東海大学大学院令和５年度博士論文

Activity Recognition using Magnet Sensors and its Applications in Elderly Care

（磁石センサーを用いた行動認識と高齢者介護への応用）

指導　　　撫中達司 教授

東海大学総合理工学研究科

総合理工学専攻

PAPEL Joao Filipe

THESIS TITLE	Activity Recognition using Magnet Sensors and its Applications in Elderly Care
STUDENT NAME	PAPEL João Filipe
STUDENT ID	1CTAD006
DEGREE	Doctor of Engineering
PROGRAMME	Program of Information Science and Technology
ADVISOR	Dr. Tatsuji MUNAKA (Professor)

Abstract

The challenges posed by an ageing population have led to an urgent need for innovative solutions that can monitor and improve the quality of life for the elderly. This thesis presents a multi-faceted approach to address this issue, combining advanced sensor technologies and data analytics techniques to recognize activities of daily living (ADL) and detect potential early signs of cognitive decline in particular dementia.

The first part of this research focuses on leveraging magnet sensors to recognize ADL. It also covers the principles, applications, sensor implementation, data processing, and validation of this method. By employing only magnets sensor to detect events and correctly identifying the activities of daily living, the study demonstrates a significant level of accuracy when performing the activity recognition. This approach minimizes the need for human intervention and ensures privacy, as the data collected is non-intrusive. A novel system is introduced, which incorporates these sensors into the daily living environment of the elderly. The system is designed to be low-maintenance and highly reliable, addressing some key challenges existing solutions face. Moreover, it incorporates an ontological model to interpret the sensor data, providing a more nuanced understanding of the activities being performed.

In the first part it is also possible to get a glimpse of the previous studies related to the activity recognition systems and their challenges. The challenges the previous research found and solved as well as the challenges that remained unsolved. This part also describes in detail the results and issues found by me when decided to improve and use the most promising sensor-based solution (sound sensors) based on previous studies results.

The second part of the thesis focuses on applying this advanced activity recognition method in the healthcare sector, specifically for the elderly care. In this part is illustrated a variety of case scenario where the activity recognition system can help medical professionals identifying the early stages of different diseases by monitoring the activities of daily living (cooking, eating, drinking water, taking a shower, urinating, defecating, sleeping, cleaning, laundering, and brushing teeth) that we monitored on the part I of this thesis. Particular attention is given to the possibility of identifying abnormal behaviors in the elderly's activities of daily living leading this way to the potential indicators of the early stages of detection of dementia through the detection of behavioral

changes that could be indicative of cognitive decline or the onset of dementia. While the primary objective is to develop a method for activity recognition, the research also delves into how this method can be applied to identify abnormal behaviors in the elderly. It should be noted that while the goal is to aid in the early detection of dementia, the effectiveness of this application has not been fully validated, and it serves as a supplementary discussion in this work.

In summary, this thesis comprehensively explores the development and application of advanced sensor-based methods for activity recognition. It presents an innovative solution that addresses the limitations of existing systems, both in terms of technology and applicability. The research contributes to sensor technology, data analytics, and healthcare, providing a robust foundation for future work to improve the quality of life for the aging population.

Acknowledgment

The journey to completing this doctoral thesis has been an incredible experience, filled with challenges, learning, and growth. It would not have been possible without the support, guidance, and encouragement of numerous individuals and organizations. I would like to take this opportunity to express my deepest gratitude to all who have contributed to this significant milestone in my academic career.

First and foremost, I extend my heartfelt thanks to the Japanese International Cooperation Agency (JICA) for awarding me the scholarship that made it possible for me to fulfill my dream of studying in Japan. I am particularly grateful to Mr. Simões Victorino from JICA Mozambique for his unwavering support and guidance. I also wish to express my appreciation to Oki-san and Maki-san from JICA Yokohama for their invaluable assistance and for making my transition to Japan smoother.

I owe a debt of gratitude to the entire staff of Tokai University for their relentless support over the past 3.5 years. Special thanks go to Yoko-san, the International Dormitory Manager, for her kindness and for making my stay comfortable. I am also grateful to Ms. Iwasaki-san and Mr. Furuya-san for their administrative support, which has been instrumental in making my academic journey as smooth as possible. Their efforts, along with those of many others who have supported me directly or indirectly, have been invaluable.

I would also like to acknowledge the professors who led the collaborative seminars during my time at Tokai University. Their expertise and insights have broadened my horizons and enriched my understanding of diverse subjects, thereby contributing to my academic and personal growth.

My sincere thanks go to Professor Takao for his invaluable input and comments. His perspectives have opened my eyes to the enormous possibilities that my research holds in the healthcare field, thereby adding a new dimension to my work.

The emotional and moral support of my wife, Arminda Salvador Dramusse Papel, has been my pillar of strength throughout this journey. Her understanding, patience, and unwavering support have been the bedrock upon which I have built my academic endeavors.

Last but certainly not least, I owe my deepest gratitude to my Academic Advisor, Professor Tatsuji Munaka. His guidance, mentorship, and encouragement have been nothing short of

transformative. Under his tutelage, I have achieved milestones I never thought possible, such as having papers accepted at IEEE conferences. The journey was fraught with challenges, but with his support, we conquered them all. Words fall short of expressing the profound impact Professor Munaka-san has had on my academic and personal development.

In conclusion, this thesis stands as a testament to the collective efforts, support, and faith of all those mentioned above. I am eternally grateful and consider it an honor to have been associated with each one of them during this pivotal phase of my life.

Dedication

I want to dedicate this thesis and my doctoral degree to my fathers, Jorge Olivio Penicela Nhambiu and João Papel.

My special gratitude goes to my beloved mother, Arminda Amina Elias Nhambiu, who unfortunately passed away in 2021 and can't be here among us to see and witness the end of my academic journey. A journey that, thanks to her efforts and persistence, started in 2011 with me starting my bachelor’s degree in computer engineering. This journey wasn't easy, but thanks to her insensible efforts and constant "support" in her own way made me continuously push myself toward my master's degree and finally to this doctorate program. I know that wherever she is now in heaven, she is proud and celebrating this achievement. Despite she said to me at the moment of departure from Mozambique that she was delighted with the fact that I got this scholarship and that she fulfilled her mission of ensuring that I had studied until I reached the highest level in the academic world and she could go in peace, I'm still not ready to truly accept that she will not be waiting for me upon my return to Mozambique to celebrate this achievement with me.

Dear Mother, Aunty, and Friend, today, November 3rd of, 2023, I can proudly say that against all the odds, we did it one more time. I'm so grateful and forever will be for everything you fought and did for me, for never giving up on me, and for pushing me to be a better person.

With love and sadness from the son that God gave you.

List of Figures

List of Tables

Table of Contents

Part I: Advanced Methods of Activity Recognition

I.I. Introduction

1. Background

The aging population is a global phenomenon that has led to an increased need for efficient monitoring systems to ensure the well-being and safety of the elderly. According to the 2019 Annual Report on the World Population Ageing Report issued by the United Nations [1], it is estimated that the number of older people who are 65 years or older will exceed 1548.9 million in 2025. The most significant increase (+312 million persons) is projected to occur in Eastern and South-Eastern Asia, growing from 261 million in 2019 to 573 million persons aged 65 years or over in 2050 [1]. The number of older persons is expected to grow fastest in Northern Africa and Western Asia, from 29 million in 2019 to 96 million in 2050 (+226 percent) [1], The second-fastest rise in the number of older persons is foreseen in sub-Saharan Africa (+218 percent), with expected growth from 32 million in 2019 to 101 million in 2050 [1], In contrast, the projected increase is relatively small in Australia and New Zealand (+84 percent) and Europe and Northern America (+48 percent) [1], Table 1 provides a better view of this situation.

With aging also comes a variety of diseases. Some are related to the elderly's physical body, and others are related to the elderly's emotional and cognitive parts. This thesis focuses on presenting a system capable of detecting different events and, with the sequences of the events, identifying the activities of daily living.

Since older people live apart from their families, their families cannot notice immediate problems that may occur to them, such as cognitive and psychological diseases. There have been several studies on activity recognition to watch or care for older people to solve such problems using the Internet of Things (IoT) [2-5]. By using IoT, we mean using any microcontroller or processor and any sensors to collect information and to provide information based on the results obtained from the process of the collected data.

Current monitoring systems face several challenges, including reliability, the need for constant maintenance, accuracy, and privacy. During our research searching for the best activity of daily living system we developed and tested an activity recognition system based on the sounds of daily life. This system involved the improvement of the MFCC feature extraction to make possible to identify the sounds of daily life since the traditional or conventional MFCC was made to create a compact representation of audio signals for distinguish different phonetic contents in spoken words in the speech processing domain, including speech recognition, speaker identification, and more. There is a difference on frequencies between the human voice and the sounds of daily life, because of these differences we needed to make improvements on the MFCC to be able to capture the correct sounds to help us identifying the correct events and consequently the correct activities. Due to issues found when detecting activities of daily living that co-occurred at the same time due to sounds overlapping affecting this way the system accuracy, consequently the overall reliability and to the rise in concerns of privacy issues regarding illegal conversations recordings and used without permission for different unlawful uses such as blackmail, the elderly tend to be more resistant to adopting technologies that record their activities, fearing that they may be exposed later [5]. The privacy of older people must always be taken into account. It is necessary to develop strategies and techniques for monitoring ADLs and IADLs that are not considered invasive, which can risk exposure to intimate activities of the elderly, such as bathing, toileting, and dressing [6-9].

While there have been numerous attempts to develop systems for activity recognition, many of these have faced challenges related to reliability, maintenance, accuracy, and privacy [8] [10-19]. This thesis aims to address these issues by leveraging the unique properties of sound and Magnet sensors for activity recognition.

Table 1. Number Of Persons Aged 65 Years or Over, By Region, 2019 And 2050 [1]

Region	**Number of persons aged 65 or over in 2019 (millions)**	**Number of persons aged 65 or over in 2050 (millions)**	**Percentage change between 2019 and 2050**
World	**702.9**	**1 548.9**	**120**
Sub-Saharan Africa	31.9	101.4	218
Northern Africa and Western Asia	29.4	95.8	226
Central and Southern Asia	119	328.81	176
Eastern and South-Eastern Asia	260.6	572.5	120
Latin America and the Caribbean	56.4	144.6	156
Australia and New Zealand	4.8	8.8	84
Oceania, excluding Australia and New Zealand	0.5	1.5	190
Europe and Northern America	200.4	296.2	48

2. Objectives

The primary objective of this research is to advance the methods of activity recognition using sound and magnet sensors. Specifically, the study aims to:

- Enhance feature extraction methods in sound sensor technologies.
- Develop an ontological model for magnet sensor-based activity recognition.
- Explore the applications of these methods in detecting abnormal behavior as potential indicators of early stages of dementia.

3. Research Questions

1. How can sound sensors with improved MFCC effectively recognize activities of daily living?
2. Can Magnet sensors provide a reliable and efficient means for activity recognition?
3. What are the benefits of integrating an ontological model in magnet sensor-based activity recognition?
4. What are the potential applications of these activity recognition methods in healthcare?
5. Can these advanced methods be applied to detect abnormal behavior in the elderly, particularly as potential indicators of early stages of dementia?

4. Methodology

The research employs a data-driven classification approach to attach labels to the collected data and uses a generative approach to predict activities based on the input data. The reliability of the sensors is validated in natural environments, addressing issues that previous studies faced, such as false triggers by pets or other environmental factors [8][10].

5. Thesis Outline

The thesis is divided into two main parts. Part I focuses on advanced methods of activity recognition using magnet sensors. It covers the principles, applications, sensor implementation, data processing, and validation of this method. In this part it is also possible to get a glimpse of the previous studies on the activity recognition systems and their challenges. The challenges the previous research found and solved as well as the challenges that remained unsolved. This part also describes in detail the results and issues found by the author when deciding to improve and use the most promising sensor-based solution (sound sensors) based on previous studies. Finally, this part presents a novel approach for the activity recognition field based on the implementation and use of magnet sensors, an approach never used before in this field.

Part II delves into the applications of the novel activity recognition method in elderly care. This part is illustrated a different case scenario where the activity recognition system can help medical professionals identify the early stages of different diseases by monitoring the activities of daily living (cooking, eating, drinking water, taking a shower, urinating, defecating, sleeping, cleaning, laundering, and brushing teeth) that we monitored on the part I of this thesis. Particular attention is given to the possibility of identifying abnormal behaviors in the elderly's activities of daily living, leading this way to the potential indicators of the early stages of detection of dementia.

I.II. Literature Review

1. Activities of Daily Living

Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL) are critical metrics for assessing the functional status of the elderly. ADL includes basic self-care tasks such as bathing, dressing, and eating [6] [20-23]. IADL encompasses more complex activities like cooking, cleaning, and shopping [6]. These activities serve as indicators of an individual's ability to live independently and are often used in healthcare settings to monitor the well-being of the elderly [20-23].

2. Activity Recognition

Activity recognition aims to identify human activities through the use of various sensors and technologies. Traditional methods often rely on wearable devices or camera-based systems, which can be intrusive and raise privacy concerns [24 26]. Recent advancements have shifted the focus towards less intrusive methods, such as sound, RFID, Pressure, IF Motion sensors, and others, which offer a balance between reliability and privacy [10][12] [18-24] [26-30].

Methods to collect data with sensors and recognize events and activities using machine learning based on the data are roughly classified into two types: Data-driven and Knowledge-driven [31]. Data-driven can be classified into two types: one called the "generative method," which creates a model using collected data [32-33], represented by HMM (Hidden Markov Model) and Bayesian classification (They are called "model type" in this thesis). The other classification of Data-driven is called the "discriminative method," which attaches labels to collected data to classify subjects to be discriminated [34-35], represented by SVM (Support Vector Machine) and KNN (K-nearest neighbor algorithm). They are called "classification types" in this thesis.

On the other hand, knowledge-driven approaches are classified into logic-based and ontological approaches. Logical-based approaches collect knowledge of a domain and define a knowledge model in which activities and performance are logically represented. Events are mapped onto a knowledge model, and activities that occur are judged by an inference algorithm. Methods such as Event Calculus are mainly used to realize the above. A visual description of the data types described can be seen in Figure 1.

This section of this dissertation is based on "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

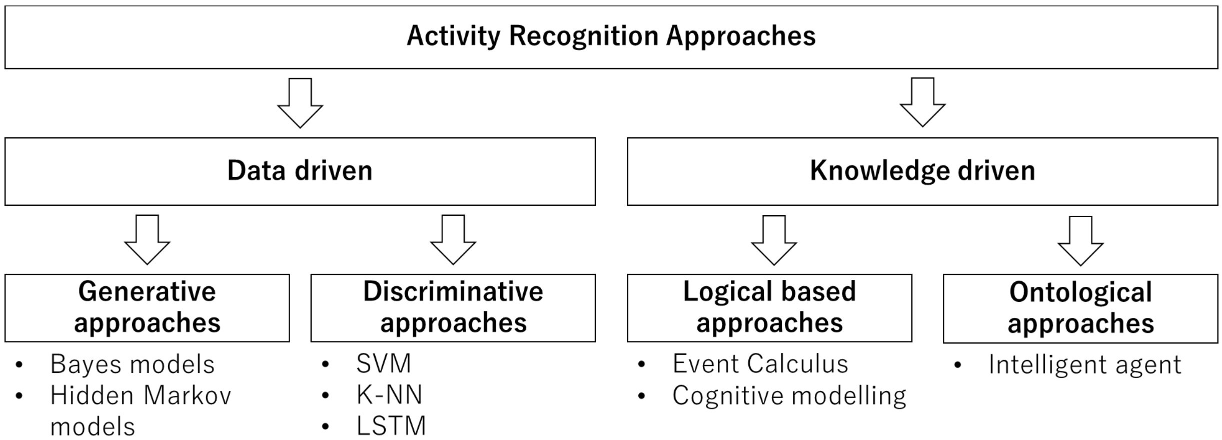

Figure 1. Activity Recognition Approaches (Copyright(c) 2023 IEICE, [42] Fig. 1).

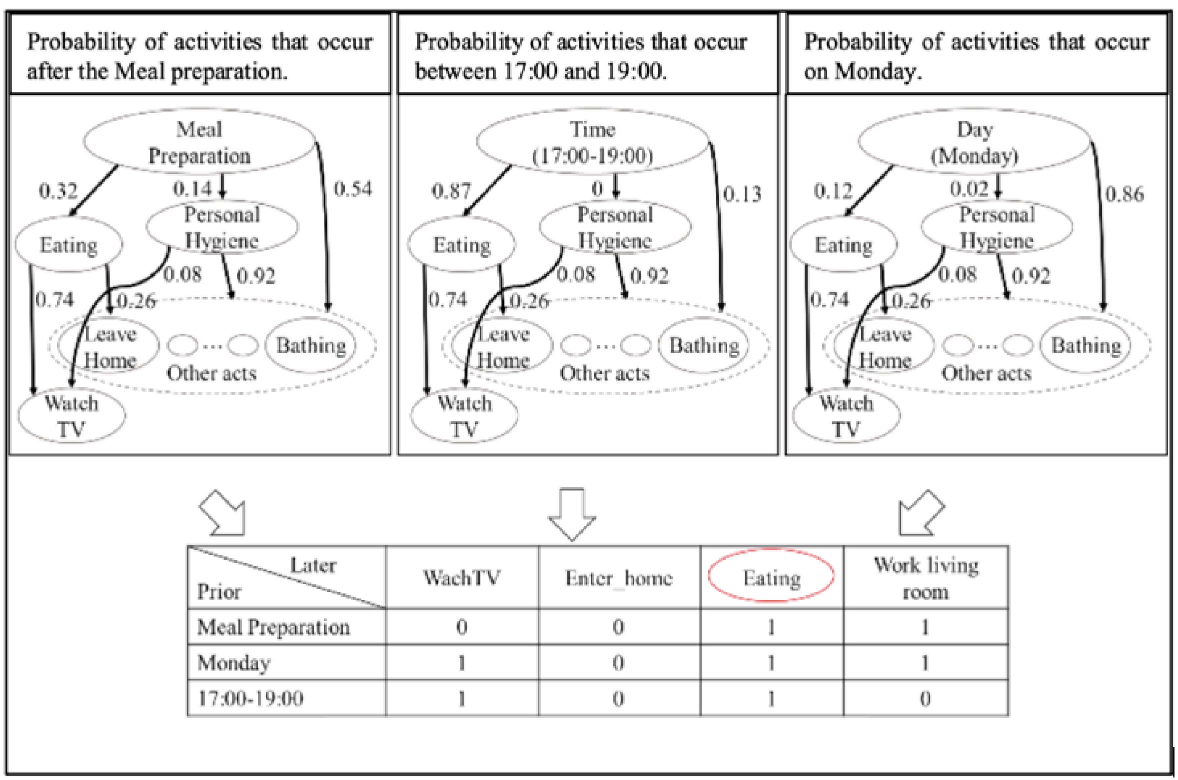

Figure 2. Activity Recognition method using a Bayesian network (Copyright(c) 2023 IEICE, [42] Fig. 2).

