ADADL : Automatic Dementia Identification Model based on Activities of Daily Living using Smart Home Sensor data

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Abstract

The activity of daily living (ADL) assessment is a diagnostic tool used to identify patients with dementia. However, as the assessment is performed in a questionnaire format by patients, it depends on the subjective judgment of a clinician, which may cause an issue of poor accuracy. In this study, we have proposed an objective ADL assessment method that utilizes smart home data for efficient identification of early dementia. For data collection, we built IoT sensor-based smart homes and performed clinical trials. Through pre-processing and analysis of the collected data, we generated new features that reflect ADL and patient characteristics. To build the dementia prediction model, three machine learning and deep learning models were trained on the collected and generated features. The performance of each model was compared for combinations of each feature set. Thus, it was determined that the ADL and patient characteristics-based features contributed mainly to the prediction. Consequently, the proposed method can be developed as a baseline for more efficient and objective ADL assessments that can be performed by monitoring patients without any domain knowledge.

Introduction

Dementia is a chronic neurodegenerative disease that leads to severe cognitive impairments, such as memory loss, concentration loss, and mood changes, and is diagnosed mainly in the elderly over the age of 60 with a mild cognitive impairment (MCI) (Prince et al. 2015). With the global trend of the aging population, dementia is diagnosed in approximately 10 million people every year, and is the fifth leading cause of death worldwide (WorldHealthOrganization 2017).

The physical, psychological, social, and economic aspects of dementia have a huge impact on the overall society, including nursing people, families, and patients (WorldHealthOrganization 2012). Although dementia imposes a significant social and economic burden, especially in terms of treatment costs, a treatment that can completely cure dementia, or change its progression has not yet been developed. In addition, the medicine that has been developed so far, only alleviates the progression of dementia. It is known that the effectiveness of the medication treatment is conditional on being started from an early stage, or the MCI phase (Lao et al. 2019). Various biological and neuropsychological studies have revealed the importance of identification and appropriate treatment at an early stage of dementia (Kinsella et al. 2009; Marshall et al. 2011). The US MCI guidelines also emphasize the importance of early diagnosis of dementia for effective treatment (Petersen et al. 2018).

In hospitals, early diagnosis and cause identification of dementia are performed using the mini mental state examination (MMSE) (Kim et al. 2010), neuropsychological tests (Lee et al. 2002), and activities of daily living (ADL) assessments (Mioshi et al. 2007). However, as these assessments are performed through a questionnaire format by patients, or their families, the diagnosis is dependent on the subjective judgment of the clinician, which may cause an issue of poor accuracy. To alleviate these shortcomings, several studies have been conducted to predict dementia by directly monitoring patients at homes, or in the laboratory (Kaye et al. 2011; Karakostas et al. 2015; Alberdi et al. 2018). Although objective and efficient dementia identification was possible, it showed relatively low accuracy, as compared to the assessments in the hospital due to lack of medical domain knowledge.

In this study, we proposed an early dementia prediction method that reflects ADL using smart home sensor data and machine learning models. For data collection, we built IoT sensor-based smart homes and performed clinical trials. Through pre-processing and analysis of the collected data, we generated new features based on the individual characteristics of the patients and the ADL questionnaire, which is known to reflect the behavioral tendencies of dementia patients. Subsequently, we built an efficient dementia prediction model by training three machine learning and deep learning models, each on the collected and generated features. Additionally, we investigated the important features that contributed to dementia identification using the explainable artificial intelligence (XAI) method to address the trustworthiness of the proposed method (Lundberg and Lee 2017).

The Proposed Method

Data Collection and Pre-processing

In order to collect data for this study, a total of 13 elderly people aged 65 years, or older living alone in Seoul, Korea were recruited as clinical trial subjects. Through the MMSE test, participants were classified into two groups: dementia (MMSE score < 24) and normal (MMSE score > 24). Table 1 lists the characteristics of the participants of the clinical trial.

Table 1: Characteristics of clinical trial participants.

Category	Age	MMSE	Category	Age	MMSE
Normal group (n=7)	86	26	Dementia group (n=6)	87	20
	79	29		76	13
	84	25		86	18
	72	27		76	23
	67	26		85	11
	74	30		72	14
	90	30			
Average	78.8	27.5	Average	80.3	16.5

Seven participants were categorized in the normal group. The mean age of the normal group was 78.8 years old, and their average MMSE score was 27.5. Whereas, six participants were categorized in the dementia group. The mean age of the dementia group was 80.3 years old, and their average MMSE score was 16.5.

To monitor the activities of the participants, IoT sensor-based smart homes were built in actual living spaces, and sensor data for each participant were collected through clinical trials for 13 months (2020–2021). Table 2 lists the types of sensors installed in each smart home.

Table 2: Types of sensors installed in each smart home.

