorithms [63]. In this paper, we have selected diverse scalers for enhancing the performance of the proposed methodology. The scaled PCA generates 90 new variables in converting the input data to a new coordinated dimensional space. The combinations of principal components (PCs) of four different scalers are shown in Figure 5: (a) 4th and 7th PCs with standard scaler; (b) 2nd and 5th PCs with quantile transformer scaler; (c) 3rd and 4th PCs with min/max scaler; and (d) PCA with no scaler. As can be seen in Figures 5 (a) and (b), the high-risk dementia data (red rectangles) tend to be gathered into one group, making it possible to see that the standard/quantile transformer scalers and PCA provide meaningful feature values compared to other PCA combinations.

E. CLASSIFICATION

We classified dementia risk into high-risk and low-risk groups based on the K-MMSE scores, with a score less



(a) Standard (-0.538, -0.354) (b) Quantile transformer (0.394, 0.445)

(c) Min-max (0.383,0.404) (d) PCA without scaler

FIGURE 5. Diverse feature scaling plots with the PCA: class 0 is high-risk of dementia subjects (blue triangle) and class 1 is low-risk of dementia subjects (red rectangular). Each subfigure includes correlation coefficient values of each PC: (a) 4th and 7th PCs with standard scaler; (b) 2nd and 5th PCAs with quantile transformer scaler; (c) 3rd and 4th PCAs with min-max scaler; (d) 1st and 2nd PCAs without scaler.

than 25 classified as representing a high-risk-for dementia group and other scores classified as representing a low-risk-for-dementia group. We used all 90 proposed features as input variables to the classification algorithm. Eight representative classification algorithms were considered: Deep Neural Network (DNN) [64], Random Forest (RF) [65], AdaBoost (ABC) [66], Gaussian Naïve Bayes (GNB) [67], Decision Tree (DT) [68], Multi-Layer Perceptron (MLP) [69], K-Nearest neighbors (KNC) [70] and Support Vector Machines (SVM) [71]. The proposed methodologies were implemented using Python Keras [72] and TensorFlow [73], and Figure 6 shows the proposed DNN architecture for applying the classification of dementia risk.

IV. RESULTS AND ANALYSIS

18 elderly participants, each having produced 30 days of records, were selected for evaluation of the proposed dementia-risk monitoring system. The total number of the

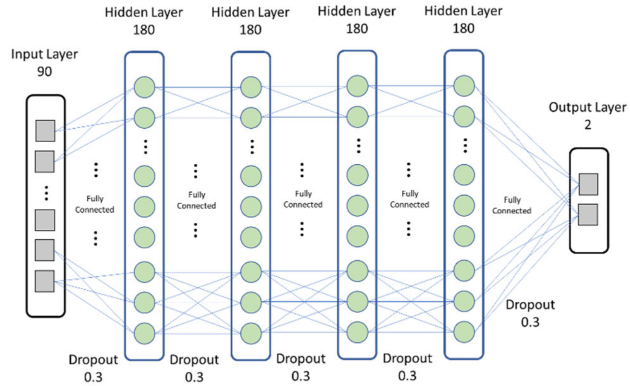


FIGURE 6. The architecture of the proposed DNN.

TABLE 2. Performance comparison of AUC results based on different scalers and PCAs.

AUC	Quantile	Standard	Min-Max	No Scaler	No PCA
DNN	**0.990**	0.971	0.956	0.912	0.895
RF	0.681	0.578	0.706	0.729	0.984
ABC	0.975	0.931	0.932	0.881	0.938
GNB	0.886	0.852	0.827	0.706	0.953
DTC	0.741	0.820	0.679	0.688	0.789
MLP	**0.989**	0.982	0.972	0.825	0.862
KNC	0.951	0.987	0.973	0.833	0.833
SVC	0.982	**0.990**	0.987	0.912	0.914

used instances is 399, which excludes data damaged due to system malfunctions (33 instances). We initially compared the AUC values for selecting acceptable combinations of classification algorithms and preprocessing methods, and the overall dataset was divided into two groups, with 66% for training and 34% for testing. A leave-one-subject-out (LOSO) was applied to verify the overall results.

A. PERFORMANCE MEASURES

Five common quality metrics were considered: sensitivity (*Sn.*), specificity (*Sp.*), positive predictivity value (*Pp.*), accuracy (*Acc.*), Equal Error Rate (EER) and area under the ROC curve (AUC). AUC was used for initial performance evaluation for better comparison based on only one performance metric, because as indicated by Kegl [74], accuracy cannot explain the measure for sparse (imbalanced) datasets due to minor high-risk dementia data and major low-risk dementia data. AUC can also be used for evaluating overall performance using one performance metric without requiring a threshold of the calculated probabilities from the classification algorithms.

