Machine-learning-driven Wearable Healthcare for Dementia: A Review of Emerging Technologies and Challenges

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Abstract: As personal mobile devices, such as smartphones and smartwatches, are increasingly commoditized, it has become easier to measure individual physiological and physical states and record them continuously. Applying machine learning techniques to the data, we can detect early signs of diseases in older people, such as dementia, and predict probabilities of future disorders. This review paper describes the machine learning technologies in realizing wearable healthcare for older people. First, we survey the literature on machine-learning-driven wearable technologies for the early detection of dementia. Second, we discuss issues of the datasets for constructing ML models. Third, we describe the need for a service framework to collect longitudinal data through continuous monitoring of the user's health status. Finally, we discuss the socially acceptable implementation of the service framework.

1 INTRODUCTION

Dementia is caused by brain disorders and diseases, such as Alzheimer's Disease (AD), Dementia with Lewy Bodies, Vascular dementia, Frontotemporal dementia, Parkinson's disease with dementia (PDD). Because there is no cure for dementia, early detection of the symptoms is essential to prevent disease exacerbation.

Many medical screening methods for dementia have been proposed (Turner et al., 2020; Thabtah et al., 2020). Cognitive assessment tools (Cordell et al., 2013; Giebel and Challis, 2016) are often used for detection by investigating cognitive domains (attention, language, memory, and visuospatial function) because of their simplicity. The tools are essential for the diagnosis of dementia in the hospital. However, most persons with dementia (PwDs) do not notice a decline in their cognitive function in the early stages. They do not go to the hospital until noticeable dementia symptoms are progressing. Thus, detecting the individual cognitive decline at home is an important issue. A home screening system that informs doctors about user changes is required.

To capture changes in the cognitive functions of individuals, the use of digital biomarkers has drawn attention in recent years. They collect, track, and analyze patients' social, behavioral, and physiological states using sensors, such as cameras, accelerometers, barometers, GPS, and microphones (Kourtis et al., 2019; Piau et al., 2019; Husebo et al., 2020). Because recent wearable devices (e.g., smartwatches) have these sensors, they can be used to detect digital biomarkers of users' unnoticeable diseases. As many people use smartwatches, there is a large medical impact on the early detection of individual cognitive decline at home. In addition, recently, machine learning (ML) technologies are also used to detect dementia(Tsang et al., 2020; Tanveer et al., 2020). It is still a new challenging research area to apply ML to detecting early signals of dementia from the sensor data on commercially available wearable devices.

In this short review, we survey the literature on using wearable and ML technologies to detect early symptoms of dementia and discuss its current status and future challenges. First, we conduct a literature review of relevant articles from major publishing sites and academic libraries. Second, we discuss issues of constructing the datasets for ML models. Third, we point out the need for a framework construction to collect longitudinal data through continuous monitoring of the user's health status. Finally, we describe the challenges of making such a data collection framework socially acceptable.

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2 WEARABLE DEVICES AND DIGITAL BIOMARKERS FOR DEMENTIA

In this section, we review the literature on detecting early symptoms of dementia by applying ML methods to various types of digital biomarkers. We conducted a literature review by examining relevant articles from major publishing sites and academic libraries. We selected appropriate literature related to the digital biomarkers sensed by the wearable devices. The summary of the literature is shown in Table 1.

2.1 Physiological Signals

Rim et al. (Rim et al., 2020) provided a review paper on DL applications in physiological signal data. For early detection of AD, electroencephalogram (EEG) has recently become a promising area of AD (Al-Jumeily et al., 2014; D. Kim and K. Kim, 2018). Bi et al. (Bi and Wang, 2019) proposed an EEG spectral image classification with a multi-task learning strategy based on a convolutional high-order Boltzmann machine. Since current wearable EEG devices allow long-term noninvasive recording of brain signals outside of a laboratory (Casson, 2019), ML-driven wearable EEG is an important research area for the early detection of dementia.

2.2 Human Activities

Patients of MCI and PwDs are characterized by decrements in instrumental activities of daily living (IADL) (Sacco et al., 2012; Lindbergh et al., 2016). PwDs often show specific patterns of behavioral and psychological symptoms of dementia, such as hyperactivity (van der Linde et al., 2016). By monitoring and recognizing their daily activities using wearable devices, we may be able to detect the specific behavioral patterns of dementia. Besides, the amount of social interaction and physical activity in the lifestyle of older people directly affects cognitive decline that may progress to dementia (Kelly et al., 2017; Najar et al., 2019). Thus, human activity recognition (HAR) can be used as an assessment tool for estimating the risk of dementia.

