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Ah-hwee TAN
Singapore Management University, ahtan@smu.edu.sg

Weng Yan YING
Singapore Management University, wyying@smu.edu.sg

Budhitama SUBAGDJA
Singapore Management University, budhitamas@smu.edu.sg

Anni HUANG
Singapore Management University, annihuang@smu.edu.sg

Shanthoshigaa D
Singapore Management University, shanthod@smu.edu.sg

Predicting Mild Cognitive Impairment through Ambient Sensing and Artificial Intelligence

Ah-Hwee Tan, Weng-Yan Ying, Budhitama Subagdja,
Anni Huang, Shanthoshigaa D
School of Computing and Information Systems
Singapore Management University
Singapore
{ahtan, wyying, budhitamas, annihuang, shanthod}@smu.edu.sg

Tony Chin-Ian Tay and Iris Rawtaer
Department of Psychiatry
Sengkang General Hospital
Singhealth Duke NUS Academic Medical Centre
Singapore
tony.tay.c.i@skh.com.sg, iris.rawtaer@singhealth.com.sg

***Abstract*—This paper reports an emerging application leveraging ambient and artificial intelligence techniques for in-home sensing and cognitive health assessment. The application involves a prospective longitudinal study, wherein non-pervasive sensing devices are installed in homes of over 63 real users undergoing clinical cognitive assessment, and digital signals of the users' activities and behaviour are transmitted to a central cloud-based data server for further processing and analysis. Based on the sensor readings, we identify a set of digital biomarkers covering four key aspects of daily living, namely physical, activity, cognitive, and sleep, and develop a suite of customized feature extraction methods for deriving them from the sensor readings. As sensor data captured from real world are inherently sparse and noisy, we build predictive models using various machine learning techniques and evaluate their sensitivity to missing and noisy data. Validated with findings of clinical assessment, our experiments show that machine learning-based predictive models are able to identify mild cognitive impairment (MCI) cases based on the extracted digital biomarkers with reasonably high $F1$ scores of more than 0.85. This shows that the sensor-based digital biomarkers are indicative of the users' cognitive health status and could be further exploited for more general health assessment applications. With a vision of massively deploying such sensor-based AI systems, the paper discusses the challenges we encountered and shares our lessons learned.**

***Index Terms*—Predictive modelling, mild cognitive impairment, biomarker extraction**

I. Introduction

The use of sensor technology has been gaining traction for healthcare and medical use in recent years [1]. They are relatively simple to use and have promising applications for detecting behavioral changes. In particular, initial studies have shown that sensor systems and machine learning techniques are a feasible solution for the early detection of cognitive decline within the community setting and allows remote monitoring of changes in activities of daily living [2]. However, deployment of such sensors in a home-based environment could present various challenges due to human factors and hardware limitations in real world.

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Accordingly, though there have been studies in using digital biomarkers for early detection of cognitive impairment [3], most are done via specific cognitive tasks, such as game playing [4], or in a controlled lab-based environment [5]. On the other hand, extensive work have investigated the use of activity of daily living (ADL) to detect the changes in cognitive abilities of elderly [6], [7] and anomaly in key activities [8]. To overcome the anomalies arising from the sensors, some employed hierarchical clustering to build ADL clusters [9] and used the cluster variability to assess changes in the activities and behaviour of the participants. Though these work have obtained promising results on recognizing ADL types and differentiating ADL log images between MCI and healthy participants, they need the participants to provide their activity logs with those sensor data in order to train the ADL classification models, which is time-consuming and prone to errors when transferring from lab to real life scenarios.

Different from previous work typically conducted in lab-based platforms, this paper presents an application based on a large-scale study called SINEW (in short for "Sensors IN-home for Elder Wellbeing") [10], which combines non-intrusive ambient sensing and AI technologies in a **real life home-based setting** for health monitoring and wellness analysis. Specifically, the application aims to determine the utility of continuous activity monitoring for early detection of mild cognitive impairment, a window of opportunity for timely intervention, and whether behavioral change patterns can be used to classify between normal cognition, mild cognitive impairment, and dementia. SINEW is arguably the first longitudinal study focusing on MCI detection through sensor data automatically captured from a sizable number of real homes. In comparison, a similar study made use of sensor data collected from the homes of 49 subjects over a period of just two months [11] and another only had 13 participants in the reported longitudinal study [12].