TABLE 3. Performance comparison of EER results based on different scalers and PCAs.

EER	Quantile	Standard	Min-Max	No Scaler	No PCA
DNN	**0.042**	0.069	0.069	0.181	0.194
RF	0.347	0.472	0.333	0.333	0.083
ABC	0.083	0.167	0.111	0.167	0.111
GNB	0.139	0.208	0.236	0.319	0.111
DTC	0.194	0.125	0.319	0.153	0.069
MLP	**0.028**	0.069	0.083	0.250	0.194
KNC	0.069	0.083	0.111	0.333	0.333
SVC	0.056	0.069	0.056	0.208	0.167

TABLE 4. Performance comparison of LOSO results based on different scalers and PCAs.

Scaler	tp	fp	fn	tn	*Sn.*	*Sp.*	*Pp.*	*Acc.*
Quantile	54	89	44	138	55.1	60.79	37.76	59.08
Standard	**130**	**172**	**66**	**282**	**66.33**	**62.11**	**43.05**	**63.38**
Min-Max	226	298	68	383	76.87	56.24	43.13	62.46
No Scaler	274	409	118	499	69.9	54.96	40.12	59.46
No PCA	321	522	169	613	65.51	54.01	38.08	57.48

tp = true positive, fp = false positive, fn = false negative, tn = true negative.

B. INITIAL RESULTS BASED ON AUC AND EER

To verify the performance of preprocessing related to the PCA and different scalers, we needed to compare results using one performance metric, the AUC or EER values. Table 2 and 3 compare the overall performances using either AUCs or EERs from different combinations of PCAs and scalers. The best AUC performances, 0.990 and 0.990, marked in bold, were by the DNN with PCA-quantile scaler or the SVC with PCA-standard scaler, followed by SVC with a PCA-min-max scaler. In terms of EERs, Table 3 shows that the best EER performance was the MLP with a quantile scaler, marked in bold. Figure 7 compares ROC curves based on the combination of PCA and different scalers, with DNN, RF, ABC, GNB, MLP, KNC, and SVC throughout the three different scalers.