Wu et al. [36] conducted a study through activity recognition using a Bayesian network of generative approaches, aiming to grasp users' activities. In this method, probabilities of "an activity after a certain activity," "an activity in a certain range of time," and "an activity in the day" are calculated to create a Bayesian network with these as conditional probabilities. The activities with

This section of this dissertation is based on "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023. Copyright(C)2023 IEICE.

high possibilities are extracted from each, the results are added up, and those presented a lot are selected (Figure 2). In the evaluation experiment, they constructed a model adding three parameters of “day,” “time,” and “place” and using the data set of the CASAS (Center for Advanced Studies in Adaptive Systems) project [37]. This method achieved an 81.3% recognition rate in predicting an activity next to a specific activity.

As a problem of this method, it is difficult to distinguish activities whose recorded information “day,” “time,” and “place” are similar and those having no relationships with activities before and after, and thus being unable to be expressed as a habit. For example, the activity of Watch TV has fewer relationships with the activities before and after it, and the “day” and “time” of their occurrence are different depending on the individual (Table 2). The result of Wu et al. [36] agrees with the point made by Rafferty [31] that recognition mentioned above is difficult to some extent only by data-driven approaches, which are activity recognition based on sensor data.

Table 2. Examples of activities having similar recorded information. (Copyright(c) 2023 IEICE, [42] Table. 1)

Times of Day	**Time**	**Day of the week**	**Location**	**Month**
12:00	30 minutes	Sunday	Living	October
12:00	30 minutes	Sunday	Living	November

Cook et al. [38] employed four types of sensors, acceleration sensors, temperature sensors, infrared sensors, and so on, and placed 50 of them in a house to create a model using a large quantity of data obtained and recognize activities by Bayesian classification. On the other hand, Sutton et al. [35] have reported that activity recognition with higher accuracy than that of HMM is realized by using CRF (conditional random fields), which is one of the classification types that uses less data than the model type that collects data from acceleration sensors mounted on a user. Moreover, Rafferty [31] et al. have shown that machine learning such as SVM, KNN, Random Forest, and the classification types are valid for activity recognition by relatively small data obtained by a few sensors. However, most studies on activity recognition assume that sensors are attached to users. Therefore, subjects like the elderly may feel inconveniences and mental burdens in daily life caused by the attached sensors. Those with dementia may take them off unconsciously, making it challenging to use wearable sensors.

This section of this dissertation is based on “Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method,” [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023. Copyright(C)2023 IEICE.

Activity recognition methods with a fixed camera as a sensor have been proposed [24-25]. However, users feel uncomfortable, and some even resist being watched by a camera. Methods of using sensors, except cameras, have been proposed due to privacy problems [27-28]. Gierad et al. [27] proposed a method to recognize events by installing a composite sensor of plural sensors such as acceleration, sound, and human detecting sensors in a house. Their system can recognize approximately 40 kinds of events, including opening and closing a door and a microwave oven sound. AutoEncoder was used for machine learning in the evaluation experiment, and the average event recognition rate in the kitchen was approximately 88.5%. Their result showed that a sound sensor effectively recognizes various events such as water service utilization, ON/OFF of an electric kettle or kitchen paper utilization, and so on. Therefore, sound sensors are considered one of the reliable candidates as an activity recognition method for which privacy is considered. However, Gierad et al. [27] focused on the process until the recognition of events and did not mention activity recognition such as ADL and IADL.

As a precedent study that is classified as a study on the model type with sound sensors, Inoue et al. [29] modeled life sounds by HMM and attempted to recognize what kind of event the life sounds are, including a sound of the sink, a sound of opening and closing curtain, a sound of vacuum cleaner, and so on. However, the mechanism of life sound generation differs in each source, and therefore, it is challenging to create a standard model. They point out that a large quantity of data is required to create a standard model to recognize activity correctly. Moreover, as a precedent study that corresponds to the classification type with sound sensors, Ouchi et al. [30] proposed an activity recognition method for ADL and IADL, for which acceleration sensors and sound sensors built-in smartphones were used. A person's movement is recognized with an acceleration sensor, and sound recording is started with a sound sensor. The collected sound data recognizes six activities, including excretion and cleaning. The average discrimination rate was approximately 90.5%, with the MFCC algorithm as a method to discriminate sounds and SVM, which is one of the machine learning schemes, as a classifier. However, the only activity recognized among ADL was excretion. Moreover, the system's utilization of smartphones is assumed, although it is challenging to get the elderly to carry smartphones, as mentioned earlier. Furthermore, the system will not work in a place where they cannot bring their smartphone, such as bathing, which is one of the ADL activities. As a precedent study on discrimination of sound data, a mobile application

---

This section of this dissertation is based on “Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method,” [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

that provides information to a smartphone based on human activity recognition and environmental sounds has been proposed [39], and MFCC is used for the algorithm as feature extraction, same as Ouchi et al. [30].

This section of this dissertation is based on "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

Nevertheless, sufficient recognition has not been achieved. MFCC is often used for voice recognition and feature extractions from low-frequency bands considering the characteristics of the sound. However, since the features of a life sound appear in high-frequency bands, the features are not sufficiently extracted by conventional MFCC. Based on the above precedent studies, this study aims to watch the elderly living alone. Therefore, the primary condition was using the machine learning classification type with a relatively small data size that utilizes a sound sensor considering privacy and a sensor that does not require to be attached to a user. Moreover, we attempt to recognize events with higher accuracy by improving MFCC, which has been widely used to extract features suitable for life sounds. This thesis discusses its applicability to elderly activity recognition.

3. Sound Sensors

Sound sensors primarily use Microphone Frequency Cepstral Coefficients (MFCC) for feature extraction [33]. These sensors have been employed in various applications, from speech recognition to environmental sound classification. The use of improved MFCC in activity recognition has shown promising results, particularly in distinguishing between similar-sounding activities [34]. Various algorithms like Gaussian Mixture Models and Hidden Markov Models have been used in conjunction with MFCC for more accurate activity recognition.

3.1. Principles

The principle behind activity recognition using sound sensors is rooted in the concept of acoustic scene analysis. Sound sensors, typically microphones, capture the acoustic signatures of various activities and events occurring in an environment. These acoustic signatures are then processed and analyzed to identify the specific activities taking place [42]. The fundamental theory relies on the uniqueness of the sound patterns generated by different activities, making it possible to distinguish between them [42]

3.2. Applications

Sound sensor-based activity recognition has a wide range of applications, especially in the healthcare sector. One of the most prominent applications is in monitoring the elderly, particularly those living alone [42]. By recognizing the sounds of daily activities, caregivers can remotely monitor the well-being of the elderly and respond promptly to any unusual activities or

This section of this dissertation is based on "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

emergencies [42]. Other applications include smart homes, security systems, and industrial automation.

3.3 Activity Recognition Proposal

The recognition process is described in detail, starting from the definition of events that consist of activity, recognition of events based on sound, and finally, a selection of some activities that are candidates of an activity by using the results of the recognition of the events.

3.3.1 Definition of events that consist of an activity.

To define an activity, it is necessary to consider that it is composed of a different sequence of events that, when performed individually, are insignificant [42]. Still, when performed in a particular series, they can serve as solid indicators for identifying an activity [42]. Below, we will describe some events that can indicate activity when analyzed together and in sequence.

For instance, let us assume that our elderly want to do the following activities: take a shower, dress, groom, do laundry, clean, and watch TV.

Take a shower: Open the Bathroom door, close the bathroom door, turn on the exhaust fan, open the shower (it must take at least 5 minutes), and close the shower. If all these events occur simultaneously or in a sequence, they are good indicators that our elderly are taking a shower.

Dress: If the previous activity was taking a shower, they would probably get dressed after taking a shower, and the same activity (dress) occurred before the take shower activity.

Groom: Brushing teeth, shaving, and using a hairdryer (at least 2 minutes) are events that represent the grooming activity.

Laundry: Turning on the washing machine for at least 10 minutes is an event that indicates that someone is doing laundry.

Cleaning: Turning on the vacuum cleaner for at least 5 minutes is an event that indicates that someone is cleaning.

Watching TV: Turning on a TV for at least 5 minutes is an event that indicates that someone is probably watching TV.

3.3.2 Recognition of events based on their sound.

To describe how the event identification process occurs using the sounds obtained and processed by our algorithm, we will consider four scenarios: take a shower, groom, dress, and cook.

This section of this dissertation is based on “Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method,” [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

Before describing the scenarios, it should be noted that our algorithm always saves the last event and activity identified to help identify the next one.

Take a shower: The elderly person wakes up, takes off his clothes (it is not directly detectable), and opens the shower (the sound sensor near the bathroom is activated and identifies the shower sound). During this moment, it is also recorded how long the sensor is capturing the sound and what time the shower was opened and closed. Our algorithm eliminates activities that cannot occur next, depending on when this episode happens. For example, if the elderly take a shower at 5 p.m., it is automatically known that the elderly cannot prepare breakfast or lunch afterward.

Groom: Assuming that the last activity detected was taking a shower at 8:00 a.m., and the sound sensor detected the sound of the hairdryer at 8:20 a.m., we can assume that the user had just taken a shower and then decided to dry the hair.

Dress: Based on these last two events and the order in which they happened, the algorithm can assume that the order of activities was Dress, Take a Shower, Groom, and Dress.

3.3.3 Selection of some candidates' activities using results of the recognition events

In tables 3 to 6, a relationship between the collected data to identify activities in the form of Causality, Time-Series, Independent Activities, and Timeless Activities is demonstrated.

Causality: It covers actions that apply to the rules of "performing [means] to achieve [purpose]" and "performing [result] of [purpose]" based on a human sense of purpose. For example, it can be said that there is a causal relationship because the relationships of "doing [Cook] to do [Eat]" and "doing [Wash_Dishes] because of doing [Eat]" are established. Probably, these behaviors occur continuously.

Independent Activities: Activities that do not fall under any of the following relationships: [means], [purpose], and [results]. That is activities that have no causal relationship with other behaviors. These activities can occur before and after any activity.

Time-Series: It does not correspond to the relationship of [means] [purpose] [result] of A, but it is considered that it can occur continuously. For example, Taking a Shower is an activity in the morning, so it is considered an activity that occurs before and after Groom.

Timeless Activities: Activities that do not have a fixed time zone and are considered to be performed an unlimited number of times a day. These behaviors can occur 24 hours a day, and it

This section of this dissertation is based on "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

is impossible to judge that "I have already done n times today, so they will not occur anymore," like washing hands.

Table 3. Causality Activities. (Copyright(c) 2023 IEICE, [42] Table. 2)

Means	Objectives	Results
Cook	Eat	Wash_Dishes, Personal_Hygiene
Dress	Take_a_Shower	Dress, Personal_Hygiene
#	Enter_Home	Personal_Hygiene, Take_a_shower, Cook, Eat

Table 4. Independent Activities. (Copyright(c) 2023 IEICE, [42] Table. 3)

Watch_TV
Clean
Laundry

Table 5. Timeless Activities. (Copyright(c) 2023 IEICE, [42] Table. 4)

Personal Hygiene
Watch TV

Table 6. Time-Series Activities. (Copyright(c) 2023 IEICE, [42] Table. 5)

Before	After
Dress, Take_a_Shower	Groom
Groom. Dress	Take_a_Shower
Groom, Take_a_Shower	Dress
Groom, Take_a_Shower	Cook_Breakfast
Dress, Groom, Take_a_Shower, Cook_Breakfast	Eat_Breakfast
Cook_Breakfast, Eat_Breakfast, Use_Water	Wash_Breakfast_Dishes
No specific activity	Cook_Lunch
Cook_Lunch	Eat_Lunch
Cook_Lunch, Eat_Luch, Use_Water	Wash_Lunch_Dishes
Arriving_Apartment	Wash_Hands
No specific activity	Cook_Dinner
Cook_Dinner	Eat_Dinner
Cook_Dinner, Eat_dinner, Use_Water	Wash_Dinner_Dishes
No specific activity	Laundry
No specific activity	Clean

This section of this dissertation is based on “Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method,” [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023. Copyright(C)2023 IEICE.

3.3.4 Identify the activity using behavioral characteristics.

The algorithm can also identify activities based on behavioral characteristics. For instance, it is known that for someone to take a shower, they must remove the clothes first. After taking a shower, the person may dry their hair and then dress again, so based on this information, it can be assumed that whenever the activity (taking a shower) happens, the dress activity also occurs twice before and after taking a shower. It can be assumed that if someone turns on the stove for at least 5 minutes and turns on the exhaust fan during the same period, the person is cooking. If the person thus is between 7-8 am, the person is probably preparing breakfast because, based on the time, it can be assumed that it is not preparing dinner. Based on expected behavior, we only turn on the washing machine when doing the laundry. When turning on the vacuum cleaner, we can assume that we want to clean. Of course, we can accidentally turn it on, but if this is the case, we will turn it off before 2 minutes unless it was intentional. Taking this behavioral characteristic, we can use the vacuum cleaner's working time to determine if the person was cleaning or not. The same principle is used to identify if the person is watching TV.

3.4. Feature Extraction Algorithm MFCC

A feature extraction algorithm MFCC based on human auditory sense properties is widely used in the field of voice recognition [48-50]. The amplitude of the tone signal becomes smaller with an increase in frequency, making it challenging to extract frequency components. Therefore, to make it easy to extract high-frequency components, the pre-emphasis process (1) is applied to emphasize the frequency components.

$$y(n)=s(n)-p*s(n-1) \tag{1}$$

With the number of samples n in s (n) as a variable, the difference between the value of one sample before and the current sample's value is taken to emphasize the entire frequency. The pre-emphasis coefficient p is to be 0.97 for voice recognition. Next, the pre-emphasis-processed tone signal is digitized, and framing is performed to pick up a certain length. The value 0.8[s] is usually used for the frame length. After framing, we perform FFT (Fast Fourier Transform) on the framed digital signal. By performing FFT, it is possible to convert the digital signal's horizontal axis to the frequency representing the pitch of the sound from time to time. Features close to human auditory sense information are extracted from amplitude spectra obtained by FFT with a Mel Filter Bank. For a Mel Filter Bank, the Mel scales with fine and rough filters are used for low-frequency and

This section of this dissertation is based on “Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method,” [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

high-frequency parts, respectively, based on the human auditory sense properties. The number of filters for the Mel Filter Bank was 20. Mel band spectra close to the human auditory information are obtained by performing the Mel Filter Bank. The Mel Filter Bank discretizes the Mel band spectrum. Since the Mel Filter Bank describes the Mel Bank spectrum, the frequency components are more than the discrete cosine transform (2).

$$Ci = \sqrt{\frac{2}{L}} \sum_{l=1}^{L} \log m(l) \cdot \cos\left\{\left(l - \frac{1}{2}\right)\frac{i\pi}{L}\right\} \tag{2}$$

In equation (2), L represents the number of filter bank channels, and logm (l) represents the logarithmic filter bank's amplitude.

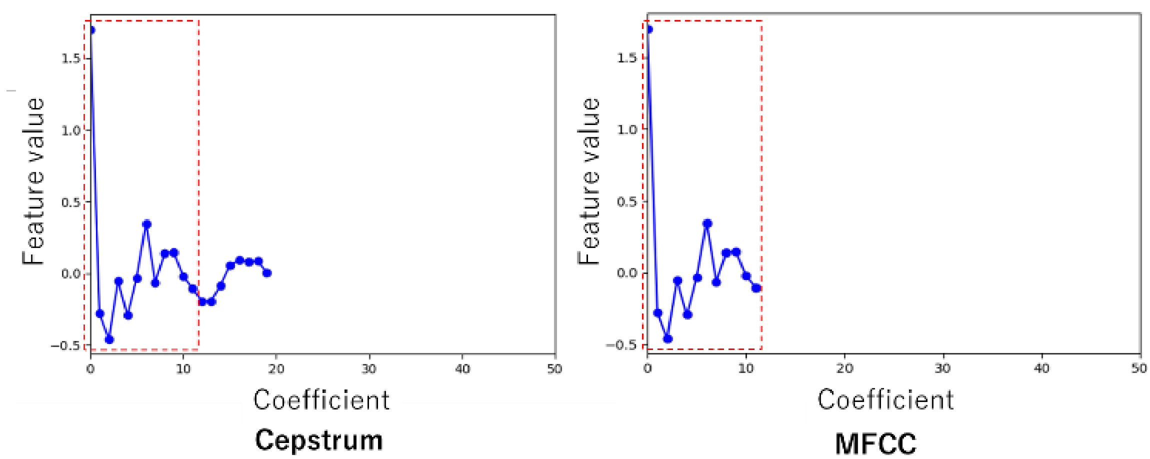

Figure 3. Cepstrum and MFCC (Copyright(c) 2023 IEICE, [42] Fig. 3)

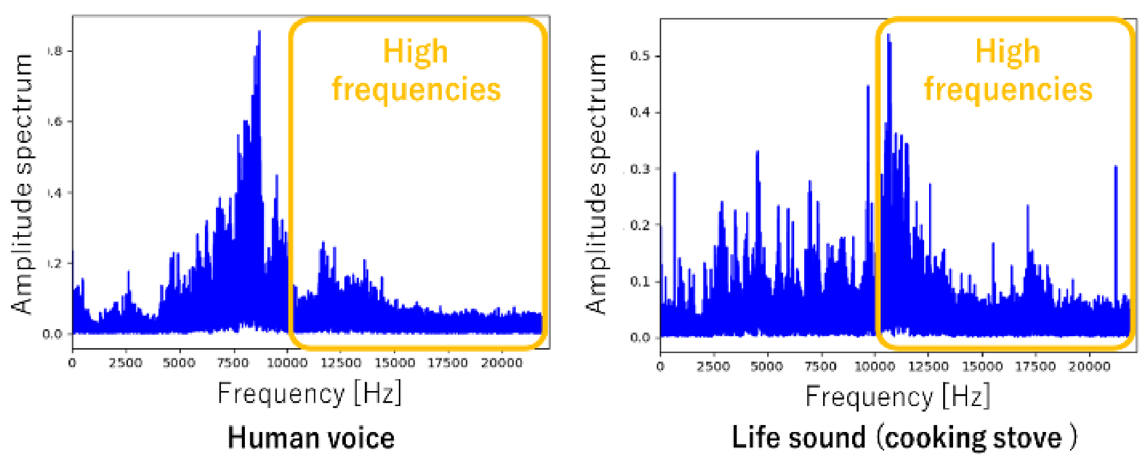

Figure 4. Amplitude spectrum of voice and life sound (Copyright(c) 2023 IEICE, [42] Fig. 4)

This section of this dissertation is based on “Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method,” [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023. Copyright(C)2023 IEICE.