HAR using wearable devices is a popular application area of ML. To capture human motion, we can use sensors in smartphones or smartwatches placed on the user's body. The sensors include accelerometers, gyroscopes, and inertial measurement units. By applying various ML methods to the sensor data, such as CNN with transfer learning (Akbari and Jafari, 2019), we can recognize the activities of the user correctly.

Although using HAR with ML could be useful for the early detection of dementia, currently, there is little available literature on this topic. Bringas et al. (Bringas et al., 2019) proposed a method that processes accelerometer data of Alzheimer's patients and a CNN that classified the stage of the disease. They applied it in a case study with thirty-one patients with AD, in which the classification success rate was ninety-one percent. Li et al. (Li et al., 2018) showed time-aware Toeplitz inverse covariance-based clustering (Hallac et al., 2017) and CNN for predicting AD using actigraphy data provide a solution for continuously monitoring changes of physical activity of subjects in daily living environments. Abnormal behaviors related to the stage of dementia can be detected by monitoring daily life patterns. Arifoglu et al. (Arifoglu et al., 2020) applied graph convolutional networks to HAR, and abnormal behaviors related to dementia were detected using activity recognition confidence probabilities. Using long short-term memory (LSTM) networks, Zhan et al. (Zhan and Haddadi, 2019) proposed a system to predict patients' activities and timing to enable caregivers to provide timely and appropriate care. Okada et al. (Okada et al., 2019) used IoT sensors and mobile robots to monitor daily activities and interactions of PwDs at home. They proposed an ML-based estimation method, e.g., Random Forest (RF), for the dementia stages based on the sensor data. González Díaz et al. (González Díaz et al., 2013) showed a support vector machine (SVM) based method of recognizing IADL from an egocentric camera view as a context for Alzheimer's disease research.

2.3 Gait Patterns

Gait analysis is a study of the body movements during walking, that is, human locomotion. It is known that mobility disorders, such as freezing of gait (FOG), are often identified as early symptoms of AD and PDD (Shull et al., 2014; Block et al., 2016). Mc Ardle et al. (Mc Ardle et al., 2018; Mc Ardle et al., 2020) proposed an application of wearable technology as a clinical tool to differentiate the subtypes of dementia. Xie et al. (Xie et al., 2019) showed that a sensor-based wearable device for gait measurement might be a convenient tool for screening cognitive impairment called amnestic mild cognitive impairment.

To identify irregularities in gait patterns in older persons with cognitive decline and dementia, monitoring their gaits using ML-driven mobile and wearable devices can be used to detect digital biomarkers of dementia. Xu et al. (Xu et al., 2018) proposed an improved subsequence dynamic time warping, a pattern matching method of two time-sequence data to detect FOG, a typical symptom of PDD. Rodríguez-Martín et al. (Rodríguez-Martín et al., 2017) proposed detecting FOG using SVM through a single waist-worn triaxial accelerometer. Zhang et al. (Zhang et al., 2020) presented an ML-based PD diagnostic model that exploited PD pathological information from two independent accelerometers and gyroscope records.

2.4 Eye Movements

Tracking eye movements can be a practical diagnostic tool in assessing dementia (Crawford et al., 2005; Marandi and Gazerani, 2019). Subtle impairments in cognitive inhibition of people in the early stages of AD can be detected using relatively simple eye-tracking paradigms (Wilcockson et al., 2019; Carr and Grover, 2020).

Recent progress in eyeglass-type wearable devices has shown the potential of wearable eye-tracking for mental health monitoring in daily life settings (Vidal et al., 2012; Liu et al., 2019; Li et al., 2020). Pavisic et al. (Pavisic et al., 2017) proposed an ML approach using a classification method based on the smooth pursuit of raw eye-tracking data and significant correlations between eye-tracking metrics and standard visual cognitive estimates of young-onset Alzheimer's disease. To assess apathy in patients with AD, Chung et al. (Chung et al., 2018) used recurrent neural networks to detect differences between visual scanning behaviors on emotional and non-emotional stimuli to classify apathetic and non-apathetic AD patients.

2.5 Linguistic Features

Dementia can affect a person's speech, language, and conversational interaction capabilities (Peelle and Grossman, 2008; Colman and Bastiaanse, 2011; Reilly et al., 2011). With the recent advances in speech recognition systems on mobile devices, it may be possible to record and analyze the speech of older people to detect and assess abnormalities in their language and conversations.