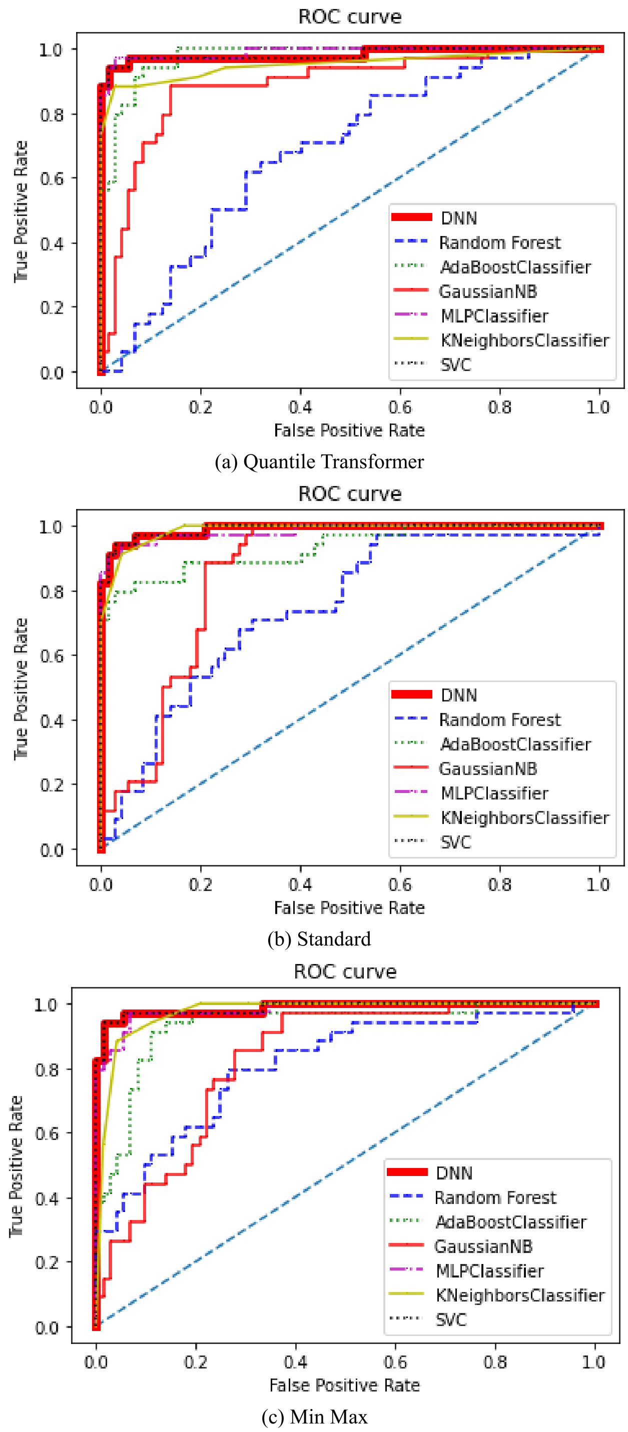


FIGURE 7. Comparison of ROCs based on the combination of the PCA and scalers. (a) Quantile transformer (b) Standard (c) Min max.

C. LOSO PERFORMANCE OF DNN

Table 4 summarizes the performance characteristics of the five preprocessing methods using a DNN algorithm for classifying high-risk dementia subjects for a given test data set using the LOSO method. We obtained the best dementia-risk prediction with a DNN architecture that included 4 hidden layers, each containing 180 neurons. The testing environments set the number of training epochs as 200 and the batch size as 25. The confusion matrixes are shown in Table 4 for all scalers. The best performance was DNN-PCA-Standard, the DNN classifier with PCA and standard scaler. Although the *Acc.* value was 63.38% in the best performance case, *Sn.* was relatively low.

V. DISCUSSION

This study presented an unobtrusive sensing environment with a new feature extraction system for monitoring physical activities of elderly individuals and determining their dementia risks using eight popular classification algorithms and preprocessing methods such as PCA and diverse scalers. We implemented the proposed system and tested its performance in actual testing environments at 13 elderly residential homes (18 subjects) and conducted the experiments over a period of 30 days (1 month). Determination of dementia risk in different types of sensing environments was processed using data from the proposed dementia risk detection system correlated well with questionnaire interviews (K-MMSE), indicating that unobtrusive sensing systems and intelligent learning algorithms can be used as effective and practical solutions for monitoring mental health of the elderly. This approach is much less labor-intensive than earlier methods and does not require the user to conduct regular surveys. The system, compared to surveys, has the additional advantage of being able to automatically and quickly detect changes or abnormalities in physical activity of the elderly, enabling the proposed system to quickly request necessary medical care.

While K-MMSE has been widely used in Korea as a primary dementia screening tool in community-centered dementia projects, it is well-known that MMSE was not originally developed for diagnosing dementia [18]. Many studies have been conducted on just how accurately the MMSE, a simpler mental state test developed for wide use in a variety of groups without specifying a target group, can accurately select a specific clinical group such as dementia sufferers. Such studies applied MMSE to a general group and a dementia group and revealed the extent of sensitivity and specificity the MMSE displayed in differentiating these two groups [19]. According to a previous study by Oh *et al.*, when K-MMSE was performed on patients with low educational background, there was a relatively high likelihood of erroneously indicating the presence of cognitive impairment even though their cognitive function was actually normal [75]. It was found that the false-positive group identified in a previous study [75] included many illiterate people, and that among the items of the K-MMSE, ''attention and calculation'' and ''language,'' including reading and writing, received low scores. Therefore, when K-MMSE is used to screen for dementia, it seems likely that a follow-up study combining memory testing and neuropsychological evaluation would be necessary even if it takes more time.

We tested combinations of eight classifiers and preprocessing methods, and among the combinations of data processing considered, DNN/PCA with quantile transformer scaler and SVC/PCA with standard scaler outperformed other combinations.

Tree-based algorithms with PCAs did not perform well in our experiments, and without PCA, RF displayed good performance, i.e., based on this experiment the characteristics of tree-based and neural network-based algorithms exhibit opposite features. We have tested LOSO analysis, meaning that testing data from one subject can be totally new data to the trained model, and left-out data may include more outliers than other data to the trained model. Standard scaling subtracts the mean value from all samples then divides them by the standard deviation, so the standard scaling is much less affected by outliers. On the other hand, the Min-Max scaling normalizes sample values to the range of 0 to 1. We could in the case of multiple possible outliers thus expect the overall performance of PCA with a standard scaler to produce better results than the Min-Max scaler. The five selected timeslots (1st night, morning, afternoon, evening and 2nd night), are also fundamental and essential units related to many physical activities and types, and the separate time slot features can provide unique information about the different living patterns of subjects residing as a couple in a single house. Although information on such physical activities could be easily monitored and derived using wearables, since the elderly subjects in our study were resistant to the use of such technology over the long term, we used an alternative method based on use of PIR sensors to monitor their physical activities.