The left graph in Figure 3 is a cepstrum obtained from a discrete cosine transform. Information for which low dimensional 12 dimensions presenting audio features are extracted from the cepstrum is called MFCC (right graph in Figure 3). The dimension here (right graph in Figure 3) means an individual value of the cepstrum. The horizontal axis in Figure 3 indicates coefficients, and coefficients with small values are called "low dimension." The left figure in Figure 3 shows 20 dimensions of the cepstrum, and that for which 12 dimensions are extracted sequentially from the small coefficient is MFCC, which is shown in the right graph in Figure 3.

3.5. Introduction Proposal of Improved Model MFCC

3.5.1. Reasons for improving MFCC with life sounds.

MFCC is based on human auditory properties and is a characteristic value used by voice recognition. Since frequency components that become acoustic features appear in low frequencies, corresponding low dimensions are extracted. However, features of life sounds appear not only in low frequencies but also in high frequencies. Figure 4 shows the difference in frequency components between a voice sound and a life sound. The vertical axis indicates sound intensity, and the horizontal axis indicates amplitude spectra that present frequency height. For the sound shown in the left graph of Figure 4, apparent features of the frequency components are seen in the low-frequency part, while features are not seen in the high-frequency part. On the other hand, the life sound shown in the right graph of Figure 4 presents features of the frequency components in both low and high-frequency parts. Based on the above, we examined a method to extend MFCC under the assumption that discrimination accuracy obtained by machine learning is improved by increasing the number of dimensions of the features of life sounds and extracting frequency components of the high-frequency part.

3.5.2. Policy on improving MFCC and its method.

Since features of life sound's frequency components appear in a broad range from low to high-frequency parts, we propose a method to improve the features that aim to extract essential features from both low and high-frequency parts.

The improvement method consists of two phases. In the first stage, the frequency components were emphasized so that the features of the frequency components in the original sound signal appeared, and the number of dimensions to extract features of the high-frequency part was increased.

In the second stage, only important features were extracted by principal component analysis (PCA) for the 45 dimensions extracted in the first stage, and eventually, the number of dimensions became 33. It has been confirmed in the evaluation that the activity recognition rate tended to fall more with the greater number of dimensions of features, and the number of dimensions was determined based on this result.

<u>3.5.2.1. First Stage</u>

3.5.2.1.1. Purpose

- Expand the frame size of a sound of daily life
- Emphasis on frequency components of a sound of daily life
- Extract high-frequency components of a sound of daily life

3.5.2.1.2. Method

- Adjust a frame length to be framed
- Change the number of samples of FFT
- Change a pre-emphasis coefficient
- Increase the number of filters for a Mel Filter Bank

3.5.2.1.3. The parameters used to process the First step are as follows:

- Frame length: 3.5[s]
- Pre-emphasis coefficient p: 0.99
- Sample size for FFT: 50,000
- The number of filters for a Mel Filter Bank: 4t
- Number of dimensions to be extracted: 45

<u>3.5.2.2. Second Stage</u>

3.5.2.2.1. Purpose

- Reduce dimensions that are not important.

3.5.2.2.2. Method

- Optimize the number of dimensions by the principal component analysis PCA.

The following evaluation is only for the recognition of events, not activities. The objective of the evaluation is to determine how accurately we can capture the different sounds inside an apartment and identify them.

This section of this dissertation is based on "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023. Copyright(C)2023 IEICE.

3.6. Evaluation and Discussion of Event Recognition

3.6.1 Verification environment

The software structure and system configuration that evaluated the improved MFCC are shown in Figure 5. In the evaluation, Raspberry Pi3 was used to acquire and analyze life sounds. MM-MCU01BK of Sanwa Supply Inc. was used as a sound sensor to collect the input data. The data were converted into digital data with a sampling rate of 44.1[kHz]. Features were extracted from digital data with MFCC. From the features, the software discriminated against which life sounds the input sound is by the machine learning algorithm, using learning data stored in the system beforehand.

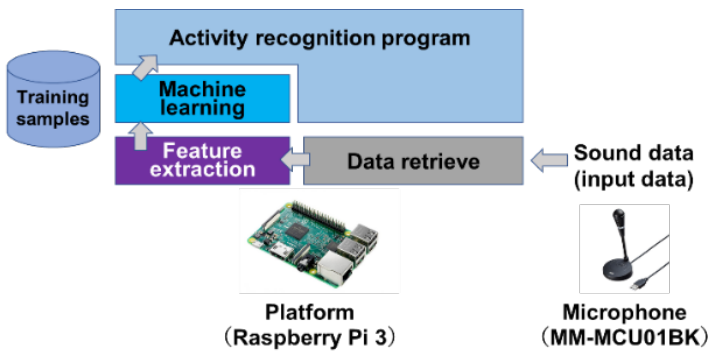

Figure 5. System and software configuration for evaluation (Copyright(c) 2023 IEICE, [42] Fig. 5)

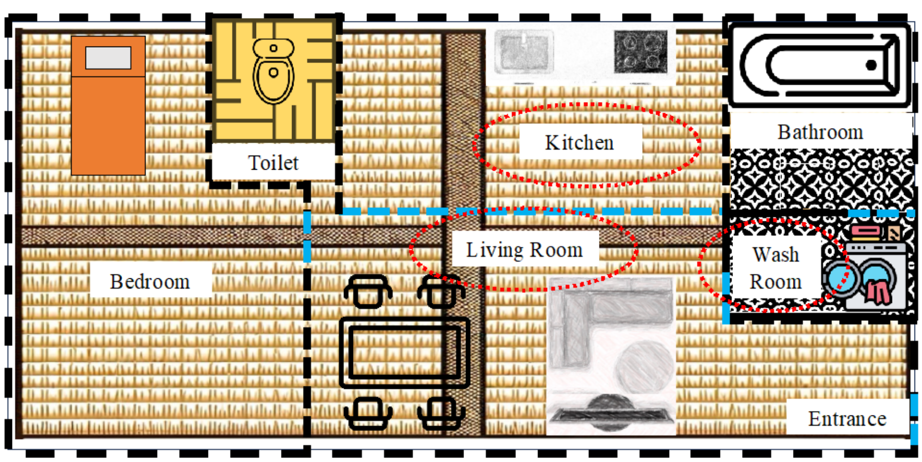

Figure 6. Assumed floor plan

3.6.2 Life sounds for evaluation

<u>3.6.2.1. Location for activity recognition</u>

Figure 6 shows a floor plan for the evaluation and measurement subjects of the room assumed for the assessment. The washroom, living room, and kitchen were selected as locations to

This section of this dissertation is based on "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023. Copyright(C)2023 IEICE.

discriminate sound occurring from washing face or hands, shaving, brushing teeth, drying hair, bathing, cooking, cleaning, and other activities, which are ADL and IADL.

3.6.2.2. Type of house and collected life sounds.

Considering the difference in life sounds by the environments, two houses, a single house (House A) and an apartment (House B), were used as subjects for tests. Tables 7 and 8 show lists of sound data collected in each house. The number of events to be discriminated against in House A in Table 7 was 19, and the number of those in House B was 11. The number of data sets collected from the two houses was 3,950. This time, the collected data were divided in half by labels, and evaluation was performed using training data and evaluation data.

Table 7. List of life sounds collected at House A. (Copyright(c) 2023 IEICE, [42] Table. 6)

Place	**Label**	**Contents**	**# of samples**
Kitchen	Cooking Stove	Use Cooking Stove	284
	Range	Use Range	160
	Water	Use Water	148
	Exhaust Fan	Use Exhaust Fan	110
	Vacuum Cleaner	Use Vacuum Cleaner	120
	Cooking Stove+Water	Use a Cooking Stove and Water	60
	Cooking Stove+Range	Use a Cooking Stove and Range	60
	Cooking Stove+Exhaust Fan	Use Cooking Stove and Exhaust Fan	60
Living Room	TV	Watch TV	200
	Vacuum Cleaner	Clean Rooms	100
Washroom Bathroom	Washing Machine	Do Laundry	360
	Water	Wash Face or Hands	120
	Brushing Teeth	Brushing Teeth	200
	Shaving	Shave	160
	Shower	Take a Shower	280
	Hairdryer	Dry Hair	110
	Exhaust Fan	Ventilate	100
	Bathroom Door	Open or Close the Bathroom Door	40
	Vacuum Cleaner	Clean Rooms	60

This section of this dissertation is based on “Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method,” [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023. Copyright(C)2023 IEICE.

Table 8. List of life sounds collected at House B. (Copyright(c) 2023 IEICE, [42] Table. 7)

Place	Label	Contents	# of samples
Kitchen	Cooking Stove	Use Cooking Stove	64
	Range	Use Range	60
	Water	Use Water	40
	Exhaust Fan	Use Exhaust Fan	40
Living Room	TV	Watch TV	100
	Vacuum Cleaner	Clean Rooms	100
Washroom Bathroom	Washing Machine	Do Laundry	100
	Water	Wash Face, or Hands	100
	Brushing Teeth	Brushing Teeth	40
	Shower	Take a Shower	60
	Hairdryer	Dry Hair	30

3.7. Sensor Implementation

The implementation of sound sensors for activity recognition involves several steps. First, the sensors must be strategically placed in the environment where the activities are to be monitored. The placement is crucial for capturing clear and distinct sound patterns. The sensors are then connected to the Raspberry Pi, which records the acoustic data.

3.8. Data Processing

Once the acoustic data is collected, it undergoes several preprocessing steps to enhance the quality and remove any noise. The data are then segmented into smaller frames, which are analyzed to extract relevant features. Feature extraction is a critical step in the data processing pipeline, as the quality of the features directly impacts the accuracy of the activity recognition [42].

3.9. Improved MFCC

Mel-frequency cepstral coefficients (MFCC) are commonly used features in sound-based activity recognition. However, traditional MFCC features often suffer from various limitations, such as sensitivity to background noise and the inability to capture higher-order statistics of the acoustic signals [42]. An improved MFCC algorithm was developed to address these issues, which incorporates additional preprocessing steps and statistical measures to enhance the robustness and discriminative power of the features [42].

This section of this dissertation is based on "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023. Copyright(C)2023 IEICE.

3.10. Evaluation Results and Validation

The validation of the sound sensor-based activity recognition system involves evaluating its performance using various metrics such as accuracy, precision, and confusion matrix. The system is tested on a dataset comprising recordings of multiple activities performed by different individuals [42].

3.10.1. Evaluation method for improved MFCC

Based on the condition set in I. IV. Activity Recognition Using Sound Sensors – 4 Feature Extraction Algorithm MFCC, the improved MFCC was evaluated from the following viewpoints.

(1) Choice of machine learning algorithm used for evaluation

(2) Comparative evaluation of conventional MFCC and improved MFCC

(3) Evaluation of differences in life sounds by environments

(4) Evaluation of multi-usability of learning data

(5) Evaluation by using mixed life sounds for which actual living environments are assumed

First, in (1), to select a machine learning algorithm to be used for evaluation after (2), machine learning algorithms with improved MFCC were compared and evaluated. The machine learning algorithms used for the evaluation were SVM, KNN, Random Forest, and logistic regression (Table 9).

In (2), the discrimination accuracy of the improved MFCC was evaluated in comparison with conventional MFCC to confirm its superiority.

In (3), discrimination accuracy was evaluated by the difference in environments of the houses from the sound data recorded in different houses.

In (4), dependency (multi-usability) for the environments of the learning data was evaluated. Finally, in (5), the mixed life sounds were evaluated to evaluate the actual living environments.

3.10.2. Evaluation results

<u>(1) Choice of machine learning algorithms to be used for evaluation</u>

First, verification was performed to select a machine-learning algorithm to be used for this evaluation. Table 9 shows the assessment results based on the sound data acquired from the washroom. Algorithmic parameters used in the assessment were selected by grid search. As for the chosen parameter, for evaluation, the C parameter was 100 for SVM, and the gamma parameter

---

This section of this dissertation is based on “Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method,” [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

was 0.03. In Random Forest, the number of decision trees, the depth of decision trees, and the parameter to control random numbers were determined as 1000, 10, and 10, respectively. The number of K for KNN was assumed to be 2. The c parameter was considered to be 20 for the logistic regression. As a result, it was determined to employ SVM, which has the highest discrimination accuracy and is easy to adjust parameters.

(2) Evaluation of superiority of improved MFCC

The sound data acquired in three places in House A, the washroom, living room, and kitchen, were verified. Tables 10 and 11 show their results arranged with tables. The results revealed that the difference in discrimination accuracy for the kitchen between the improved MFCC and conventional MFCC was as small as approximately 3%. In comparison, those for the washroom and living room were approximately 12% and 10%, demonstrating improved performance. The average discrimination accuracy for the three locations was also improved by approximately 9%, which is significantly different. Moreover, Figures 7 and 8 show the results of each event of the improved MFCC and conventional MFCC in the confusion matrix, respectively.

Table 9. Discrimination accuracy results for each machine learning algorithm. (Copyright(c) 2023 IEICE, [42] Table. 8)

Machine Learning	**SVM**	**Random Forest**	**KNN**	**Logistic Regression**
Recognition Ratio	97.78%	96.34%	95.95%	97.13%

Table 10. Result of discrimination accuracy by improved MFCC at House A. (Copyright(c) 2023 IEICE, [42] Table. 9)

Place	**Washroom**	**Living Room**	**Kitchen**	**Average**
Recognition Ratio	97.78%	95.45%	97.80%	97.01%

Table 11. Result of discrimination accuracy by conventional MFCC at House A. (Copyright(c) 2023 IEICE, [42] Table. 10)

Place	**Washroom**	**Living Room**	**Kitchen**	**Average**
Recognition Ratio	85.39%	85.00%	94.21%	88.20%

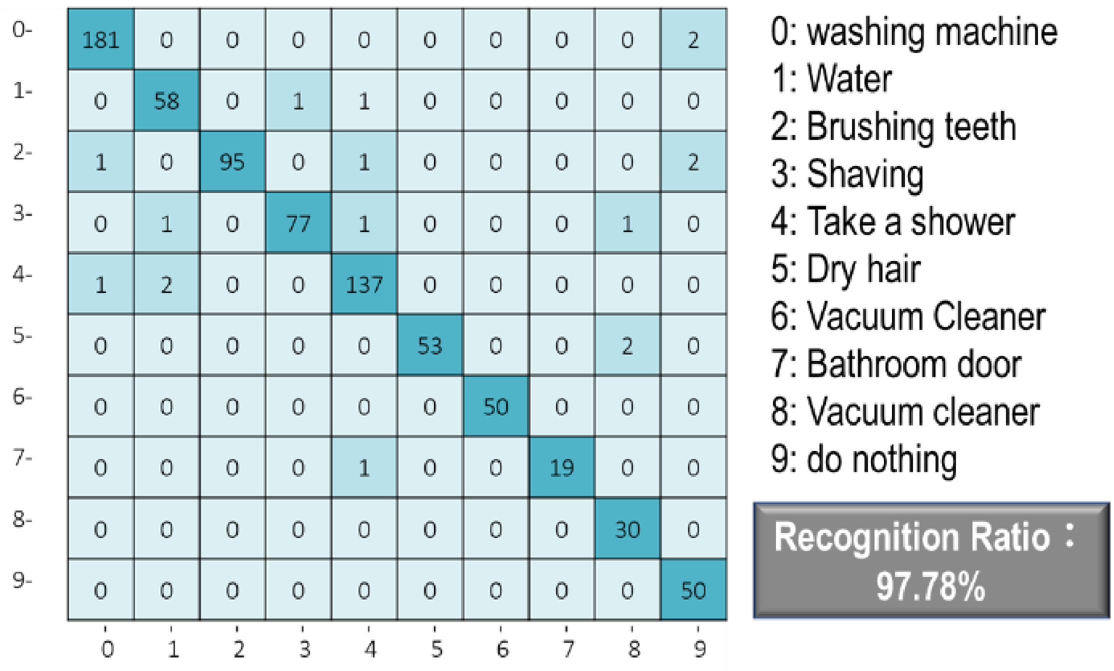

Figure 7. Confusion matrix of improved MFCC in the washroom of House A (Copyright(c) 2023 IEICE, [42] Fig. 7)

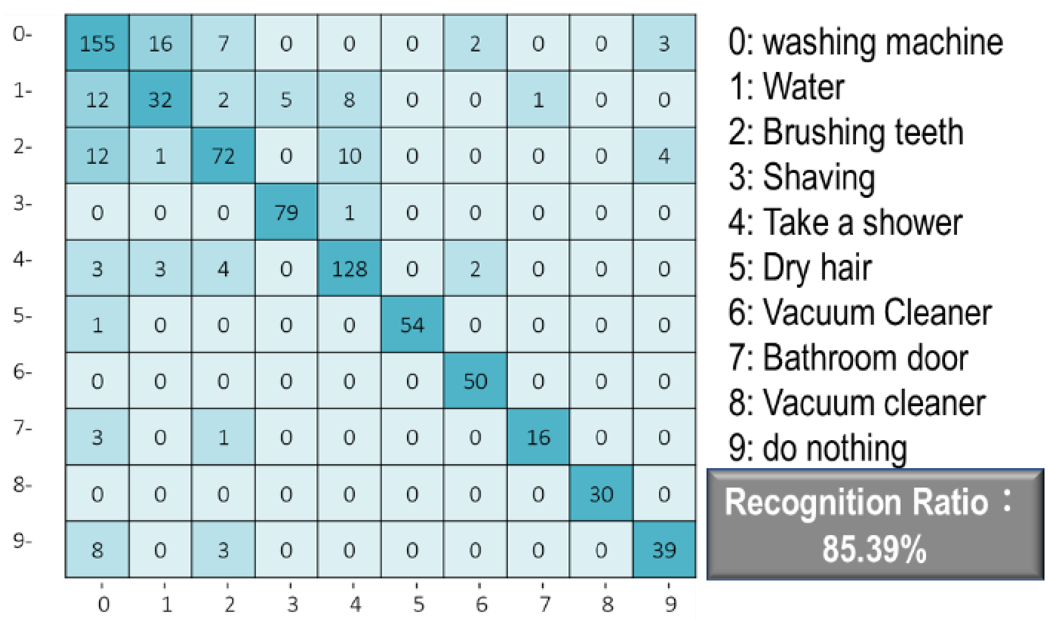

Figure 8. Confusion matrix of conventional MFCC in the washroom of House A (Copyright(c) 2023 IEICE, [42] Fig. 8)

This section of this dissertation is based on "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023. Copyright(C)2023 IEICE.