Sensor Type	Installation Place	Sensor Type	Installation Place
Door	Microwave	Smart Plug	Electric Mat
Door	Main Gate	Smart Plug	TV
Door	Medicine Box	Smart Plug	Washing Machine
Door	Furniture	Motion * 3	Room 1,2,3
Vibration	Refrigerator	Motion * 2	Living Room
Vibration	Rice Cooker	Motion	Kitchen
Vibration	Sink Faucet (Kitchen)	Lidar * 3	Living Room
Vibration	Fan	Lidar * 2	Kitchen
Vibration	Trash Bin	Temperature/ Humidity	Gas Stove
Vibration	Vacuum	Temperature/ Humidity	Bath Room
Vibration	Sink Faucet (Bathroom)		

A total of 27 sensors of six types were installed throughout the houses to monitor the overall life of the participants. To collect data, the sensors were connected to an embedded board (RaspberryPI) and ZigBee gateway, and the collected data were transmitted to the server using a long-term evolution router. All collected data consisted of the number of sensing and the duration of sensing. The collected data were integrated on a daily basis, and pre-processing was performed by subdividing it into different times namely morning, noon, evening, and late night. The pre-processed IoT feature set consisted of a total of 130 features (number of sensing: 65, duration of sensing: 65).

Features based on the Activities of Daily Living

To generate ADL-based features using the collected data, this study referred to the Seoul instrumental activities of daily living (S-IADL) (Ku et al. 2004). S-IADL is an early dementia diagnosis tool that assesses the instrumental daily living ability of patients by reflecting on the characteristics of Korean culture. Based on the advice of clinicians, out of a total of 15 activities provided by S-IADL, seven activities relevant to the collected data were selected (cooking, household chores, taking medications, grooming, using household appliances, locking the entrance door, and indoor wandering). ADL-based features were generated by combining one, or more sensor features relevant to each activity and were pre-processed in the same manner as the IoT feature set. The pre-processed ADL feature set consisted of 64 features (number of the activity: 32, duration of the activity: 32). Details of the ADL-based features are provided in Supplementary Table 1.

Features based on Individual Characteristics

Through statistical analysis of the collected and generated data, it was determined that each participant had a different lifestyle and range of normal activities. Accordingly, to build a dementia prediction model that reflects individual characteristics, personalized outlier thresholds for each feature were set based on the MMSE score, as shown in Table 3.

Table 3: Personalized outlier threshold criteria

Category (MMSE)	Cognitive Level	Outlier Criteria
Normal $(30-24)$	No Cognitive Decline	$Q1-1.5*IQR >$ Value $Q3+1.5*IQR <$ Value
	Very Mild Cognitive Decline	$Q1-1.2*IQR >$ Value $Q3+1.2*IQR <$ Value
	Mild Cognitive Decline	$Q1-1.0*IQR >$ Value $Q3+1.0*IQR <$ Value
Dementia $(23-0)$	Moderate Cognitive Decline	$Q1-0.5*IQR >$ Value $Q3+0.5*IQR <$ Value

For a higher MMSE score, a wider outlier threshold criteria range was set, whereas for a lower MMSE score, a narrower criteria range was set. Therefore, even if the same activity was performed, the outlier criteria were applied more strictly to the dementia group. According to the threshold criteria, the individual characteristic-based feature set was created for all IoT-based and ADL-based features. Each feature of every participant was set to 1 if the value exceeded the threshold, and 0 otherwise.

Machine Learning-based Dementia Prediction Model

To build an efficient dementia prediction model that reflects ADL and individual characteristics, we trained machine learning and deep learning models on the collected and generated feature sets (IoT features: 130; ADL features: 64; individual characteristic features: 194). Machine learning and deep learning are essential technologies in the age of artificial intelligence (AI), which have achieved great success in various fields (Yang et al. 2021; Brown et al. 2020; Karras et al. 2020). Among the numerous models, we considered three machine learning models: logistic regression (LR), support vector machine with radial basis function kernel (SVM-RBF), and random forest (RF), and three deep learning models: artificial neural network (ANN), convolutional neural network (CNN, ResNet10), and long short-term memory recurrent neural network (RNN-LSTM). Note that, unlike the input data of other models that were pre-processed as daily data, in the case of RNN-LSTM, all data were pre-processed as hourly data, and 24 h data (1 day) were simultaneously used as input.

Additionally, the Shapley additive explanations (SHAP) algorithm that is an XAI technique, was utilized to investigate the significant features that mainly contribute to the proposed model. The SHAP is based on game theory and is used to interpret results from deep learning and machine learning-based models (Lundberg and Lee 2017).