The Alzheimer's Dementia Recognition through Spontaneous Speech Challenge (Luz et al., 2020) provided a benchmark dataset of spontaneous speech. In the challenge, different approaches to the automated recognition of AD based on the dataset were compared. Searle et al. (Searle et al., 2020) analyzed spontaneous speech datasets and compared performance across numerous classification models of AD and prediction of MMSE scores. They showed that an SVM model and a "DistilBERT" model (Sanh et al., 2020) showed good prediction performance.

Beltrán et al. proposed an ML-based approach using the microphones of wearable sensors to detect audible cues of problematic behaviors, such as tapping and mumbling (Beltrán et al., 2019). They classified the audio signals based on the hidden Markov model and SVM. Rosas et al. (Rosas et al., 2019) analyzed the lexicon (mental dictionaries and the ability to understand complex words) and the speech fluency of PwDs. They proposed two ML algorithms to automatically classify the presence/absence of dementia. Troger et al. (Tröger et al., 2017) showed an ML-based dementia screening tool trained on the French Dem@Care corpus (Karakostas et al., 2016). Utilizing vocal features, they confirmed the prediction accuracy of 89%. Karlekar et al. (Karlekar et al., 2018) proposed a CNN-LSTM model based on the DementiaBank dataset (Boller and Becker, 2005) to classify AD. Orimaye et al. (Orimaye et al., 2018) also used the DementiaBank dataset to realize a combination of deep neural networks and deep language models for classifying diseases. Several types of research (Chinaei et al., 2017; Pan et al., 2019; Kong et al., 2019; Di Palo and Parde, 2019) apply ML to the DementiaBank dataset. Zhou et al. (Zhou et al., 2019) apply a natural language processing approach to extract lifestyle habits from free-text electronic health record data. They found that patients with AD were exposed to more potential risk factors than the comparison group. Such a method implemented on a smartphone can be a novel assessment tool for estimating the risk of dementia.

3 DISCUSSIONS

Based on the results of the previous section, we discuss the status and issues of the studies.

3.1 Use of Clinical Datasets

Although there are many studies on ML-driven mobile/wearable technologies, there are still few applications to early detection of dementia. A reason is that only a few datasets are appropriate as follows.

A dataset on oral speech during the clinical examination of dementia, called DementiaBank, is available for linguistic analysis. As the dataset has already been used for international competitions, the latest deep learning algorithms have been applied actively for linguistic analysis. In gait analysis research, some researchers have developed datasets of gait disorders, such as PD; they have focused on the diagnosis and treatment of gait disorders and applied ML to

Table 1: Summary of the studies on ML and digital biomarkers.

Analysis	Sensor	Method	Literature
Physiological signal	EEG	PCA	(Al-Jumeily et al., 2014)
		DNN	(D. Kim and K. Kim, 2018)
		convolutional Boltzman machine	(Bi and Wang, 2019)
Human activities	accelerometer	CNN	(Bringas et al., 2019)
	actigraphy	TICC&CNN	(Li et al., 2018)
	door&motion sensor	GCN	(Arifoglu et al., 2020)
	activity sensor	LSTM	(Zhan and Haddadi, 2019)
	location&interaction sensor	RF, SVM, GBDT, etc.	(Okada et al., 2019)
	egocentric camera	SVM	(González Díaz et al., 2013)
Gait	accelerometer	micro features and correlation	(Mc Ardle et al., 2018; Mc Ardle et al., 2020; Xie et al., 2019)
		dynamic time warping	(Xu et al., 2018)
		SVM	(Rodríguez-Martín et al., 2017; Zhang et al., 2020)
Eye movement	head-mounted infrared eye tracker	Correlation&HMM	(Pavisic et al., 2017)
	display mounted infrared eye tracker	RNN	(Chung et al., 2018)
Linguistic analysis	spontaneous speech (microphone)	SVM, GBDT, CRF &DNN	(Searle et al., 2020)
		SVM, HMM	(Beltrán et al., 2019)
		3-Layer NN, SVM	(Rosas et al., 2019)
		SVM	(Tröger et al., 2017)
		CNN, LSTM-RNN, CNN&LSTM-RNN	(Karlekar et al., 2018)
		D2NNLM	(Orimaye et al., 2018)

detecting them. Thus, it is desirable to develop clinical datasets applied to other analyses, such as eye-tracking data of PwDs, when they see their doctors.