(3) Evaluation of the difference in life sounds by environments

The discrimination accuracy of the improved MFCC is verified in a different environment. Table 12 shows results obtained by ascertaining the sound data from House B's washroom, living room, and kitchen. Results of House A (Table 10) and B (Table 12) indicate that there is no significant difference in discrimination accuracy between the environments of those two locations, and the improved MFCC is effective without depending on the environment.

(4) Evaluation of multi-usability of learning data

Since SVM's discrimination depends on the learning data, we verified three types of learning and verification data combinations.

(a) Perform verification with the sound recorded in House A as learning data and the sound recorded in House B as verification data.

(b) Perform verification with the sound recorded in House B as learning data and the sound recorded in House A as verification data.

(c) Separate the sound data recorded in both House A and B into learning data and verification data and verify them. Tables 13 and 14 show results verifying learning data and verification data exchanged between Houses A and B. As a result, in the case of using the learning data made in a different house (a)(b), discrimination accuracy was low. Table 15 shows the verifying results of both Houses A and B as learning data (c). It indicates that there is no significant difference in the recognition rate between the cases in which common learning data and learning data of each were used (Tables 10 and 12). Even if learning data from the two places were used, the possibility that they may become common learning data that does not depend on the environment (multi-usability) is low. Moreover, it is indicated that creating learning data in each environment is necessary, considering the labor for creating common learning data.

(5) Evaluation by mixed life sounds for which the actual living environment is assumed

Steps (1) - (4) were verified, assuming that only a single sound was generated. However, in actual human life, mixed sounds in which plural sounds overlap occur. Figure 9 shows the results of verifying a single sound that occurred mixed sounds in the kitchen of House A. The discrimination accuracy was 93.06%. However, discrimination accuracy considerably fell to 36.67% for the mixed sounds that occurred when the cooker and water supply were used simultaneously. This indicates that discrimination accuracy for condition close to the actual living

---

This section of this dissertation is based on “Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method,” [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

environment is insufficient, suggesting the necessity to study methods to improve discrimination accuracy, for example, those that make a single sound using the noise-canceling technique.

Table 12. Result of discrimination accuracy by improved MFCC at House B. (Copyright(c) 2023 IEICE, [42] Table. 11)

Place	Washroom	Living Room	Kitchen	Average
Recognition Ratio	92.22%	94.66%	99.18%	95.35%

Table 13. Learning data of House A, evaluation data of House B. (Copyright(c) 2023 IEICE, [42] Table. 12)

Place	Washroom	Living Room	Kitchen	Average
Recognition Ratio	61.29%	65.33%	33.60%	53.40%

Table 14. Learning data of House B, evaluation data of House A. (Copyright(c) 2023 IEICE, [42] Table. 13)

Place	Washroom	Living Room	Kitchen	Average
Recognition Ratio	63.88%	83.18%	33.66%	60.24%

Table 15. Learning data of House A and House B, evaluation data of House B. (Copyright(c) 2023 IEICE, [42] Table. 14)

Place	Washroom	Living Room	Kitchen	Average
Recognition Ratio	97.43%	94.05%	98.66%	96.71%

On the other hand, assuming that the goal is to recognize the activities of ADL and IADL, and assuming that the simultaneous use of the rice cooker and water was generated by one activity that is preparing a "meal/cook," it does not need to distinguish them because it only needs to learn the mixed sounds as the activity "meal preparation./cooking" A mixed sound with a cooker and water is regarded as one event and can be used as learning data.

However, when assuming a scene where a person makes a meal while watching TV, it is crucial to be able to judge that a person is making a "meal/cook" as an action different from the action of watching TV from the life sounds collected in this situation. For the elderly living alone, which is our target in this study, it is necessary to clarify the activities that may co-occur and the associated events and examine if each event is correctly detected by utilizing the position information.

This section of this dissertation is based on “Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method,” [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023. Copyright(C)2023 IEICE.

Moreover, as an approach that is different from improving discrimination accuracy for recognizing events, Joseph [31] expressed human activities as an ontology of knowledge base beforehand when performing activity recognition from sensor data. He proposed a highly precise activity recognition method obtained by combining both of them.

There are several approaches for mixed sound recognition, such as improving the accuracy of individual events, utilization of position information, utilization of knowledge base, and so on, which will be the future works.

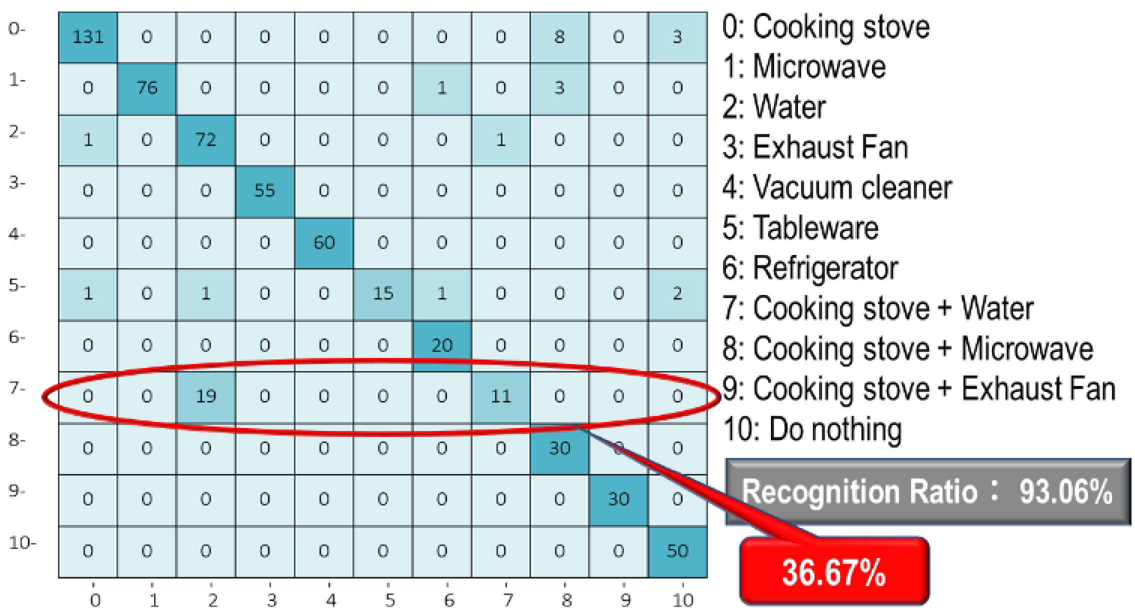

Figure 9. Confusion matrix with mixed sounds in the kitchen of House A (Copyright(c) 2023 IEICE, [42] Fig. 9)

3.11. Results Evaluation - Gap Analysis

While sound sensors have shown promising results in activity recognition, they are not without limitations. Sound sensors couldn't fully address the issues presented by the previous researchers in the field of activity recognition. Table 16 illustrates some of the problems found and raised by previous researchers.

The sound sensors could fully address the maintenance issues thanks to the fact that they did not require extra calibrations after installation and no battery replacements because they were connected wired to the Raspberry Pi.

The sound sensors solved the issues related to reliability when it comes to resilience against external factors, limited working time due to battery issues, and detection errors (false inputs

This section of this dissertation is based on "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023. Copyright(C)2023 IEICE.

caused by pets and persons inside the house). Still, at the same time, we have issues when trying to distinguish between activities that produce similar sound patterns. For example, the sound of washing dishes can be easily confused with the sound of running water for a shower. Additionally, sound sensors are less effective in recognizing co-occurring activities, as the acoustic signatures can overlap and create ambiguities.

The sound sensors solve the accuracy issues by identifying the activities correctly when they occurred independently, but as mentioned, the same result was not fully achieved when activities co-occurred.

When it comes to privacy, while the sound sensor does not expose any images of the elderly performing his activities, ensuring that no image or video of the elderly can be used to shame him or to blackmail him at the same time opens another door that is the possibility of an illegal voice recording of the elderly to record and listen to private conversations that can later be used to blackmail or shame the elderly.

This limitation points to the need to explore other types of sensors, such as magnet sensors, for activity recognition. Magnet sensors offer several advantages over sound sensors, including detecting activities with higher accuracy, less susceptibility to environmental noise, and full privacy assurance as they only collect binary data (0s and 1s). Moreover, magnet sensors can effectively recognize simultaneous activities, thus addressing one of the major limitations of sound sensors [40-41].

Table 16. Issues presented by previous researchers

Reliability	**Maintenance**	**Accuracy**	**Privacy**
➢ Detection Errors (false inputs caused by pets and persons inside the house) [8][59]. ➢ Limited Working time due to battery issues [11-12]. ➢ External Factors interference (Radio Waves from Microwave, Wi-Fi, others) [8] [10-12].	➢ Constant sensors calibration [11][13]. ➢ Constant battery replacement [11-12].	➢ Low Accuracy Level predicting ADLs [5] [8] [17-19]. ➢ Not able to detect all the expected activities [8] [17].	➢ The elderly are uncomfortable with constant visits for maintenance performance [8] [11]. ➢ The elderly felt uncomfortable with the idea of being monitored by cameras or other recording devices [5] [9] [14-16]. ➢ The elderly was concerned about blackmail or private activities being exposed due to unauthorized access to the monitoring devices.

This section of this dissertation is based on "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," [42], by the same author, which appeared in the IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

I.III. Methodology

1. Research Design

The research design for this thesis is a combined approach, incorporating both qualitative and quantitative research methods. The primary focus is on experimental research, where magnet sensors are employed to recognize various activities of daily living (ADL) and instrumental activities of daily living (IADL). The experimental setup is designed to be as realistic as possible, simulating a typical home environment where elderly individuals might reside. The research design is divided into three main phases: the development phase, the testing phase, and the evaluation phase. In the development phase, algorithms for events detection and activity recognition are designed and implemented. The testing phase involves the collection of data using the developed algorithms, and the evaluation phase focuses on the analysis of the collected data to validate the effectiveness of the algorithms [40-42].

2. Data Collection

Data collection is a critical component of this research. Magnet sensors were installed in various household items and appliances for events detection and used as an input for the correct activity recognition. Activities such as opening a fridge, turning on a light, and using a microwave and others were monitored [40-41]. The Magnet sensor data were collected in real time and stored in a CSV file for further analysis [40-41].

The data collection process was conducted with the utmost ethical consideration. All participants involved in the study provided informed consent, and their privacy was maintained throughout the research [40-42].

3. Data Analysis

The data analysis phase is perhaps the most crucial part of this research. The magnet sensor data, an ontological model was developed to understand the semantics behind each activity [41]. The ontological model helped in the classification of complex activities and also in the identification of abnormal behaviors, which could be potential indicators of early stages of cognitive decline [41].

The data were analyzed to validate the effectiveness of the activity recognition algorithms. Various performance metrics such as accuracy, reliability, maintenance capabilities and privacy were used to evaluate and validate the proposed method [40-41]. The results were then compared with existing methods to establish the superiority of the developed system [40-41].

In summary, the methodology section outlines the research design, data collection methods, and data analysis techniques employed in this thesis. The combined approach allows for a comprehensive understanding of activity recognition using magnet sensors, with its unique advantages and limitations.

I.V. Activity Recognition Using Magnet Sensors

1. Magnet Sensors

Magnet sensors offer a unique advantage in that they are not affected by environmental factors such as light, temperature, or obstructions [12-13]. These sensors have been used in a variety of applications, including navigation systems and healthcare monitoring. In the context of activity recognition, Magnet sensors have shown high reliability, especially when combined with ontological models [40]. The ontological models provide a semantic layer that enhances the context-awareness of the system, allowing for more nuanced activity recognition [40].

2. Principles

The principles behind Magnet sensors are rooted in the fundamental laws of electromagnetism. These sensors operate based on the hall effect, which allows them to detect Magnet fields and translate them into electrical signals [44-47]. This unique capability makes them highly suitable for a variety of applications, including activity recognition [40-41] [44-47]. Unlike other sensors that may require line-of-sight or could be affected by environmental factors such as light and heat, Magnet sensors offer the advantage of being largely unaffected by such external conditions [40-41] [44-47].

The Magnet sensors tackle the four main issues found and presented by previous research in the field of activity recognition, as shown on Table 16. The following are the specific forms on which Magnet sensors solve each of the issues:

a) Reliability: Magnet sensors demonstrated exceptional reliability in detecting events without being triggered accidentally by external factors such as radio waves, temperature changes, earthquakes, or vibrations. The use of Magnet sensors, known for their inherent reliability, ensured that the system functioned without any false triggers, unlike other sensor types such as infrared, Bluetooth beacon, and Wi-Fi sensors. This level of reliability is crucial for the effective monitoring of elderly individuals and their activities.
b) Maintenance: Magnet sensors eliminated the need for constant maintenance and adjustments, a common issue faced by previous researchers. Magnet sensors' inherent resistance to external factors, along with their almost unlimited service life, contributed to

This section of this dissertation is based on “Detecting Activities of Daily Living for the Elderly Using Magnet Sensors,” [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023.

a low-maintenance system that could function effectively without constant attention. This advantage is essential for the feasibility and scalability of the system in real-world settings.

c) Accuracy: Magnet sensors capabilities in identifying activities was remarkable, as it successfully detected all expected events leading to the correct activities. The system's ability to differentiate between various events and associate them with specific activities showcases its potential to be a valuable tool for monitoring elderly individuals. This high level of accuracy ensures that caregivers and medical professionals can confidently rely on the system's output for decision-making and intervention.

d) Privacy: Magnet sensors ensure that privacy concerns are effectively addressed by the prototype's design, which collects and stores binary data (0s and 1s). This approach ensures that even if unauthorized access occurs, no sensitive information can be stolen. The binary data would be meaningless because no one can use 0s and 1s to blackmail or shame someone.

3. Applications

Magnet sensors have found a wide range of applications, particularly in the healthcare sector. One of the most promising applications is in the monitoring of Activities of Daily Living (ADL) [40-41]. These sensors can be placed in various parts of a living space to monitor movement and activity, providing valuable data that can be used for healthcare monitoring [41].

4. Activity Recognition Proposal

To solve the issues found by previous research in this field of study, our research team developed a prototype system that runs on Raspberry Pi 3 and requires 3v energy to power the system. This prototype fixes the reliability issues, as described by [40-41] [44-47]. Magnet sensors are non-ferrous metals and do not get affected by radio waves, external temperature changes, earthquakes, or any kind of vibrations. Based on these characteristics, Magnet sensors provide a high level of reliability and do not require a constant maintenance process. This solves the issues pointed out by the elderly who feel uncomfortable with constant visits for sensor calibration or maintenance. Since Magnet sensors do not suffer influence from external factors [40-41] [44-47], this also ensures a high level of accuracy because the sensors are not triggered accidentally by external factors. The prototype also fixes the privacy issue by collecting and storing binary data (1s and 0s), ensuring that even if someone hacks the system and gathers all the collected data, they

This section of this dissertation is based on “Detecting Activities of Daily Living for the Elderly Using Magnet Sensors,” [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

won't be capable of blackmailing the elderly with 1s and 0s. Apart from that, the prototype is the only one that knows how to combine the binary data collected with the sensor ID, sensor location, and the sensor's timestamp to properly assign the data to the right label to generate the right output. Our prototype uses encrypted names for each sensor ID and locations that only our team knows.

4.1. Why the Magnet Sensors

Thanks to their unique properties, electronic and Magnet switches with magneto-resistive or hall elements are ideal for many applications. They can be used for position, angle, or speed recording and are insensitive to shock, impacts, vibrations, and weather variations [40-41] [44-47].

The fact that many non-ferrous metals allow Magnet fields to pass unhindered also extends the area of use for Magnet sensors. This allows the sensor to be encapsulated with pressure resistance in a sturdy metal casing. However, it can also be installed concealed in pipes or behind non-Magnet metal surfaces [44] [46-47]. Some advantages of using magnet sensors described by [40-41] [46-47] are reliability and insensitiveness to earthquakes or any vibrations, almost unlimited service life, high level of accuracy, rapid responsivity, and unaffected by external temperature changes and external radio waves. During our lab tests, we also verified that different than sensors like infrared sensors, Bluetooth beacon sensors, Wi-Fi sensors, and others that radio waves can accidentally trigger, the magnets never showed an accidentally triggered event, which proved to be a very reliable source of input data [40-41].

4.2. The Prototype Model

The system prototype model consists of using magnet sensors and neodymium magnets that will collect the data that will be used as input data. All the data collected will be sent to the Raspberry Pi 3 (Figure 10). An algorithm will analyze the collected data with the stored data to decide which activity is the most likely (Figure 16). The following Figure 10 gives an overall view of the system prototype. Figure 11 illustrates the assumed floor plan during the test phase.