SINEW is a prospective cohort study, wherein community-dwelling seniors above 65 years were recruited from nationally representative cohorts in the community. The longitudinal study involves close to one hundred subjects over a period of three years from 2020 to 2023. Each recruited senior is living alone and functioning independently in the community with

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normal cognition (NC) or mild cognitive impairment (MCI). Upon recruitment, a home-based sensor system was installed in the participant's home for non-intrusive monitoring of daily activities. Concurrently, detailed neurocognitive assessments and consensus panel diagnosis are repeated annually to determine the cognitive status of the participants. The main outcomes of this study are to detect cognitive decline and transition of cognitive states, i.e., conversion from healthy cognition to mild cognitive impairment/early dementia.

Based on the sensor readings, we identify a set of digital biomarkers that capture four key aspects of daily living, namely physical, activity, cognitive, and sleep. We further develop a suite of customized feature extraction methods for deriving them from the sensor readings. As sensor data captured from real world are inherently sparse and noisy, we build predictive models using various machine learning techniques and evaluate their sensitivity to missing and noisy data. Validated with findings of clinical assessment, our experiments show that machine learning-based predictive models, in particular fusion Adaptive Resonance Theory (fusion ART) [13], are able to identify mild cognitive impairment (MCI) cases based on the extracted biomarkers with a reasonably high level of $F1$ scores. The results show that the non-intrusive sensor-based digital biomarkers are indicative of the users' cognitive health status and could be further exploited for more general health assessment applications. This innovative approach thus could pave the way toward a reliable, scalable and effective home-based sensor system to facilitate the early detection of cognitive decline, potentially revolutionizing the way elderly care and interventions are delivered.

In summary, the key technical contributions of this work include: (1) demonstrating the feasibility of using high level digital biomarkers, automatically derived from raw sensor data, for MCI detection; (2) evaluation of a suite of machine learning models in handling noisy sensor data with a high level of missing rate, an issue arising from real-time sensing and human data collection in a real world environment; and (3) the use of a class of self-organizing neural networks called fusion ART which shows high resilience in learning from a small number of training samples, with a high missing rate.

II. Clinical Protocol and Methodology

A. Participant Recruitment

One hundred participants were initially recruited from the community. All potentially eligible participants were screened using pre-defined eligibility criteria. Community-dwelling seniors above 65 years who can communicate and provide written informed consent in English and/or Mandarin were selected for the study. They should also be living alone and functioning independently in a community with no history of dementia or other psychiatric disorders. They would also not be recruited if they have limitations in basic activities of daily living, are unwilling to deploy sensors in their homes, or are currently participating in any cognitive or motor training intervention trial.

The potential participants were identified and referred to this study by study members of existing cohort studies, by partners from voluntary welfare organizations, hospitals memory and psychogeriatric clinics and word of mouth recommendation. The study would be explained in detail to potential participants and ample time was provided for potential participants to consider their participation and discuss with their family members. Once the potential participant expressed interest in taking part in the study, a baseline visit was arranged to obtain informed consent and conduct screening procedures. The study would be explained in detail to potential participants with the participant information sheet before informed consent was obtained.

B. Clinical Assessment

Trained research staff screened potential participants for eligibility. A structured questionnaire was utilized to gather essential information, including socio-demographic data, medical history, family background, and lifestyle habits. Mini Mental State Examination (MMSE) [14], Montreal Cognitive Assessment (MoCA) [15], Lawton's Instrumental Activities of Daily Living Scale (Lawton's iADLs) [16], Clinical Dementia Rating (CDR) [17], and neuropsychological assessment batteries were administered at this stage. Eligible participants were enrolled in the study and completed remaining baseline assessments.

Outcome and Health Measures: Participants completed comprehensive assessments using validated instruments to measure various aspects of health including functional, psychosocial, mental, and cognitive well-being. These validated assessments were administered by trained research assistants. The instruments used to understand function and social vulnerability included the Lawton's iADL scale [16], the Friendship Scale [18], and the Lubben's Social Network Scale [19]. Mental health and sleep was assessed using the Zung Self-Rating Depression Scale [20], the 15-item Geriatric Depression Scale [21], Pittsburgh Sleep Quality Index (PSQI) [22], and the Apathy Inventory [23]. Lastly, for cognitive health, a series of neurocognitive tests adapted to local populations were conducted. All clinical assessments were repeated annually for three years.