Experiments

Experimental Setup

All proposed methods were implemented using Python 3.7 libraries, such as PyTorch 1.5, Scikit-learn, and SHAP based on NVIDIA TITAN RTX 24 GB $\times$ 2. All hyper-parameters of machine learning and deep learning models, such as the number of layers, number of nodes, running rate, and batch size were chosen as optimal values for each model, through a grid search (Shekar and Dagnew 2019). To verify the performance of the proposed model, 10-fold cross-validation was performed, and the performance of each model was compared for combinations of each feature set. The following performance evaluation metrics were used: accuracy, area under the receiver operating characteristic (AUROC), area under the precision-recall curve (AUPRC), precision, recall, and F1-score. We have described our experimental results in the next subsection.

Experimental Results

Figure 1 shows the comparison of dementia prediction performance of the machine learning models (Figure 1A) and the deep learning models (Figure 1B) for each feature combination. All models performed better when trained on all three feature sets (IoT-based features, ADL-based features, and individual characteristic-based features), as compared to when trained excluding individual characteristic-based features, or using only IoT-based features. Especially, the RF-based model, that trained on all three feature sets, exhibited the best performance (Accuracy: 0.98, AUROC: 0.99, AUPRC: 0.99, Precision: 0.96, Recall: 0.98, and F1-score:

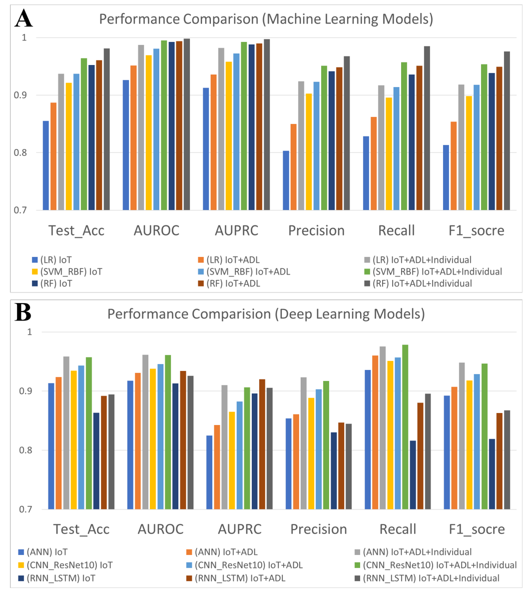

Figure 1: Comparison of dementia prediction performance by features and models.

0.97). It attained a 3%, 5% and 4% improvement in precision, recall and F1-score, respectively, as compared to the model that trained only on IoT features. Through these results, it is suggested that the proposed dementia prediction method that uses the ADL and individual characteristic-based features is more efficient than the method that only employs IoT sensors without medical domain knowledge.

Meanwhile, deep learning-based models exhibited relatively lower performance and lower improvement, as compared to machine learning-based models. It seems that overfitting occurred because of insufficient data in comparison to the model capacity. In the case of RNN-LSTM, the model was unable to appropriately learn the time series owing to a lack of information on hourly data. These issues can be addressed by collecting additional data in the future.

To investigate the significance of features that contributed to prediction of dementia, the SHAP algorithm was applied to the RF-based model that exhibited the most stellar performance. Table 4 presents the top 10 features of the predictive contribution calculated using the SHAP algorithm.

Out of the total of 388 features, four IoT features, three ADL features, and three individual characteristic features were included in the top 10. Although it was observed that the contribution of the IoT features to the prediction of the proposed model was greater, the ADL features and individual characteristic features were also included, thus suggesting that these features also contributed to the accurate prediction of the model, through interaction with the IoT features.

Conclusion

In this study, we have proposed an efficient early identification method for dementia using smart home sensor data,

Table 4: Top 10 features of predictive contribution on RF-based proposed Model

Ranking	Features
1	(Individual) IoT noon TV watching duration
2	IoT morning TV watching duration
3	(Individual) ADL cooking duration
4	ADL morning TV watching duration
5	(Individual) ADL cooking duration (refrigerator–gas stove)
6	IoT morning TV watching count
7	IoT bathroom sink faucet duration
8	ADL shower duration
9	IoT evening electric mat count
10	ADL household chores - washing dishes duration

and a machine learning model as an objective ADL evaluation method. Data were collected by building an IoT sensor-based smart home for the elderly living alone. Based on the collected data, we generated new feature sets reflecting the characteristics and ADL of patients. Subsequently, we built an efficient dementia prediction model by training three machine learning and deep learning models, each on the collected and generated features. The proposed model, which trained on all feature sets, outperformed the other models, exhibiting an improved performance compared to the model using only IoT features. In addition, it was determined that ADL and individual characteristics-based features contributed to the accurate prediction of the proposed model. Consequently, the proposed method can be developed as a baseline for more efficient and objective ADL assessments that can be performed by monitoring patients. Furthermore, it is also expected to be developed as a personalized dementia prediction tool that can more efficiently identify the risk of dementia at an early stage without any additional domain knowledge in the medical field.

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