This section of this dissertation is based on "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

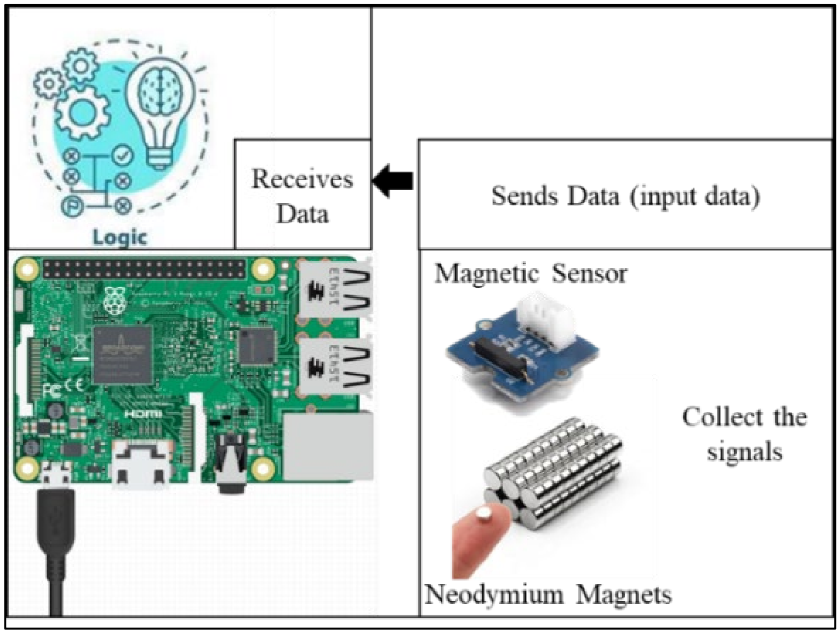

Figure 10. System Prototype Configuration. (© 2023 IEEE – SWC 2023, [40] Fig. 2)

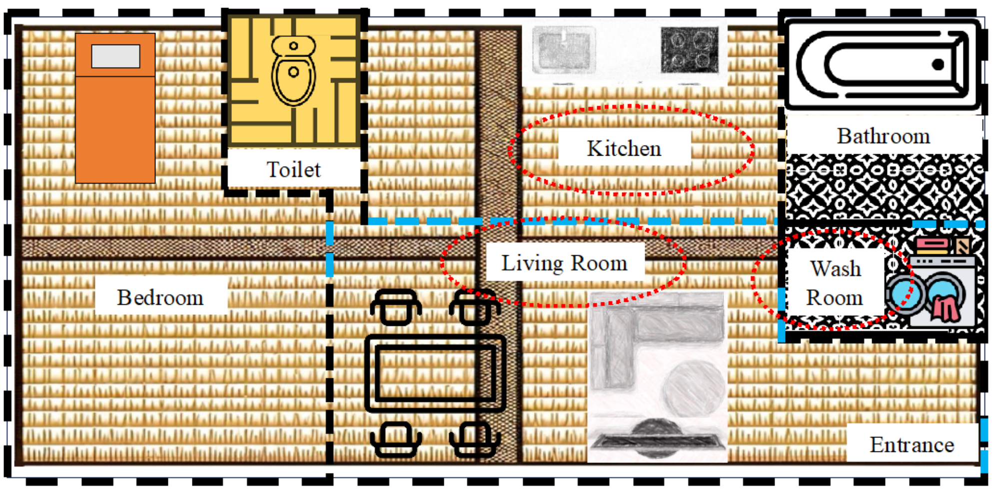

Figure 11. Assumed Floor Plan

4.3. Data Gathering and Storage

The process of obtaining the model and storing the collected data is as follows:

<u>Data Collection:</u>

The process begins by collecting data from the Magnet sensors, which are placed at strategic locations within the elderly person's home. When an activity is identified, the state of all sensors, which is expressed as 0s and 1s, is logged. These states, alongside the time, location, and any prior activities, are the key features used in predicting the current activity.

This section of this dissertation is based on "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

Data Storage:

The sensor states are then sent to a Raspberry Pi device, which serves as the central hub for data collection. For each successful activity identification, the system stores the sensor states, the timestamp of the state changes, and any additional features like location and prior activities into a CSV file. Each row in this file represents an event and includes details like the sensor state, the timestamp, and the activity that was happening at the time.

To get a better understanding of how the data were collected, Figure 12 illustrates part of the pseudocode used to get inputs from the triggered Magnet sensors (Bathroom Sensors) and to save the Magnet sensors states (1/0) on the CSV that was later used on the process of activity recognition.

This section of this dissertation is based on "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

```
#Data Analysis and Gathering
if MG_Door==1:
    Dr="Door_OPEN"
    door_report=1
    door_open=datetime.now().strftime("%H:%M:%S")
elif MG_Door==0:
    Dr="Door_CLOSED"
    door_report=0
    door_close=datetime.now().strftime("%H:%M:%S")
if MG_HW==1:
    Hw="Hot Water Open"
    hw_report=1
    hw_open=datetime.now().strftime("%H:%M:%S")
elif MG_HW==0:
    Hw="Hot Water Closed"
    hw_report=0
    hw_close=datetime.now().strftime("%H:%M:%S")
if MG_CW==1:
    Cw="Cold Water Open"
    cw_report=1
    cw_open=datetime.now().strftime("%H:%M:%S")
elif MG_CW==0:
    Cw="Cold Water Closed"
    cw_report=0
    cw_close=datetime.now().strftime("%H:%M:%S")
if MG_L==1:
    Lt="Light_ON"
    light_report=1
    light_on=datetime.now().strftime("%H:%M:%S")
elif MG_L==0:
    Lt="Light_OFF"
    light_report=0
    light_off=datetime.now().strftime("%H:%M:%S")
if MG_F==1:
    Fa="Fan_ON"
    fan_report=1
    fan_on=datetime.now().strftime("%H:%M:%S")
elif MG_F==0:
    Fa="Fan_OFF"
    fan_report=0
    fan_off=datetime.now().strftime("%H:%M:%S")
```

Figure 12. Pseudocode is used to collect data from Magnet sensors. (© 2023 IEEE – SWC 2023, [40] Fig. 4)

This section of this dissertation is based on “Detecting Activities of Daily Living for the Elderly Using Magnet Sensors,” [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

As event detection is based on sequence checking, it can be represented as a state machine where each state transition is triggered by an event. This uses a probability function to estimate the likelihood of a sequence of events representing an activity. The equivalent formula is (3):

$$P(\mathrm{A}) = \sum(Ei|A) * P(Ei-1|A) * \ldots * P(E1|A) \tag{3}$$

Where, P(A) is the probability of an activity A, and P(Ei|A) is the probability of an event Ei given activity A. This formula is based on the assumption that the occurrence of each event is independent given the activity. In the context of taking a shower, A represents the "Taking a Shower" activity, and Ei could be an event like "water tap open".

4.4. Events and Activities

The detailed description of the recognition process begins with defining events, which are the base of each activity. This is followed by identifying events using auditory cues and ultimately selecting potential activities as candidates through the analysis of recognized events.

To identify an activity, it's crucial to understand that it consists of various sequenced events, which may be irrelevant when performed individually but can serve as reliable indicators of activity when executed in a specific order. We will discuss some events that, when analyzed collectively and sequentially, can suggest an activity.

Events: Events are all actions performed by the elderly with the intention of achieving a particular result. In other words, the events are the meanings of an end, which in this study are the activities. These actions include turning on a light, opening a door, or any other actions the elderly perform in conjunction with an object. For our study, the actions that are considered events are opening and closing doors or any other objects, switching lights or any other electronic objects, and using specific objects such as chairs, beds, or any other objects that can be used to perform the activities described of the following section.

Activities: Activities are the result of sequenced events. In other words, an activity is the goal of a sequenced event performed by the elderly. For instance, let's assume that the elderly want to engage in activities such as cooking, eating, taking a shower, doing laundry, and cleaning.

This section of this dissertation is based on "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

a) Cooking: To identify this activity, the magnet sensors will be attached to the following:

1. Fridge (to detect every time the elderly opens and closes the refrigerator).

2. Microwave (to detect every time the elderly opens and closes the microwave, to monitor for how long the microwave will be working).

3. Kettle (to detect when the elderly puts water in, how many times the elderly will turn it on and off, and how many times the kettle will be removed and put back into the kettle base).

4. Kitchen water tap (to detect every time the elderly will open and close the water tap and for how long they will be using the water tap open).

5. Gas tap (to detect every time the elderly opens the gas tap and for how long it will remain open).

6. Stove (to detect every time the elderly will turn on and off the stove, to track for how long the stove has been on).

7. Shelf (to detect every time the elderly opens it to take objects such as plates, cups, pots, spoons, forks, knives, chopsticks, and other relevant objects).

The system will analyze the sequence of these events to see any correlations between them and will compare the time these events occur. If they happen in a sequence that indicates a meal preparation, it will add the time to check if the meal candidate is breakfast, lunch, or dinner.

b) Eating: To identify this activity, the magnet sensors will be attached to the following:

1. Kitchen and Living room chair (to detect every time the elderly sits and for how long he sits on the chair).

2. Kitchen and Living room table (to detect every time the elderly sit at the table and for how long).

To predict this activity, the system will use antecedent events and activities to determine if the elderly are eating or if he is sitting at the table. If the previous activity was cooking, the chances he is eating are high. If the event of opening the fridge, using the microwave, using the stove, or using the kettle happens before sitting at the table, this will also contribute to identifying the eating activity and, finally, the time (Morning, Afternoon, or Evening) that the elderly is sitting on the table and also for how long he has been sitting will be used to make the final decision.

This section of this dissertation is based on "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

c) Drinking Water: To identify this activity the sensors must be attached to the following:

1. Fridge Door Sensor: This will enable the system to monitor every instance the elderly individual opens and closes the refrigerator, as well as the duration for which it remains open.

2. Water Container and Glass Sensor: Attached to the water container and the glass within the fridge, this sensor will help the system track each time the elderly individual retrieves and replaces the water container.

3. Cup Shelf Sensor: This sensor, located on the cup shelf, will allow the system to record every time the elderly individual accesses the cups.

By synthesizing the data from these three sensors, the system can assess the sequence and continuity of events to successfully detect each occasion the elderly individual drinks water from the water container.

d) Taking a Shower: To identify this activity, the sensors must be attached to the bathroom door to detect the door states (Open and Closed), the sensors will also be attached to the Water Tap to detect the states (Open and Close), and our algorithm will verify the sequence of the events, the timestamp and the duration of each event. The correct sequence to identify the taking shower activity would consist of the following:

1. Open the Bathroom Door (Save the time that the door was opened).

2. Open the Water tap (Save the time that the water time was opened).

3. Track the amount of time that the water tap remained open, and as soon as the water tap got closed, compare it with the minimum standard time that a person needs to take a shower.

4. When the person opens the bathroom door to go out, the system will also analyze how long the person has been inside the bathroom to combine with the time the water tap was used.

5. The system will also add the time this process happened to identify if it was the morning, afternoon, or evening shower.

6. The system will analyze the previous and subsequent activities as reinforcing confirmation activities.

This section of this dissertation is based on "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

e) Urinating and Defecating: To identify this activity, the magnet sensors will be attached to the following:

1. Toilet door (to detect every time the elderly opens and closes the toilet door).

2. Toilet light switch (to detect every time the elderly turn on and off the toilet light and for how long the light has been on).

3. Toilet fan switch (to detect every time the elderly turn the fan on and off).

4. Toilet water tap (this will have two magnet sensors to help identify if, after using the toilet, the elderly use the urinate water side or the defecate water side).

5. Toilet seat (this will help identify if the elderly person was standing [urinating] or sitting [urinating/defecating] during the time he spent inside the toilet.

The system will combine this information and the time he spent inside the toilet to help predict if the elderly person was urinating or defecating. The system will also use the activities that happened before the elderly entered the toilet room. For example, it is known that a person tends to urinate when he wakes up (in the morning), sometimes after meals, and when he comes back to the apartment.

f) Brushing Teeth: To identify the brushing teeth activity, the magnet sensor will be attached to the following:

In order to detect the activity of brushing teeth, the magnet sensor will be affixed to the following items:

1. The base of the cup and the toothbrush: This will help the system track every time the elderly individual removes the toothbrush from the cup and places it back, thereby providing a measure of tooth brushing frequency.

2. The base of a secondary cup and the toothpaste tube: This setup will enable the system to monitor each instance when the elderly individual uses the toothpaste, offering an additional marker of tooth brushing activity.

3. The bathroom water tap: This installation will enable the system to detect every instance when the tap is turned on, as well as the duration for which it remains open. This parameter can provide a rough estimate of the brushing duration and indicate the potential need for assistance or

---

This section of this dissertation is based on "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

intervention. By tracking these three elements, the system can effectively monitor both the frequency and duration of the elderly individual's tooth-brushing activity.

g) Sleeping: To identify this activity, the magnet sensors will be attached to the following:

1. Bedroom door (to detect when the door opens and closes).

2. Window (to detect when the windows are open and closed).

3. Bed (sensors were attached to the bed base and the mattress in such a way that their digital value will change from 0 to 1 based on the contact caused by the weight on the mattress).

The system will also collect the time the elderly spend in bed to track their normal sleep habits, and the timestamp sensors will be activated and deactivated to understand if the elderly are sleeping during the day or during the night.

h) Cleaning: To identify the cleaning activity, the magnet sensor will be attached to the shelf doors that store the cleaning products. The research team proposes the adoption of standard containers for each cleaning product and will attach magnet sensors to each of them to know every time the elderly use one of them. Magnet sensors will also be attached to the cleaning tools, such as the vacuum cleaner, to detect when the elderly are cleaning and for how long they have been cleaning the apartment.

The system will build a cleaning profile about the elderly cleaning habits in terms of preferred days and hours to use as a standard evaluation criterion.

i) Laundering: To identify this activity, the Magnet sensors will be attached to the following:

1. Washing machine door (to detect every time the elderly opens and closes the washing machine, to identify when he inserts the clothes and when he removes the clothes).

2. Washing machine power button (to identify every time the elderly turn the washing machine on and off and how many times during a day, he used the machine).

Based on this information and the working time of the washing machine, which in our case is at least 10 minutes, the algorithm assumes that the elderly are doing laundry.

3.5. Methodology for detecting potential indicators of early stages of Dementia Diagnosis

Based on the insights from [10-11] [18-23] [51], our proposed methodology focuses on monitoring key Activities of Daily Living (ADLs) to track elderly behavior. These activities

This section of this dissertation is based on “Detecting Activities of Daily Living for the Elderly Using Magnet Sensors,” [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

include cooking, eating, drinking, showering, urinating, defecating, sleeping, cleaning, and laundering [40-41].

Our approach involves the development of a prototype that employs Magnet sensors and ontology to monitor these ADLs, aiming to identify potential early-stage dementia indicators. Magnet sensors can capture detailed behavioral data, detecting subtle changes in daily activities that may signify cognitive decline [41][52]. The ontology offers a structured representation of complex relationships between ADLs and dementia symptoms, aiding in identifying potential indicators of early-stage dementia [41][53].

In our initial analysis of [10-11] [18-23] [51], we identified five potential indicators that needed to be tracked when trying to find early stages of dementia. However, upon careful examination, we found redundancies and correlations among these indicators that could lead to unnecessary data and increase the complexity of the learning algorithm [41]. To streamline our approach, we consolidated these indicators into two primary categories: Events and Time.

The indicators of Short-term Memory Loss, Uncompleted Actions, and Sequenced Events all share a common element: they involve events occurring in a short-term or sequenced process. Thus, we combined these into a new indicator called 'Events' (Figure 13). Similarly, Time Management Problems and Changes in Lifestyle indicators fundamentally relate to changes in habits based on time, leading us to consolidate these into a 'Time' indicator (Figure 14).

In addition to these consolidated indicators, we identified a third crucial indicator: Location [41]. The location where activities occur can provide significant insights into early-stage dementia. For instance, if an elderly individual starts performing activities in unusual locations, it may indicate cognitive changes. Therefore, our methodology focuses on monitoring and analyzing three key indicators: Events, Time, and Location (Figure 15).

This section of this dissertation is based on “Detecting Activities of Daily Living for the Elderly Using Magnet Sensors,” [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023.

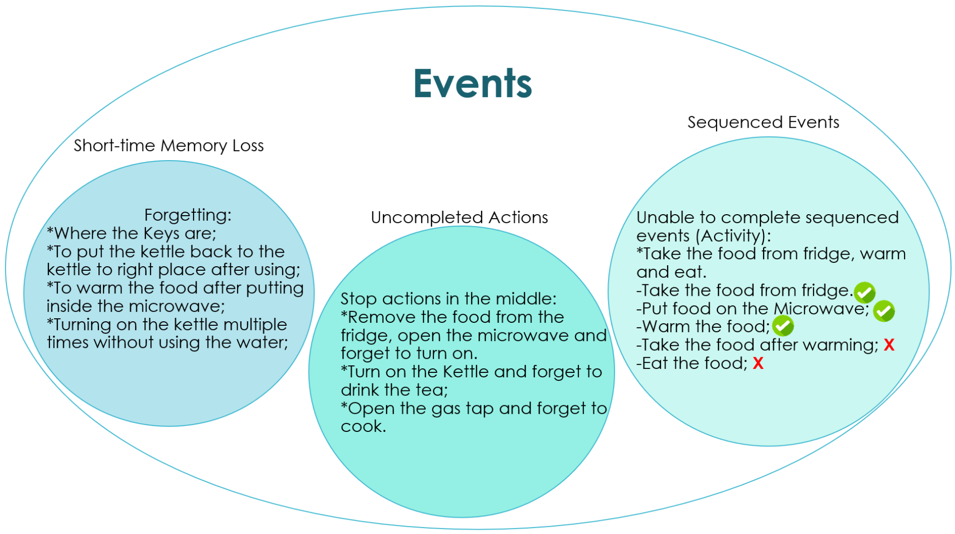

Figure 13. Transition from Multiple Indicators to the Unified 'Events' Indicator. (© 2023 IEEE – 13th ICCE, [41] Fig. 1)

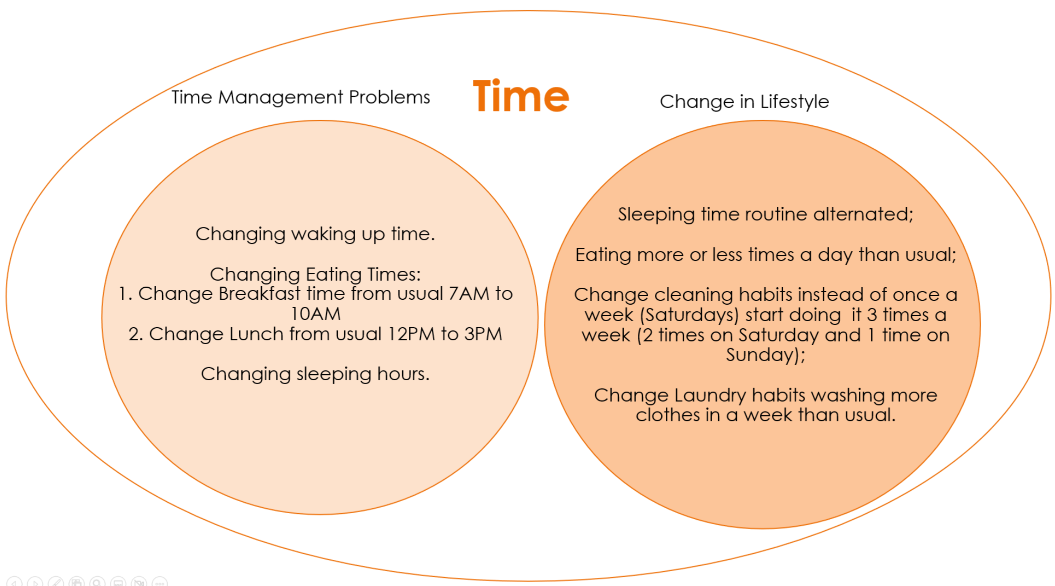

Figure 14. Transition from Multiple Indicators to the Unified 'Time' Indicator (© 2023 IEEE – 13th ICCE, [41] Fig. 2)

This section of this dissertation is based on "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023. ©2023 IEEE – 13th ICCE.