Concurrently, home-based sensors were installed within 8 weeks from baseline assessment and removed 6-8 weeks before the end of the study. Participants may drop out at any point in the study or exit the study when diagnosed with dementia. Upon completion of the three-year study, participants provided feedback through questionnaires about their experience with the home-based sensor system. The information obtained will be used to guide future iterations of this system.

III. Sensor Network and Data Collection

Data collection in the SINEW project is conducted through an Internet of Things (IOT) architecture, as shown in Figure 1, which consists of a combination of wireless devices, an intelligent gateway, and a cloud server that serves as the back-end of the home-based sensor network systems. Each SINEW sensor network system is designed to collect the raw sensor

TABLE I
A SUMMARY OF THE SENSORS DEPLOYED AND THEIR CHARACTERISTICS.

Type of Sensors	Sensor ID/ Location	Value/Interpretation
Motion Sensors	M-01 (Living Room) M-02 (Kitchen) M-03 (Bedroom)	No Motion: 0 Motion: 255 (updated every 5 mins)
Contact Sensors	D-01 (Main Door) D-02 (Medication Box)	Closed : 0 Opened : 255 Whenever triggered
Pressure Sensor	D-03 (Bed)	Pressure on: 0 Pressure off: 255 (whenever triggered)
Beacon Sensors	B-01 (Key) B-02 (Wallet)	Near Gateway: Timestamp updated every 4 mins Out of range: No update
Wearable Sensor	Step Count Heart Rate (bpm)	Number of steps Beats per minute

readings data from the home of an individual participant and transmit the data to the cloud-based database via in-house gateway device. The raw sensor readings are then further processed to extract the digital biomarker features.

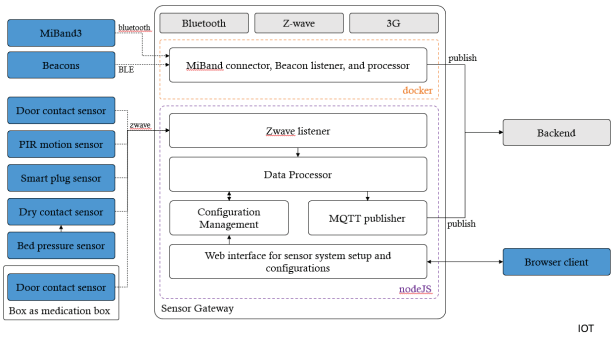

Fig. 1. The architecture of the sensor network system piping the data collected by the sensors to the back-end server.

Table I contains a list of the wireless sensors deployed, consisting of three motion sensors for living room, kitchen, and bedroom, two contact sensors for main door and medication box, one pressure-based bed sensor, two beacon sensors attached to key and wallet, and one wearable device. As illustrated in Figure 2, in each home, wireless contact and motion sensing devices are strategically positioned in various locations, encompassing the main door, medication box, living room, kitchen, and bedroom. In addition, the wearable device is to be worn by the participant at all times and the beacons are tagged to his/her key and wallet. While the contact and motion sensors make use of Z-Wave technology, the wearable and beacons employ Bluetooth Low Energy (BLE) for communication.

The home gateway device is based on Raspberry Pi and uses a combination of portable Wi-Fi dongle and Z-Wave stick. The sensors are set up in a way that they are able to periodically sense the environmental cues and send the information to the gateway device. The gateway device in turn aggregates

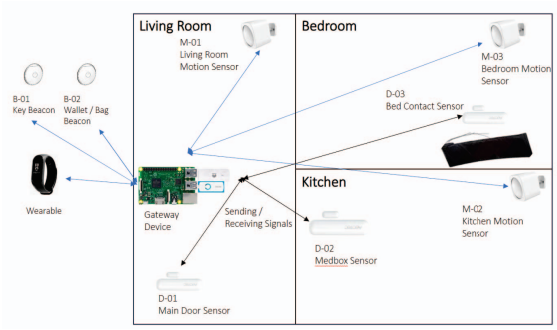

Fig. 2. An illustration of sensors' placement in the participants' homes.

the data sent by the sensors and transmit them to a cloud server hosted by Amazon Web Service (AWS) via a secure 4G cellular communication. The sensors deployed at a home are identified with a unique ID tagged to each participant. All data are stored securely in the database and only accessible by the research team. By ensuring that the participants' identities are not passed through the cloud services, the system is both secure and dependable for our research while maintaining the confidentiality of the individuals within our system.