3.2 Daily Activity Records for Datasets

HAR is the research area where ML has been most applied in mobile wearable technology. As sensors built in a smartphone or smartwatch are designed to sense the user behavior, it is natural to use the sensor data for ML. HAR can be an excellent tool for the early detection of dementia by recognizing typical behavioral patterns, such as wandering and changes in the patterns.

However, there has been little research on diagnosing dementia using HAR. That is because it is difficult to observe and accumulate the ordinal behavioral patterns of patients in the context of conventional medical diagnoses. On the other hand, with the widespread use of smartphones, it is becoming possible to sense and record the daily activities of older people. If the data can be used, it may be possible to detect differences in behavior before and after the onset of dementia. The daily activity records for datasets, including continuous HAR data, need to be developed for diagnosing dementia.

4 CHALLENGES

This section discusses future challenges to overcome the issues described in the before section.

4.1 ML-driven Data Collection Framework

Due to the difficulty in constructing datasets in daily life, not much research has been conducted on ML-driven wearable techniques for the early detection of dementia. As current smartphone sensors can collect human motions and conversations from a technical point of view, a key issue is designing a service framework that collects longitudinal data by monitoring the user's health status before the detection.

Because the service framework is different from ordinal diagnosis processes based on inspection data conducted in medical institutions, the service should be designed from an information service point of view. For example, large web companies already provide several ML-driven consumer services based on user models using longitudinal data of the users. They adjust the models by comparing predicted results with actual results and by measuring the interventions' effect. In addition, based on longitudinal personal data, the service can construct more precise user models and find more appropriate interventions for each person.

We believe that a future direction for early detection of dementia is creating a data collection framework like web marketing technologies. The framework should be a daily life support system that older people use continuously. For example, it would provide speech recognition services to mediate other Internet services. Moreover, it successively assesses users' health status based on the ML model. The learning processes may be lifelong cycles, and the model would evolve with the service continuously.

The data collection framework has the following positive effects. First, the longitudinal data obtained by the services will become the datasets to help diagnose the disease. High-quality longitudinal personal data can construct a precise diagnostic and interventional model for each person. Second, the detection results can be validated with subsequent data for more accurate future results. Third, voluntary participation in the service may positively impact the users' self-healthcare. How to encourage voluntary participation is an essential perspective considering social implementation.

4.2 Social Acceptance for Data Collection Framework

Clinicians and patients need to understand the data collection framework, which will help the framework get social acceptance. Many people have a high degree of confidence in traditional hospital diagnoses and prefer to receive their diagnosis in a hospital. Therefore, making clinicians and patients like to use the sensing data at home medically is a key issue.

An answer can be providing incentives to them to use the framework. For example, expectations and interests in telemedicine services are rapidly increasing due to the COVID-19 pandemic (Smith et al., 2020). There is a growing need to shift to a new medical service style. Clinicians and patients stay in different spaces, such as their homes, to remotely provide/receive the service. As telemedicine services are becoming more popular, home-healthcare is also becoming a common medical service.

It is also important to provide daily information services on wearable devices, such as speech recognition service described at the before section, to support older people in the post-onset phase of dementia. Useful information services can be incentives for using the framework.

There are more direct incentive approaches, such as financial incentives for physical activity (Barte and Wendel-Vos, 2017). Recently, implicit behavioral incentives such as nudges (Last et al., 2021) have also drawn attention. The design of incentives to encourage users to use the ML-based healthcare framework is a future challenge.

4.3 Personal Data and Privacy

A critical challenge for implementing the ML-driven data collection framework is how to protect users' privacy. Because it collects personal data from sensors close to the human body (Atlam and Wills, 2020; Kapoor et al., 2020), it may raise ethical challenges (Maher et al., 2019; Chang et al., 2019; Burr et al., 2020).Moreover, it is designed to focus on supporting individuals including those who have physical and cognitive disabilities.

To prevent the issues associated with the current healthcare services, some researchers have proposed personal data management models focusing on user privacy (Hasida, 2014; B. C. Singh et al., 2019; Anciaux et al., 2019). In the models, the users can manage their data on their own data storage, and they can choose service providers to access their data and set access limits.

5 CONCLUSIONS

We surveyed the literature on ML-driven wearable technologies for early detection of dementia. We found that the utilization and creation of datasets is an essential issue for realizing the technologies. We described that the datasets should be accumulated based on an ML-driven data collection framework as a continuous healthcare service. We also discussed the issues on socially acceptable implementation of the service framework. We hope that such a data collection framework becomes a part of future medical service infrastructure to support users' long-term health.

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