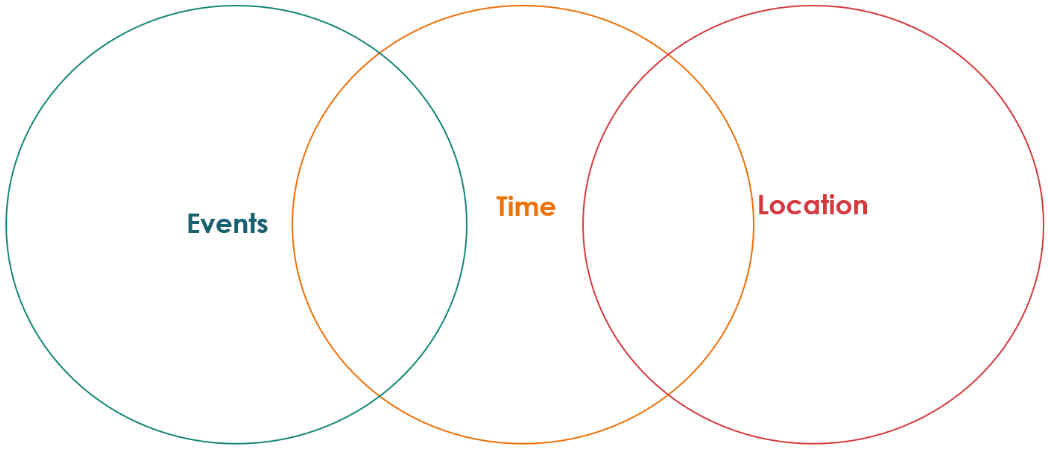

Figure 15. Key Indicators for Monitoring and Analyzing ADLs in Potential Early Stages of Dementia Detection. (© 2023 IEEE – 13th ICCE, [41] Fig. 3)

By reducing the number of indicators, we significantly decrease the learning time required to train the algorithm and the amount of redundant data the system needs to store and process. This streamlined approach also reduces the system's computational demands, decreasing the likelihood of failure [40].

Our system's strength lies in the synergy between the three components - key indicators, magnet sensors, and ontology. The indicators provide specific behavioral traits to monitor, the magnet sensors capture the data of these traits, and the ontology interprets this data in the context of early dementia detection. This integrated approach enables our system to provide accurate, timely, and meaningful insights into potential early-stage dementia.

4.5.1. Magnet Sensors

Magnet sensors are devices that detect changes in Magnet fields, allowing for the precise measurement of movements and activity [40-41] [44-47] [54]. They can be integrated into wearable devices or placed strategically throughout a living environment, monitoring ADL and capturing behavioral changes indicative of cognitive decline [55]. By continuously monitoring ADL, Magnet sensors can provide valuable insights into the early stages of dementia, enabling timely intervention [41] [52]. Thanks to their unique properties, electronic magnet switches with magneto-resistive or hall elements are ideal for many applications [40-41] [44-47] [54-55]. They can be used for position, angle, or speed recording and are insensitive to shock, impacts, vibrations, and weather variations [40-41] [44-47].

This section of this dissertation is based on "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023. ©2023 IEEE – 13th ICCE.

The fact that many non-ferrous metals allow magnet fields to pass unhindered also extends the area of use for Magnet switches. This allows the sensor to be encapsulated with pressure resistance in a sturdy metal casing. However, it can also be installed concealed in pipes or behind non-magnet metal surfaces [40-41] [44-47]. Some advantages of using magnet sensors described by [40-41] [46-47] are reliability and insensitiveness to earthquakes or any vibrations, unlimited service life, high level of accuracy, rapid responsivity, and unaffected by external temperature changes and external radio waves. During our lab tests, we also verified that different than sensors like infrared sensors, Bluetooth beacon sensors, Wi-Fi sensors, and others that radio waves can accidentally trigger, the magnets never showed an accidentally triggered event, which proved to be a very reliable source of input data [40-41].

4.5.2. Ontology and Its Structure

Ontology, a formal representation of knowledge within a specific domain, allows for the modeling of complex relationships between concepts [56]. In dementia detection, an ontology can be used to model relationships between various ADL and dementia symptoms, providing a structured framework for data analysis and interpretation [53]. Domain experts and relevant literature are consulted to identify key concepts, relationships, and attributes to create an ontology [57-58]. Once developed, the ontology can be used with Magnet sensor data to identify patterns and deviations in ADL that may indicate early-stage dementia. Integrating this formal knowledge representation with the Magnet sensor data provides a comprehensive understanding of the complex interplay between ADLs and dementia symptoms. This synthesis enhances the possibility of successfully identifying the potential early stages of dementia detection by translating sensor-generated information into meaningful indicators of potential cognitive decline [53].

Our ontology is designed to capture the complex interplay between the three key indicators we identified: events, time, and location. It models the relationships between these indicators and potential dementia symptoms, thereby providing a comprehensive understanding of the complex interplay between ADLs and dementia symptoms. This synthesis enhances the possibility of a potential early detection by translating sensor-generated information into meaningful indicators of potential cognitive decline.

This section of this dissertation is based on “Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis,” [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023. ©2023 IEEE – 13th ICCE.

Figure 16 illustrates the ontology structure and function. The proposed ontology has four functional blocks: the data gathering, the real-time ADL, the evaluator, and the ADL stored block. The block functionality is described below:

.

This section of this dissertation is based on "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023.

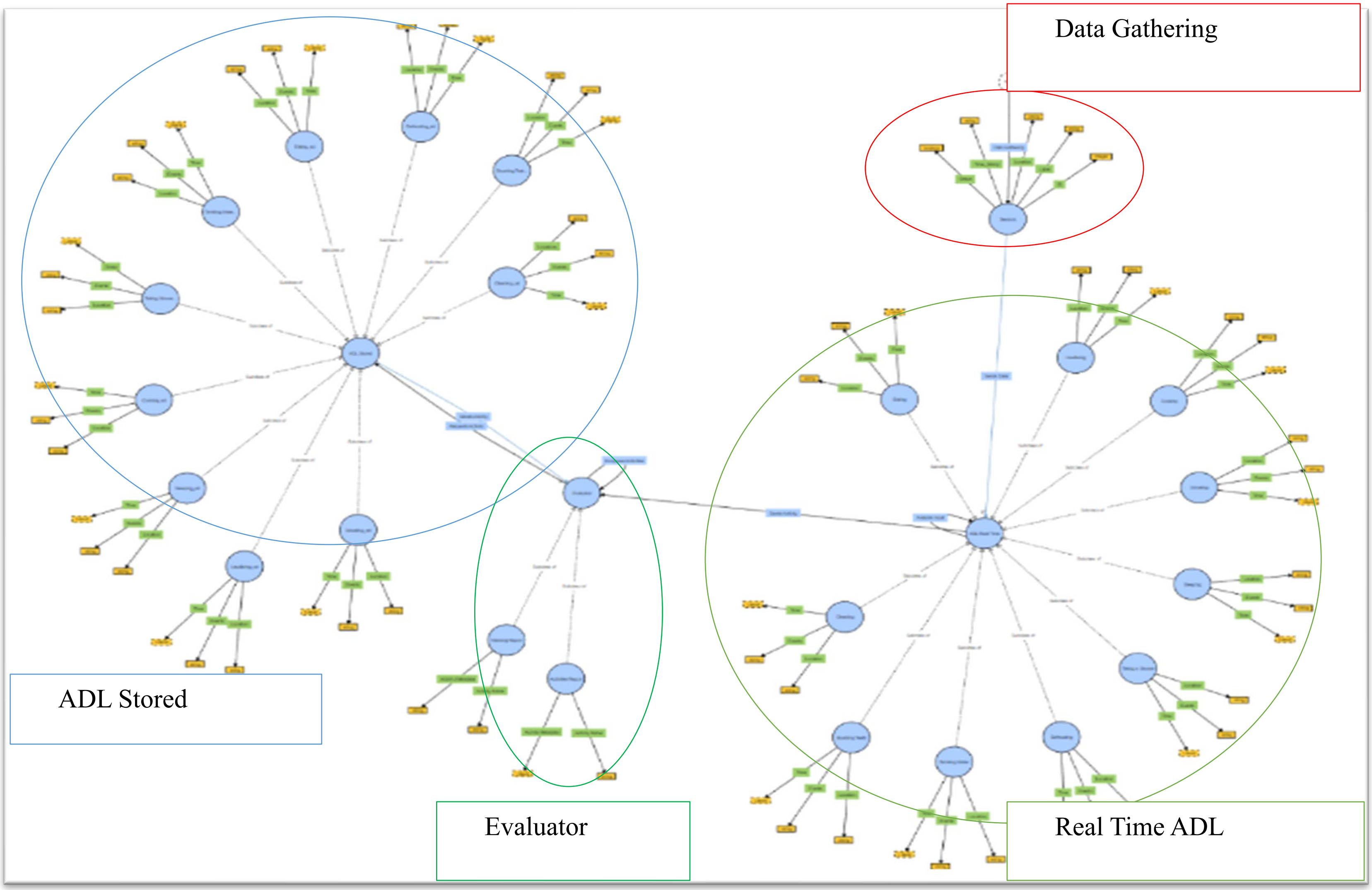

Figure 16. Ontology Illustration. (© 2023 IEEE – 13th ICCE, [41] Fig. 4)

This section of this dissertation is based on "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023. ©2023 IEEE – 13th ICCE.

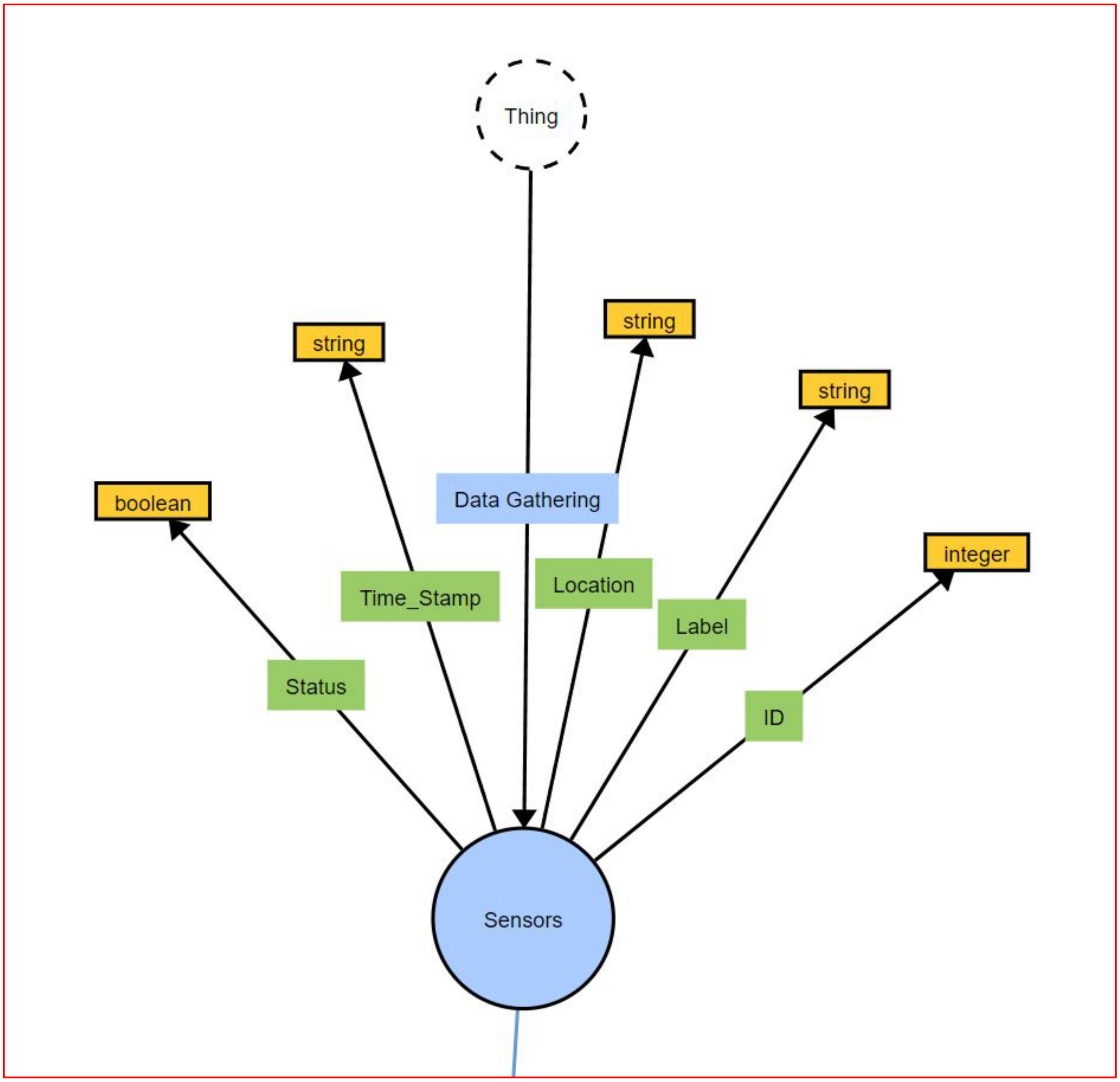

Figure 17. Data Gathering Block.

a) Data Gathering: This block is responsible for receiving all the data sent by the Magnet sensors and received by the Raspberry Pi. This block receives and processes the sensor status, timestamp, location, label, and ID, and then it sends these inputs to the next block, the real-time ADL block.

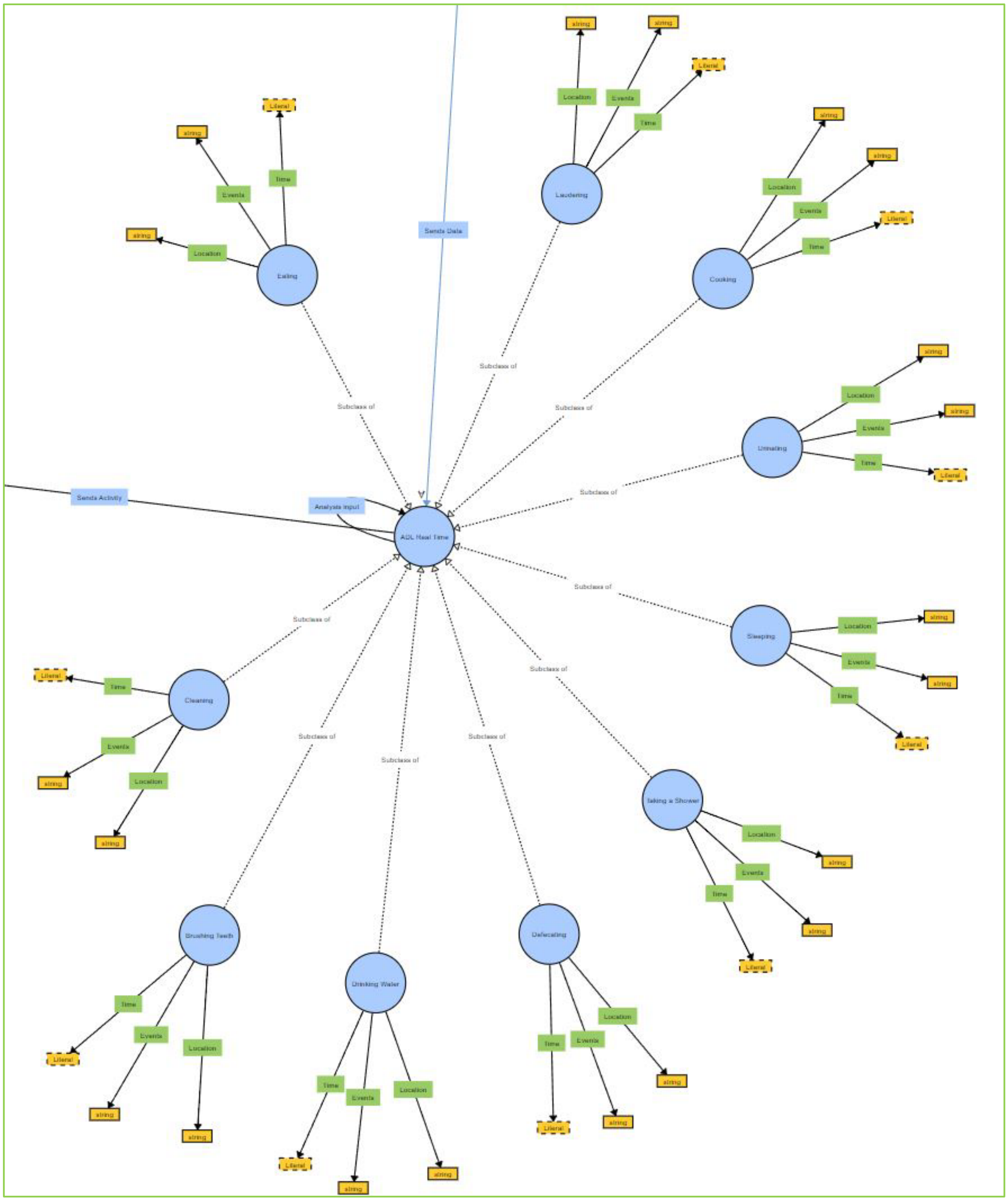

Figure 18. Real-time ADL Block.

b) Real-time ADL: This block temporarily stores the data received. First, it uses the location of the sensors to start eliminating the activities that are not associated with that particular location and keeps eliminating them until it matches the corresponding activity, then sends the correct activity and all the metadata associated with this activity received by the data gathering block to the evaluator block.