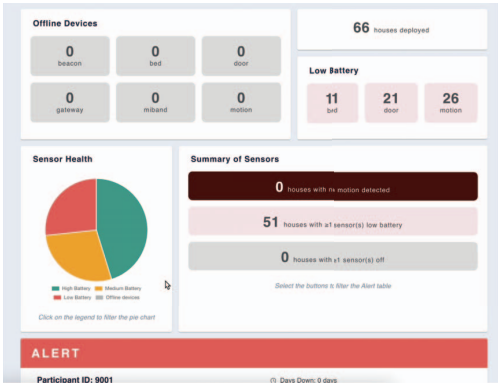

Fig. 3. The SINEW Deployment Dashboard displaying the overall status of the sensors deployed.

For monitoring the status of the sensor networks and preliminary analysis of the data collected, the SINEW project implementation further includes a dashboard designed for the research team to monitor and visualize the collected data. The SINEW Dashboard is organized into three sections. In the main section, the SINEW Deployment Dashboard (Figure 3) provides an overview of the status of the deployed sensors and the number of existing participants. In the second section, the SINEW Biomarker Dashboard provides an overview of the biomarker values captured for a selected participant/cohort over a chosen period of time. This dashboard is useful for clinical staff to conduct their analytical investigations on the participants. The third section of the SINEW Dashboard provides a list of alert messages informing any malfunction of the sensors deployed at the homes of the participants. For example, when a passive infrared motion sensor is turned off, an alert

will be sent to inform the data engineers regarding the status. The SINEW Dashboard enables the project team's prompt intervention to swiftly resolve the issues with a minimal down time, thereby helping to ensure a reasonable quality of data collection.

IV. Digital Biomarker Extraction

The data sent by the in-home sensors are raw sensor data in the sense that each entry in the sensor database indicates a single reading from a sensor at a particular time in one participant's home. As such, high level biomarker features need to be extracted from the raw sensor readings to enable further analysis and prediction.

A. Sensor Data and Digital Biomarkers

A record of the sensor data consists of four attributes, including *participant's id* as the unique identifier of the participant, *timestamp* indicating the date and time of the sensor reading, *sensor id* as the identifier of the sensor, and *sensor value* as the reading of the sensor. The *timestamp* attribute is the date and time at which the home gateway receives the sensor reading message before submitting to the cloud server. The type of sensors can also be derived from the *sensor id* attribute.

On the other hand, the digital biomarkers are designed to capture the high level information relating to the daily routines and activities of each participant. In this study, the biomarkers are used to capture different aspects of daily living that include **physical**, **activity**, **memory**, and **sleep**. Specifically, a daily record of the digital biomarkers for a person captured in a day consists of a total of 20 biomarker features organized according to the four basic aspects of daily living as follows:

- **Physical Biomarkers** track bodily movement produced by skeletal muscles that requires energy expenditure[1] which can be monitored using wearable sensors like smartwatches or body-worn sensors [10], [24]. Two basic physical biomarkers are captured in this study, namely the *heart rate* (beat per minute) and the *step count*.
- **Activity Biomarkers** track the person's activity-related behavior in relation to movement to spatial zones/locations in daily lives. Five biomarkers are captured for zonal movement, including the number of *transitions to bedroom*, *transitions to kitchen*, *transition to living room*, *outing* (number of times going outside), and the *outing duration* (total time spent outside) in a day.
- **Cognitive Biomarkers** monitors the participant's memory performance which may be indicative of cognitive decline in daily activities. There are three biomarkers related to forgetfulness, namely the number of times *forgetting wallet* (situations wherein the participant forgets to bring his/her wallet when going outdoor), *forgetting keys* (the participant forgets to bring the door key), and *forgetting medication* (forgetting to take medication according to the prescribed frequency).
- **Sleep Biomarkers** capture the statistics of sleep patterns of the participant [10], [25]. There are two sets of features for sleep in the day time and night time respectively, each consisting of five features, namely *sleep time*, *wake time*, *sleep duration*, number of *sleep interruption*, and *sleep interruption duration*.

[1] https://www.who.int/news-room/fact-sheets/detail/physical-activity

B. Daily Biomarker Extraction

To extract the daily digital biomarkers from the raw sensor data, the following steps of operations are performed.