The number of time slots and regularity of physical movement are important in accurately monitoring the risk of dementia. Because people exhibit various tendencies with respect to staying still and moving from space to space, multiple wearable type sensors would be required to accurately detect dementia risk. Subjects #13 and #14 were a couple and only subject #13 had a working time involving irregular working hours. Another couple (subjects #7 and #8) lived with two other people, a son and daughter; all other subjects mostly stayed at home, sometimes perhaps going out for walk. If the proposed system is to determine activity details of two or more people in a home, additional sensor devices would be needed. Since this would also generate additional technical complexity in the monitoring system, using minimal sensing devices along with the proposed feature extraction algorithm could be an optimal solution for predicting the risk of dementia in real home environments.

To implement a practically-useful monitoring system, we have designed low-powered IoT devices using 500 mAh battery power, and based on the proposed H/W, it could be used for one month without any problem. In terms of wireless communication, since the houses in South Korea are built using concrete, a 2.4 GHz ISM module in low-power mode was insufficient for transmitting and receiving the data; when we installed the system, houses larger than 100 m^2 could not establish good communication well between the sensors and the gateway. While some cases could be resolved based on the optimal position of the gateway, some could not, in which case we could resolve the issue by increasing the communication power consumption of both the sensing modules and the gateway.

We tested the thirteen houses of different structures and sizes ranging from 50 to 130 m^2. To minimize the effects of different room dimensions, we have categorized each room as one of five typical types and ignored differences in distances between room spaces. For minimizing privacy

TABLE 5. T-Test results based on 5th PC.

Variable	Group	Average	Standard deviation	Error	t	p
5th PC of Quantile	0	-0.1805	0.4990	0.1886	-3.020	0.013
	1	0.6068	0.3494	0.1563		

TABLE 6. Correlation Coefficient Results based on First 5 PCs.

1st PC	2nd PC	3rd PC	4th PC	5th PC
-0.3256708	0.3939000	0.0238125	-0.1014611	0.**444654**

issues, the proposed method only counts movements between the determined room spaces, so that the basic units of the proposed methodology are room-to-room movements from. If we needed to monitor detailed movements dependent on different room dimensions, concern for users' privacy would be increased.

In recent years research based on using a system that can monitor human physical activity has been actively conducted. A previous study using Kinect reported that the multi-Kinect system exhibited an accuracy improvement of 15.7% over the single Kinect system, and suggested that the system would be useful for monitoring of joint movement speed, functional working envelope, or home training. However, the multi-Kinect system requires two or more cameras, including an RGB camera, and offers poor accuracy unless the camera is placed directly in front of the user [76].

In a previous study of a mobile Android system implementation application for use in central nervous system movement disorder testing, it was reported an initial prodromal recognition accuracy of 86.4%. when applied to health status evaluation While this suggests that it would be an efficient and easy-to-use system that can support decision-making in health checkups. there are limitations; a tablet 10 inches or larger and a more detailed test mode that considers various symptoms and movement disorders are required for health-status evaluation [77].

We have used a paired t-test to evaluate statistical significance. We initially selected the first 5 PCs from standard, Min-Max, no scaler, and quantile transformer, Among these choices, the 5th PC with quantile transformer reflected statistical significance while the others did not, as shown in Table 5. Similarly, Table 6 shows that the correlation coefficient value of the 5th PC exhibited the highest value. Based on this statistical result, we could assume that there is a difference between the PCs of motion data from two populations of subjects after applying the PCA, especially with quantile transformer.

VI. CONCLUSION

The proposed system is a good early-screening tool for long-term dementia risk-monitoring for the elderly for the following reasons: (i) it provides an accurate detection and prediction function; (ii) it is non-invasive, easily to install, and comfortable for elderly use as a long-term monitoring system; (iii) it presents minimal concerns with respect to personal privacy issues; and (iv) it is affordable for most elderly participants. Even though in our sample population of 18 elderly participants there were only four elderly subjects with low MMSE score, and the results for detecting the high risk of dementia might be biased by the small sample size, our results for early detection of mentally-related disorders are promising in terms of enabling caregivers to provide timely interventions. Since the number of samples tested was small, we must seek to find more elderly participants to improve and validate our results, so as future work we intend to apply our algorithms to a larger group of elderly and to include wearable devices. The proposed methodology can be further developed to include an algorithm for predicting different levels of dementia.

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