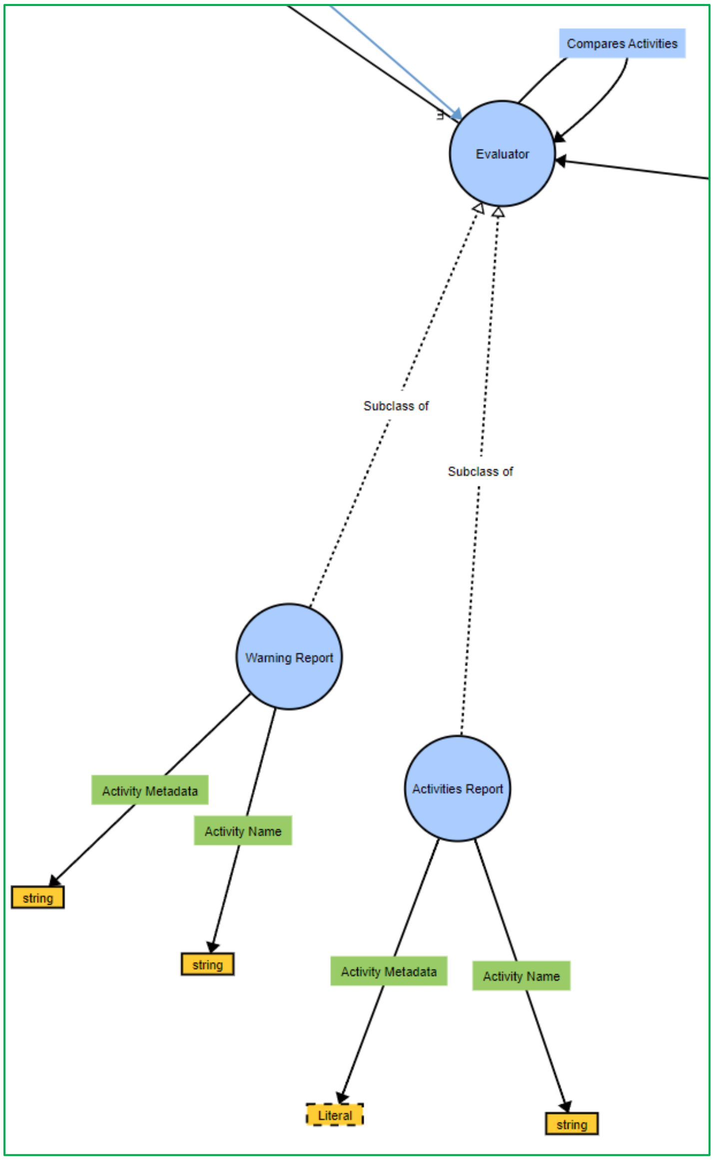

Figure 19. Evaluator Block.

c) Evaluator: This block is responsible for requesting the same activity metadata from the ADL stored block to compare with the metadata received from the real-time block and analyze if discrepancies exist between them. If there are no significant discrepancies between them, register the activity into the CSV file activity report. Still, if it detects those discrepancies, then the activity will be written in the warning report CSV file with all the data related to the activity. This block also runs a daily check to see if some activities were not registered in the activity report CSV file for some reason. If it detects that a particular activity was not recorded in the activity report, it also writes it in the warning report to show that something strange happened that day. A doctor can later examine this information to decide what to do.

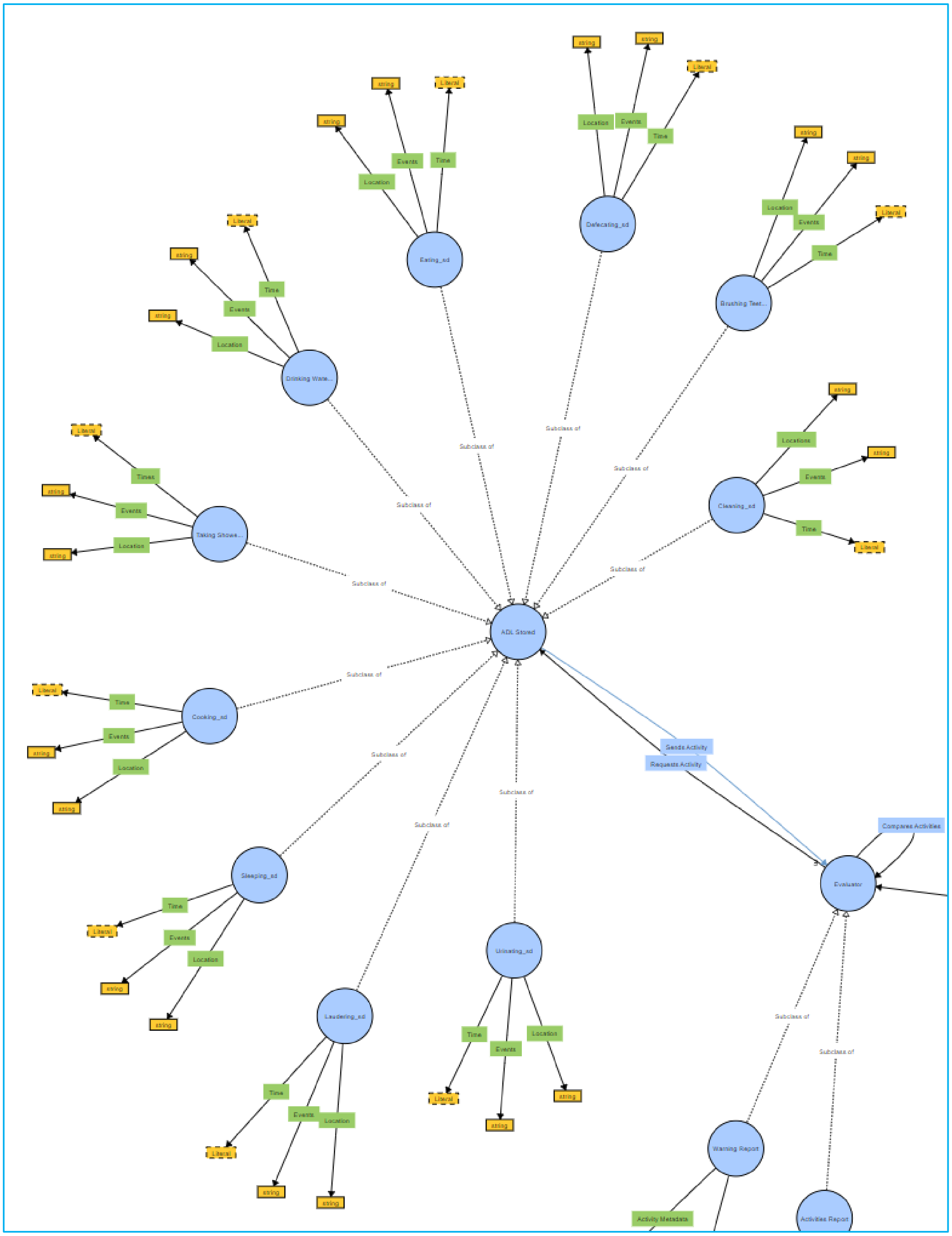

Figure 20. ADL Stored Block.

d) ADL Stored: This block is responsible for supplying the activities metadata to the evaluator block to be used as based knowledge for detecting behavioral changes.

4.5.3. Ontology Use

Our system employs an ontology as an intelligent tool to interpret and contextualize the raw data generated by the Magnet sensors. These sensors monitor key Activities of Daily Living (ADLs), and their role is to identify patterns and changes that could indicate possible early-stage dementia.

For example, consider an ADL such as Cooking. This activity can be tracked via the usage of various kitchen appliances, which are monitored by Magnet sensors strategically attached to those appliances in the kitchen. The sensors detect state changes in objects such as the refrigerator door, the stove, and specific cupboards and drawers, capturing these interactions as binary data.

The first step in the process is the identification of an ADL via Magnet sensors. The sequence of state changes recorded by the sensors can indicate an activity, such as Cooking, based on the pattern and timing of appliance usage.

This identification is made by eliminating the unlikely activities based on each sequence of events. If a particular event does not match the expected pattern for a specific activity, that activity is eliminated from consideration. This process continues until a single valid activity remains for the sequenced events.

For example, suppose the toilet Magnet sensor is activated. In that case, it's clear that sleeping, cooking, eating, taking a shower, and drinking water are unlikely activities because the person is not supposed to sleep, cook, eat, take a shower, or drink water in the toilet room.

So, the likely activities are urinating and defecating. If the person lowers the toilet seat, sits for more than 3 minutes, and activates the toilet fan, it's unlikely that the person is urinating. However, for the final decision, the system waits for the sensor allocated in urine and feces water discharge to send the elderly choice of water discharge. If the elderly use feces water discharge, this sensor sends the data that will help the system decide that the most likely activity is defecating.

Once an ADL is identified, this information serves as input for the ontology evaluator. The ontology evaluator's role is to interpret this input, recognize the activity based on the pattern, and use this understanding to search for the corresponding activity to make an analysis and correlation between them and search for any anomalies or deviations. Unusual timings, missing steps, or erratic usage could be flags, and the ontology processes these anomalies and writes a warning

---

This section of this dissertation is based on "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023.

report to point these as potential symptoms of early-stage dementia, such as memory loss or disorientation.

In summary, Magnet sensors and ontology work together, each playing a crucial role in the system's functioning. The Magnet sensors' primary role is to detect the state changes in the objects linked to specific activities and send them through patterns in binary data. The objects used information are then sent as input to the ontology, which interprets it and uses it to identify the activity.

4.5.4. Ontological Approach for Recognizing Potential Indicators of Early Stages of Dementia

Our research team employs an ontological approach to accurately recognize Activities of Daily Living (ADLs) and detect potential indicators of early stages of dementia. This approach leverages Magnet sensors strategically placed within an elderly individual's living environment. These sensors are chosen for their reliability and non-intrusive nature, ensuring high data accuracy.

The sensors collect binary data, representing state changes of specific objects or devices associated with key events. We can associate these data clusters with specific activities by combining these state changes with their corresponding location, time, and events. The equivalent formula is (4):

$$P(A) = \Pi P(S_i, L_i, T_i, E_i | A) \tag{4}$$

Where 'i' is an index of a data point in a sequence of sensor readings. 'S_i' represents the state change detected by a Magnet sensor (binary data), 'L_i' represents the corresponding location where the data has been sent, 'T_i' represents the corresponding time data, and 'E_i' represents the subsequent event data. 'P(A)' is the probability of an activity 'A,' and $P(S_i, L_i, T_i, E_i | A)$ is the probability of a specific set of state changes, locations, times, and subsequent events given the activity 'A.' This formula is based on the assumption that the occurrence of each set of state changes, locations, times, and subsequent events is independent given the activity.

We employ binary data (0s and 1s) to ensure privacy and security. This approach ensures that even in the event of a security breach, the correlation between the collected data would be incomprehensible and insufficient for any misuse.

This section of this dissertation is based on "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023.

The system construction follows an ontological approach, using predefined examples of a person's normal daily behavior. These examples are based on the time when particular activities happen, their location, and the possible activities that could occur before and after each activity. This initial learning process uses a CSV file containing the sensor's states when activities were performed correctly. This aids in the creation of a base model. The system transitions to the activity detection process with the base model established. As described in the previous section and illustrated in Figure 16, this process starts with the Raspberry Pi getting the information from the Magnet sensors and making a cross-reference between the sensor data and the different activities of daily living to detect the correct activity. Next, the system selects the correct activity and sends the information to the evaluator class that receives the activity and gets the corresponding activity from the base model knowledge, compares the metadata gathered during the activity performance, and makes a correlation between them. Nothing happens if the results do not fall too different from each other, but if the metadata does not match, a report file is created to register this activity's metadata so a human can analyze it later. This ontological approach aids in early detection and provides a foundation for proactive dementia management by interpreting and understanding the various patterns and deviations in monitored ADLs.

4.6. Sensor Implementation

Choosing the right Magnet sensor involves considering various factors such as sensitivity, detection range, and reliability. In our study, we employed sensors with a high degree of sensitivity to ensure accurate data collection [40-41].

The placement of these sensors is crucial; they were strategically located in areas where activity is most likely to occur. Figure 21 shows the wiring overview of both bathroom door and light. Figures 22 and 23 show how the sensors were placed in the bathroom door to make it possible to identify whenever the person opens or closes the bathroom door. Figures 24 and 25 show how the sensors were placed in the bathroom light to detect whenever a person turns on or off the bathroom light. Figure 26 shows the wiring overview of booth water tap and hand shower. Figure 27 shows both water tap (hot and cold), and the hand shower sensors viewer. The same pattern was adopted to the other sensors that were placed around the apartment. Calibration is another critical aspect, ensuring that the sensors function optimally under different conditions.

This section of this dissertation is based on "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023. ©2023 IEEE – 13th ICCE.

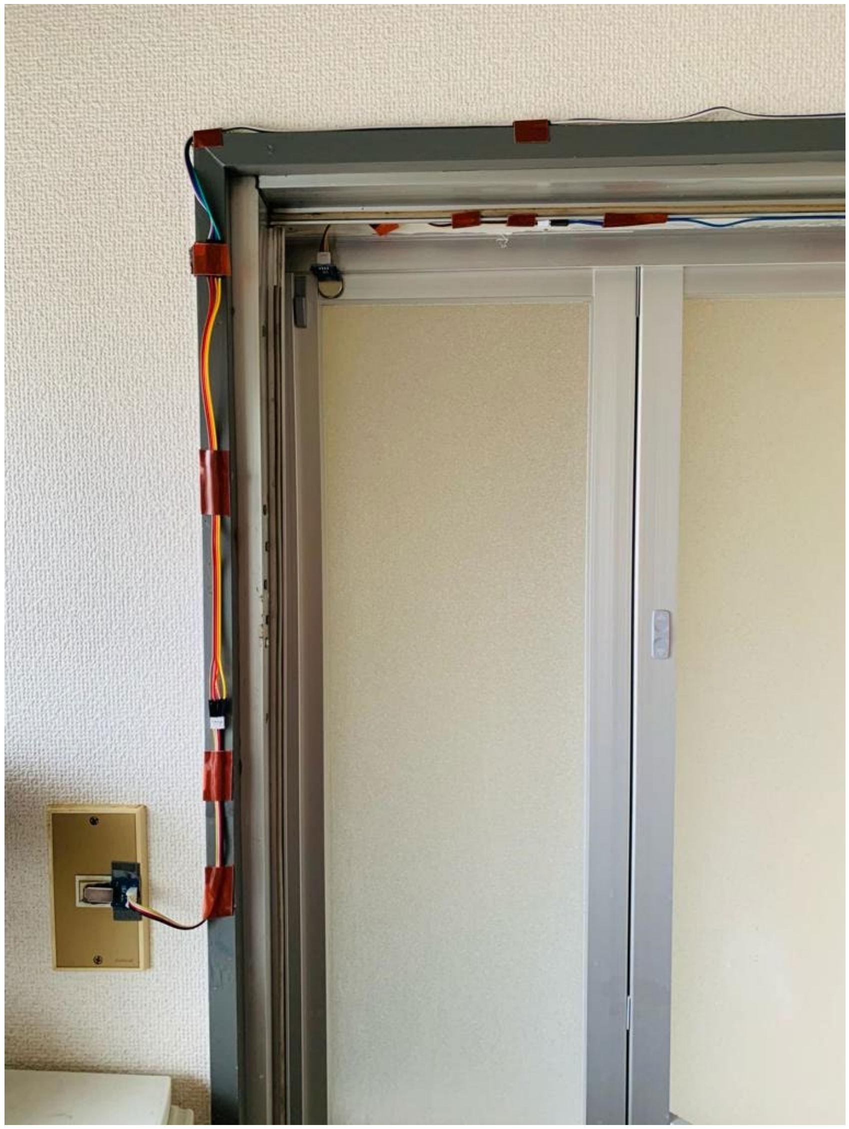

Figure 21. Door and Light Bathroom wiring overview

This section of this dissertation is based on "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023. ©2023 IEEE – 13th ICCE.

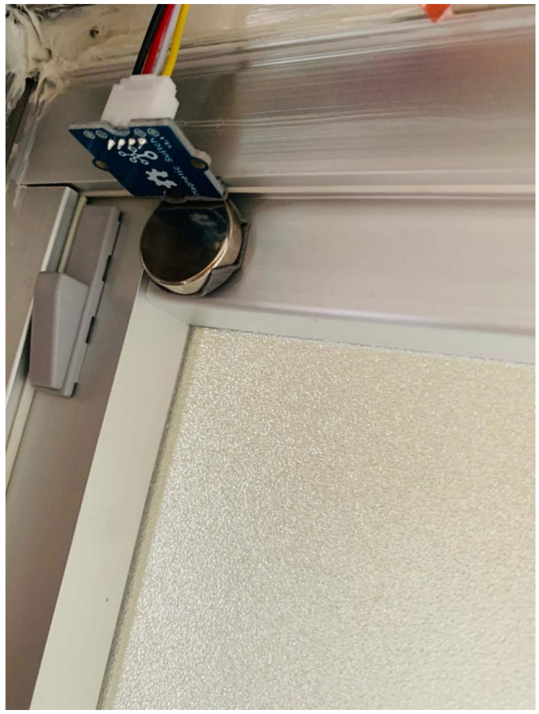

Figure 22. Bathroom Door Sensor (Door Closed - Status1)

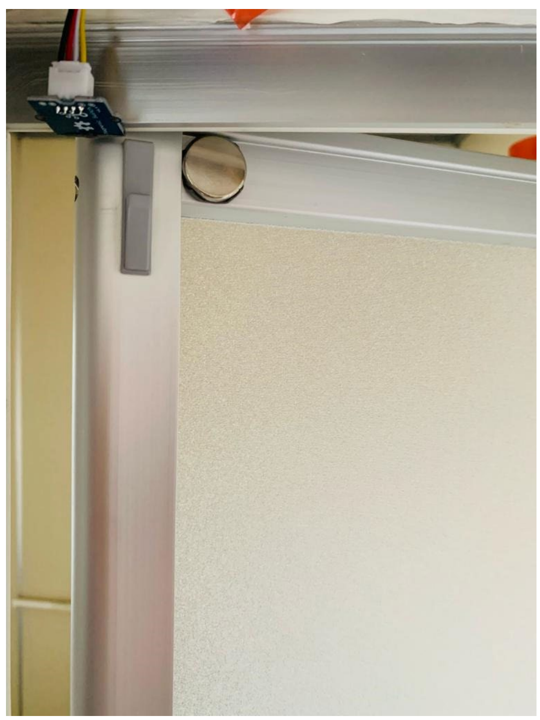

Figure 23. Bathroom Door Sensor (Door Opened - Status 0)

This section of this dissertation is based on "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023. ©2023 IEEE – 13th ICCE.