1) *Data purging*. In this operation, valid raw sensor data are selected based on the periods of availability of the participant for data collection and whether the in-home sensor gateway system was functional. This step is necessary to filter away unusable sensor data captured when a gateway is down or a participant is away over a certain period of time.
2) *Intermediate features pre-processing*. Based on the valid sensor data of every participant, each day is divided into intervals of δ minutes (currently we use $\delta = 5$) in sequential order. The number of sensor readings and their values for every sensor type occurred within each interval are then recorded.
3) *Biomarker feature extraction*. Based on the intervals of sensor readings, each biomarker feature is extracted following some predefined pattern matching rules to detect the participant's state of behavior. For example, to obtain the number of *forget medication*, a rule is used to detect the state that the participant does not take the medication as prescribed based on the absence of readings from medication box sensor (D-02) within a range of time intervals.

Figure 4 shows the process of extracting digital biomarkers from the raw sensor data. Each pattern matching rule corresponds to the detection of a participant's behavior state. Overall, there are eight behavior states to detect implying eight different pattern matching rules. Since *heart rate* and *step count* can be obtained directly from the readings of the smartwatch sensor independent from the time intervals, no state (and rule) is required to extract the two **physical** biomarkers. The rules for extracting the other three classes of biomarkers are described as follows.

- For **activity** biomarkers, four rules are required to detect the behavior states related to the location/position of the person within a time interval, namely *in living room*, *in kitchen*, *in bedroom*, and *outside* (outing). The rules combine sensor readings from motion sensors, door sensors, and the absence of their readings to determine the states.
- For **cognitive** biomarkers, three rules are required to detect the states related to forgetfulness of the participant in different time intervals: *forgetting key*, *forgetting wallet*, and *forgetting prescribed medication*. The rules combine the state of outing, readings from beacons, readings from medication box (D-02), and the participant's medication prescription to detect the states.

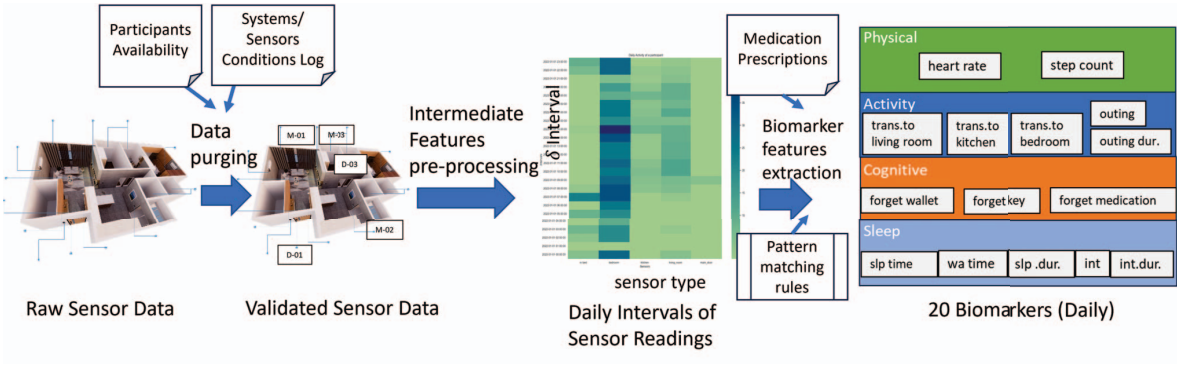

Fig. 4. The biomarker feature extraction process wherein daily readings of in-home sensors are analysed and transformed into digital biomarker features.

- For **sleep** biomarkers, two rules are needed to detect the states of *sleeping* and *awake*. The rules combine the positioning/location state (*in bedroom*) and the readings from the bed pressure sensor to detect the states.

V. Data Validation Experiments

To test the hypothesis on whether the digital biomarkers obtained based on daily activities are indicative of the participants' cognitive health, we have conducted extensive empirical experiments wherein predictive models are built using various machine learning techniques based on the digital biomarker data collected.

A. Experiments with Monthly Averaged Data

From the sensor data collected over a period of 17 months from January 2022 to May 2023, we obtained a total of 8,428 daily biomarker records from 63 participants. We did not make use of the sensor data collected from 2020 to 2021 as they were known to be more noisy. To eliminate the effect of outliers, our first set of the experiments averaged the feature values over the days within each calendar month. After filtering away those records with 100% missing feature values, we obtained a data set containing a total of just 346 monthly averaged biomarker records for our experiments. As shown in Table II, the monthly feature data obtained was still highly sparse and noisy with more than 71% of the records having more than 50% of their feature values missing. In particular, the bed sensors and wearables presented the highest missing rates largely due to the human interaction required. These missing data clearly pose a great challenge to the machine learning models in learning the task of MCI detection. While our preliminary experiments showed that removing those samples with high missing rates could potentially improve the models' performance in cross validation, the experiments reported below have made use of all the available biomarker records as long as not all the feature values are missing.

For detection of mild cognitive impairment (MCI) cases, each of the monthly averaged biomarker records for each participant was tagged with the outcome of his/her closest clinical assessment within a six month period, which served as the cognitive label of the record. Five distinct machine learning models were used in our experiments for building predictive models, namely K Nearest Neighbour (KNN) , Support Vector Machine (SVM) , Decision Tree (DT) , Random Forest (RF) , and fusion Adaptive Resonance Theory (fART) networks [13]. These models are chosen as they have been used and showed satisfactory results in previous studies on MCI prediction [11], [26]–[28]. We did not explore deep learning models which typically require a large number of training samples. Each of these machine learning models was trained and tested in a supervised learning fashion for predicting MCI cases based on the monthly-averaged biomarker features. For handling missing data, the KNN imputation method [29] was used for all machine learning models, except fusion ART, which has an in-built mechanism for encoding missing feature values using complement coding [11].

TABLE II
Distribution of biomarker records with missing features in the monthly averaged SINEW data set.

x	Records with $\geq x\%$ missing features	
	Number of Records	Percent of Records (%)
90	7	2.023
80	15	4.335
70	52	15.029
60	194	56.069
50	248	71.676

To empirically evaluate the predictive models, we performed stratified 10-fold cross validation, wherein the data set was split into ten folds with roughly the same distribution of positive and negative cases in each fold. Each machine learning model was then trained on the training set (consisting of nine folds) and tested on the remaining one fold. The performance of each learning model was evaluated in terms of the commonly used precision, recall and F_1 measure for detecting MCI cases.

Table III shows the predictive performance of the various machine learning models, including K Nearest Neighbour (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and fusion ART (fART), in identifying MCI cases based on the monthly averaged biomarker features.

TABLE III
PERFORMANCE OF MACHINE LEARNING MODELS IN IDENTIFYING MCI CASES BASED ON MONTHLY AVERAGED BIOMARKER FEATURES.

	Precision	Recall	$F1$ Score
KNN	0.661 ± 0.080	0.576 ± 0.171	0.607 ± 0.125
SVM	0.765 ± 0.142	0.569 ± 0.164	0.645 ± 0.150
DT	0.576 ± 0.106	0.603 ± 0.154	0.584 ± 0.121
RF	0.796 ± 0.135	0.634 ± 0.122	0.703 ± 0.121
fART	0.866 ± 0.064	0.835 ± 0.089	0.849 ± 0.068

TABLE IV
DISTRIBUTION OF BIOMARKER RECORDS WITH MISSING FEATURES IN THE WEEKLY AVERAGED SINEW DATA SET.

	Records with $\geq x\%$ missing features	
x	Number of Records	Percent of Records (%)
90	30	2.29
80	70	5.34
70	243	18.52
60	828	63.11
50	1058	80.64

We can see that fusion ART has produced the highest level of performance across all three measures of precision, recall and $F1$ scores. As a distant second, RF performed markedly better than KNN and SVM. DT was the worst performer.

B. Experiments with Weekly Averaged Data

We further conducted experiments wherein the daily biomarker feature values were averaged within each week to produce a weekly averaged biomarker data set. A total of 1,312 weekly biomarker records were obtained with 529 MCI cases and 783 healthy cognition (HC) cases. Besides providing more data records for training and testing the machine learning models, the weekly averaging method also produces a more balanced class distribution of MCI and HC cases. However, as shown in Table IV, the weekly average data has a even higher missing rate with 80% of the records having more than 50% of their feature values missing.

Based on the weekly biomarker data set, we repeated the predictive modeling experiments following the same stratified 10-field cross validation methodology. As shown in Table V, the predictive performance of all machine learning models improved with the weekly biomarker data set. In particular, fusion ART achieved the best $F1$ score of 0.906. By encoding missing feature values using complement coding, fusion ART appears to be well suited for handling input patterns with high missing rates. Among the other four models, KNN, RF, and SVM produced a similar level of performance while DT again performed the worst.

Besides predictive performance, the ability to interpret and explain the knowledge learned by the machine learning models is also a key consideration. For fusion ART, due to its compatibility with rule-based representation, the knowledge learned can be translated into IF-THEN symbolic rules for further analysis. For illustration, Table VI shows two sample rules extracted from the fusion ART models. The rules indicate that MCI patients generally tend to be inactive in their daily living in terms of both indoor room transitions as well as outdoor duration. In addition, they have a high tendency of forgetting their medication.

TABLE V
PERFORMANCE OF MACHINE LEARNING MODELS IN IDENTIFYING MCI CASES BASED ON WEEKLY AVERAGED BIOMARKER FEATURES.

	Precision	Recall	F_1 Score
KNN	0.862 ± 0.036	0.801 ± 0.053	0.830 ± 0.039
SVM	0.853 ± 0.031	0.760 ± 0.070	0.802 ± 0.040
DT	0.739 ± 0.034	0.722 ± 0.088	0.728 ± 0.050
RF	0.870 ± 0.045	0.784 ± 0.086	0.822 ± 0.057
fART	0.891 ± 0.041	0.924 ± 0.038	0.906 ± 0.025

TABLE VI
TOP TWO RULES FOR THE MCI CLASS EXTRACTED FROM FUSION ART.

Rule	Conditions	Interpretation
1	IF (transLivRM: [Very Low, Low]) AND (transKitchen: Low) AND (transBedRM: Very Low) AND (outingTimes: [Low, Average]) AND (outingDur: [Very Low, Low])	Very Low-Low indoor transitions Very Low-Average outing
2	IF (forgetWallet: Very Low) AND (forgetKeys: Very Low) AND (forgetMed: Very High) AND (transLivRM: [Very Low, Low]) AND (transKitchen: Low) AND (transBedRM: [Very Low, Low])	Very High forget medication Very Low-Low indoor transitions

VI. DISCUSSION

As a deployed application, the SINEW project has faced various challenges posed by the real world environment. We discuss the key issues and our countermeasures below.

Hardware limitations: To manage the deployment cost, the sensors employed in the SINEW are typically low cost and light weight mobile devices which can be deployed easily. However, as such sensors are meant to capture data in real time, failures of hardware may happen over time resulting in errors or lapses in data capture. Powering these mobile sensors on a 24-7 manner is another challenge. In particular, batteries on the contact and motion sensors need to be replaced regularly. To mitigate these issues of hardware failures, a dashboard system is developed to monitor the status of the sensors deployed and provide alerts to our data engineers for attention and maintenance.

Human factors: As sensors are installed in the homes of the participants, they are subject to the proper handling and use of their users. In particular, some participants have found the bed sensors uncomfortable to sleep on and do not use them on a regular basis. Besides reminding the users on the proper use of the devices, we have to make use of other situational factors, such as the time of the days and the signals detected by other sensors, to infer the missing sleep-related features.

Data Challenge: Related to the challenges arising from hardware limitations and human factors, the sensor readings captured are typically sparse and noisy. In particular, more than 77% of the monthly biomarker data contain more than 50% missing feature values. In addition to using data imputation techniques, we explore machine learning models, such as fusion ART, which are able to handle missing data with a high degree of efficacy and robustness.

VII. Conclusion

The SINEW project represents a large-scale study leveraging ambient intelligence devices and artificial intelligence techniques for non-intrusive sensing of human daily activities and cognitive health assessment in a home-based environment. To mitigate the issues and challenges presented by a real world environment, we have spent considerable effort in sensor network deployment, monitoring, and maintenance, as well as developing various heuristics in biomarker feature extraction and exploring various machine learning models to handle sensor data with a high missing rate. By developing a suite of customized feature extraction methods and predictive modeling techniques using machine learning models which are able to handle missing data, we have obtained promising results showing that sensor-captured digital biomarkers are indeed indicative of the cognitive statue of the participants and can be exploited effectively to detect cognitive decline.

Going forward, we shall continue to build and analyze large sensor and biomarker data sets and to explore the use of more fine-grained activity-based biomarkers for MCI prediction and early detection of transitions in cognitive states. Beyond cognitive assessment, the SINEW framework and platform could also be further expanded to support more general safety monitoring and health assessment. In the foreseeable future, we expect homes with such setting combining ambient sensing and AI analysis will become more commonplace, considering the challenges faced by the ageing populations in many countries globally.

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