Figure 24. Bathroom Light Sensor (Light ON - Status1)

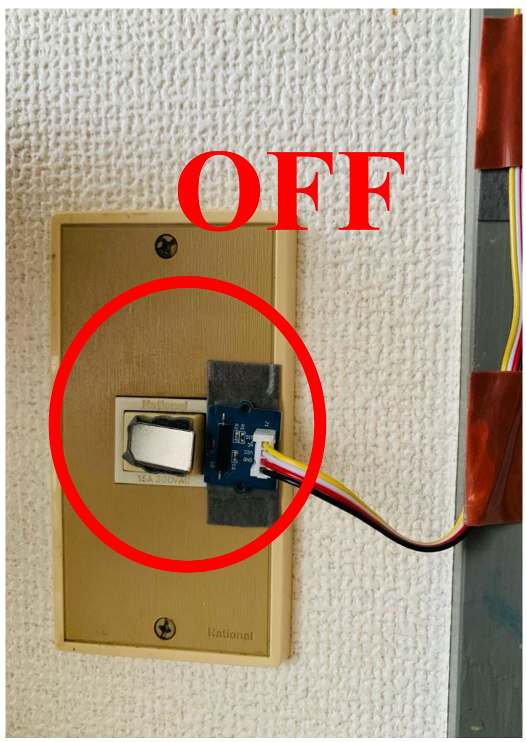

Figure 25. Bathroom Light Sensor (Light OFF – Status 0)

This section of this dissertation is based on "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023. ©2023 IEEE – 13th ICCE.

Figure 26. Water taps and hand shower wiring overview

This section of this dissertation is based on “Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis,” [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023. ©2023 IEEE – 13th ICCE.

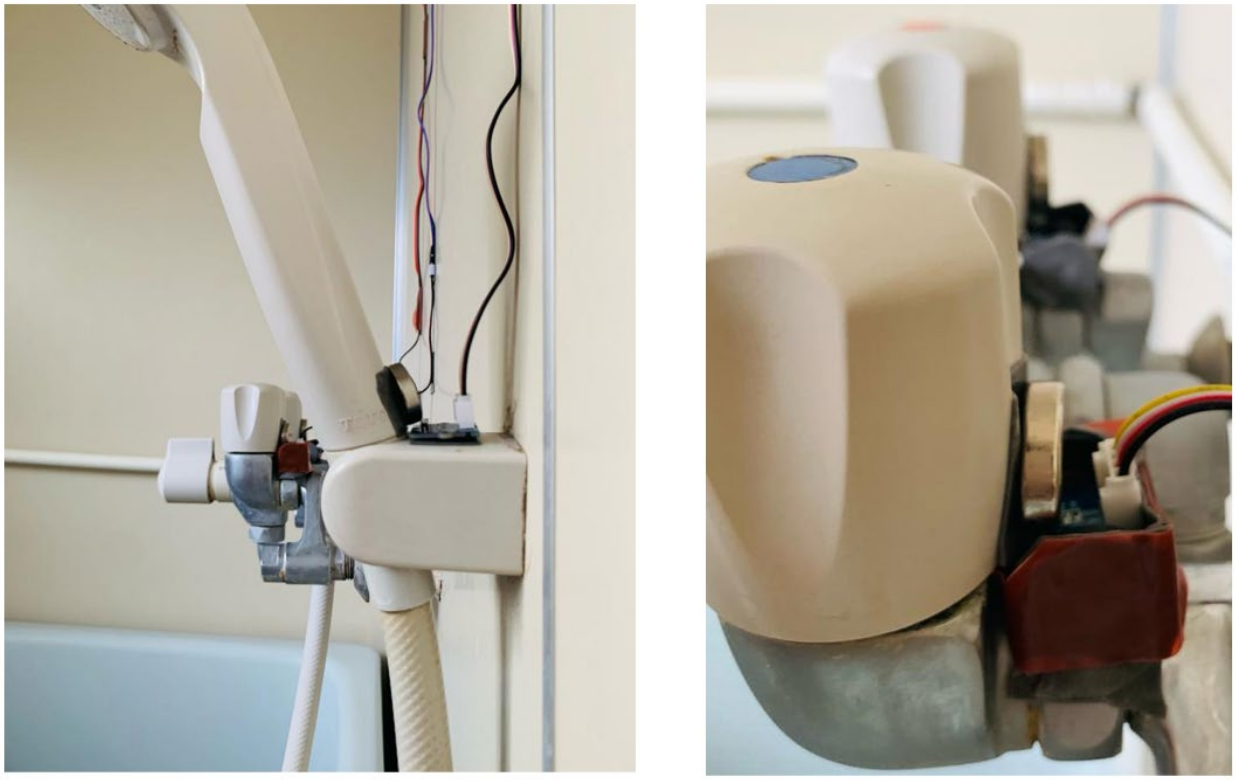

Figure 27. Water taps and hand shower sensors viewer.

This section of this dissertation is based on "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," [41], by the same author, which was presented at IEEE 13th ICCE, Berlin Germany in September 2023. ©2023 IEEE – 13th ICCE.

5. Evaluation Results and Validation

Our evaluation process consisted of two stages evaluation. The first stage was to evaluate our technology solution by comparing it to other sensor types used to recognize the activities of daily living using the four issues found in previous studies as evaluator parameters, more precisely we compared them in terms of accuracy, reliability, maintenance and privacy based on the results related by previous studies and for the sound and magnet sensors based on the results we found when testing these solutions. The evaluation information can be seen in Table 17 (the contents on the column "Reference" mean the reference number of the paper listed in the references section used to extract the information for each sensor type evaluation).

The second stage consisted of a comparison with the results obtained and published by the Singapore research team [10-13] [18-23], which studied and developed different types of prototypes to detect high-level abnormal behaviors in the elderly based on the identification of ADLs and published papers related to this study during a period of 10 years. They were focused on activities such as sleeping disorders, changes in life rhythm, and others [10-13] [18-23]. Their idea was to build a prototype capable of detecting ADLs using cheaper sensors to make it feasible for scaling deployments [10-13] [18-19]. They faced innumerable setbacks due to the inconsistency and unreliable data they collected due to faulty sensor triggers caused by pets and other external interferences [10][18].

Mokhtari et al. [20] wanted to evaluate mobility in the home and sleep monitoring by using limited and easy-to-deploy sensors such as motion sensors, force-sensing resistors, and a door reed switch. They found that implementing such a system in a real environment was more challenging than expected due to the maintenance needed resulting from the system's complexity [20]. They acknowledged that the more sensors a prototype has, the more difficult it will be to implement and maintain sustainability in the real environment. They tried to make a new prototype using only one type of sensor but couldn't succeed [20].

In this research, we directly compared the researcher's team's ideas, approaches, and results presented by the Singapore research team [10-13] [18-23]. The comparison comprises the type of activities they expected to identify and the ones they successfully identified, the number of sensors used by the researchers, and the reasons for the activities' detection failure. In Table 18, it is possible to see the list of ADLs that they could be able to identify and the ones that we expect to

This section of this dissertation is based on "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

identify. Table 18 directly compares the kind of sensors used by both teams and how they were connected to the system unit to collect and send the data. In Table 21, it's possible to see the reasons why each team failed when trying to detect ADLs, and it happened with each frequency.

Table 17. Sensors Evaluation in Terms of Accuracy, Reliability, Maintenance and Privacy

Sensor Type	Accuracy	Reliability	Maintenance	Privacy	References
Magnet	High	High	Low	High	41, 42
Sound	Medium	Medium	Low	Low	40
Accelerometer	Medium	High	Medium	Medium	103, 104, 105, 106, 107, 108, 114
Gyroscope	Medium	Medium	Medium	Medium	103, 106, 107, 108, 114
Infrared	Medium	Medium	Medium	High	117, 118, 119, 120
GPS	High	High	Low	Low	113, 114, 115, 116
LiDAR	Medium	Medium	Medium	Medium	109, 110, 111, 112
Camera	High	High	Low	Low	100, 121, 122, 123

Table 18. ADL Comparison. (© 2023 IEEE – SWC 2023, [40] Table. 1)

	Singapore Team [10-11] [18-23]		This Research	
ADLs	**Expected**	**Detected**	**Expected**	**Detected**
Cooking	O	X	O	O
Eating	O	X	O	O
Drinking Water	O	X	O	O
Taking Shower	O	O	O	O
Urinating	O	X	O	O
Defecating	O	X	O	O
Brushing Teeth	O	X	O	O
Sleeping Night	O	O	O	O
Sleeping Day	O	O	-	-
Social Activities	O	X	-	-
Cleaning	O	X	O	O
Laundering	O	X	O	O
Total ADLs	12	3	10	10

This section of this dissertation is based on "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

Table 19. Sensors Comparison. (© 2023 IEEE – SWC 2023, [40] Table. 2)

	Singapore Team [11][18]		**This Research**	
Sensors	**Used**	**Connectivity**	**Used**	**Connectivity**
Pressure Sensor	O	Wi-Fi	X	-
RF Tags	O	Wi-Fi	X	-
Reed Switches	O	Wi-Fi	X	-
Acoustic Sensors	O	Wi-Fi	X	-
IF Motion Sensor	O	Wi-Fi	X	-
Plumbing Sensor	O	Wi-Fi	X	-
Magnet Sensor	X	-	O	Wired
Total No Sensors	6		1	

Table 20. Sensors Failure. (© 2023 IEEE – SWC 2023, [40] Table. 3)

	Singapore Team [18][21]		**This Research**	
Reasons for Sensor Failure	**Failed**	**Frequency**	**Failed**	**Frequency**
Wi-Fi Disconnected	O	7%	-	-
Packet Lost	O	22%	-	-
Ran out of Battery	O	51%	-	-
Sensors Removed/Fall	O	8%	-	-
System Issues	O	12%	-	-
Wired-Cut	-	-	X	X

Furthermore, a brief description of the evaluation results related to the reliability, maintenance, accuracy, and privacy issues from previous research.

a) Reliability: Our prototype demonstrated exceptional reliability in detecting events without being triggered accidentally by external factors such as radio waves, temperature changes, earthquakes, or vibrations. The use of Magnet sensors, known for their inherent reliability, ensured that the system functioned without any false triggers, unlike other sensor types such as infrared,

This section of this dissertation is based on "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

Bluetooth beacon, and Wi-Fi sensors. This level of reliability is crucial for the effective monitoring of elderly individuals and their activities.

b) Maintenance: The prototype eliminated the need for constant maintenance and adjustments, a common issue faced by previous researchers. Magnet sensors' inherent resistance to external factors, along with their unlimited service life, contributed to a low-maintenance system that could function effectively without constant attention. This advantage is essential for the feasibility and scalability of the system in real-world settings.

c) Privacy: Privacy concerns were effectively addressed by the prototype's design, which collects and stores binary data. This approach ensures that even if unauthorized access occurs, the data would be of no value without the knowledge of how to combine it with sensor ID, location, and timestamp. Additionally, encrypted names for each sensor ID provide an extra layer of security and privacy protection.

d) Accuracy: The prototype's accuracy in identifying activities was remarkable, as it successfully detected all expected events leading to the correct activities. The system's ability to differentiate between various events and associate them with specific activities showcases its potential to be a valuable tool for monitoring elderly individuals. This high level of accuracy ensures that caregivers and medical professionals can confidently rely on the system's output for decision-making and intervention.

When compared to previous studies, our prototype outperformed other systems in terms of reliability, accuracy, privacy, and maintenance. The results obtained by the Singapore research team [10-13] [18-23] demonstrated the challenges faced in developing a reliable and accurate system for detecting ADLs. Our prototype's successful identification of activities without the setbacks experienced by previous researchers indicates its potential to be a valuable tool in elderly care and monitoring.

Table 21 presents the quantitative results of our algorithm when identifying the activities of daily living. The results shown below are based on a 60-day evaluation period. Two main factors influenced these results: the magnets' size used on each object and the durability of the adhesive securing the magnets.

The three unidentified instances in the cooking activity resulted from the misalignment between the gas tap magnet and the wall-mounted magnet sensor, which was attributed to the failure of the adhesive holding the magnet. A similar issue led to the seven unidentified instances during the eating activity.

The 69 instances of unidentified 'Drinking Water' activities were mainly attributed to two specific scenarios. First, the test subject occasionally chose to drink water directly from the kitchen tap, which complicated the accurate identification of this activity. Second, the problem is aligning the water bottle with the Magnet sensor in the fridge after drinking the water.

The 'Brushing Teeth' activity presented the lowest accuracy level. During the test phase, we observed that individuals use a variety of cup styles and sizes to hold their toothbrush. Depending on the cup's dimensions, the toothbrush rested in different positions, complicating accurate sensor activation. We understand that it is impractical and unfair to strictly impose the use of a specific cup or toothbrush size on the elderly to ensure alignment with our sensor data. Consequently, we are exploring improvements to our sensor technology to accommodate these variances.

Table 21. Quantitative Results of Algorithm Prediction. (© 2023 IEEE – SWC 2023, [40] Table. 4)

Activities of Daily Living	No Collected Samples	No Identified Samples	Accuracy Level
Cooking	180	177	98.33%
Eating	180	163	90.55%
Drinking Water	500	431	86.2%
Taking Shower	200	200	100%
Urinating	180	180	100%
Defecating	60	60	100%
Brushing Teeth	120	28	23.33%
Sleeping	60	55	91.66%
Cleaning	24	24	100%
Laundering	24	24	100%
Average Accuracy Level			89.01%

The validation process involved both simulated and real-world testing scenarios to assess the reliability and accuracy of the Magnet sensors in activity recognition [40-41]. The results were highly encouraging, with a high degree of accuracy achieved in identifying various activities. These findings were compared with existing literature to establish the effectiveness of the magnet sensors used in this study.

6. Evaluation Summary

The evaluation of results is a pivotal phase in any research, serving as the litmus test for the efficacy and reliability of the methods employed. In the context of this study, the evaluation of the results is particularly crucial given the innovative approach of using magnet sensors for activity recognition [40-41].

The first layer of evaluation involved a quantitative analysis of the sensor data. Custom metrics were developed to measure the accuracy, sensitivity, and specificity of the activity recognition algorithms [40-41]. These metrics provided a numerical basis for assessing the performance of the Magnet sensors in recognizing various Activities of Daily Living (ADL) [40-41].

This section of this dissertation is based on "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023. ©2023 IEEE – SWC2023.

A comparative analysis was also conducted to evaluate the magnet sensors against traditional sound sensors used in previous studies. This was essential to validate the superiority of magnet sensors in terms of accuracy, reliability, maintenance, and privacy. The magnet sensors demonstrated a significantly higher accuracy rate and fewer false positives compared to sound sensors, thereby confirming their efficacy.

One of the most compelling findings was the sensor's ability to distinguish between activities that occur simultaneously or in close temporal proximity. This is a significant advancement over sound sensors, which often struggle with overlapping acoustic signatures from concurrent activities [40-42].

The results also revealed the versatility of magnet sensors in various environmental conditions. Unlike sound sensors, which can be affected by ambient noise, magnet sensors maintained a consistent performance level even in less-than-ideal conditions, further solidifying their reliability [40-42].

The evaluation phase culminated in a series of real-world tests involving a test subject performing various ADLs. These tests served to validate the research findings in a practical setting, thereby bridging the gap between theoretical research and real-world applicability [40-42].

Delving into a comprehensive evaluation of our prototype, focusing on four key metrics: reliability, maintenance, privacy, and accuracy. These metrics are particularly significant given the challenges highlighted in previous research [8-19][59], including the work conducted by the Singapore research team [10-13] [18-23].

A. Reliability: Our prototype exhibited unparalleled reliability, a feature that is indispensable for the effective monitoring of the elderly. Unlike other sensor technologies such as infrared, Bluetooth beacon, and Wi-Fi sensors, which are prone to false triggers, our magnet sensor-based system demonstrated flawless performance. It remained impervious to external factors like radio waves, temperature fluctuations, seismic activities, and other environmental vibrations. This system also solved the issues that we faced when using sound sensors related to co-occurring activities that, in some cases, would overlap other activities that were taking place at the same time. This high level of reliability ensures that the system can be trusted for long-term deployment in elderly care settings.

This section of this dissertation is based on “Detecting Activities of Daily Living for the Elderly Using Magnet Sensors,” [40], by the same author, which was presented at IEEE Smart World Conference, Portsmouth England in August 2023.

B. Maintenance: One of the most compelling advantages of our prototype is its low maintenance requirement. Traditional systems often necessitate frequent adjustments and calibrations, a challenge that has stymied previous researchers. In contrast, our magnet sensors are inherently resistant to external factors and boast an almost unlimited service life. This contributes to a robust, low-maintenance system that can operate effectively without constant supervision, making it highly feasible and scalable for real-world applications.
C. Privacy: Our prototype was meticulously designed to address privacy concerns, which have been a significant obstacle in the adoption of monitoring technologies for the elderly. By collecting and storing only binary data (0s and 1s), the system minimizes the risk of unauthorized access to sensitive information. Even if a security breach were to occur, the binary data would be meaningless because no one can use 0s and 1s to blackmail or shame someone.
D. Accuracy: The prototype's performance in accurately identifying activities of daily living (ADLs) was nothing short of remarkable. It successfully detected all anticipated events and correctly associated them with specific activities. This level of accuracy is not just statistically significant but also practically meaningful, as it allows caregivers and medical professionals to make informed decisions based on reliable data.

When benchmarked against existing systems, our prototype outshined them across all four metrics. The challenges faced by previous research teams, particularly those from Singapore, underscore the novelty and utility of our approach. Our system's successful identification of ADLs without the setbacks encountered by earlier studies marks it as a groundbreaking tool in the realm of elderly care and monitoring.

In conclusion, the results evaluation provided a comprehensive and multi-faceted assessment of the magnet sensors' performance in activity recognition. The findings not only validated the research hypothesis but also highlighted the magnet sensors' superiority over traditional sound sensors. These results have significant implications for the future of activity recognition, particularly in healthcare settings where accurate and reliable data is paramount [41].

I.VI. Conclusion

1. Summary

The overarching aim of this part was to explore the efficacy and applicability of different sensors and how they perform when compared to the magnet sensors in the realm of activity recognition. The study successfully demonstrated that despite getting acceptable results with other sensors, magnet sensors offer a more accurate, reliable, and versatile solution compared to traditional sensors. In this part of the literature review, to be more precise, we also described the pros and cons faced when trying to detect the activities of daily living using the sound sensors. A sensor that appeared to be the most promising sensor based on the results from previous studies. Following are detailed results of using both sensors.

1.1. Sound Sensors

Reliability: The sound sensors solved the issues related to reliability when it comes to resilience against external factors, limited working time due to battery issues, and detection errors (false inputs caused by pets and persons inside the house). Still, at the same time, we have issues when trying to distinguish between activities that produce similar sound patterns. For example, the sound of washing dishes can be easily confused with the sound of running water for a shower. Additionally, sound sensors are less effective in recognizing co-occurring activities, as the acoustic signatures can overlap and create ambiguities.

Maintenance: The sound sensors could fully address the maintenance issues thanks to the fact that they did not require extra calibrations after installation and no battery replacements because they were connected wired to the Raspberry Pi.

Accuracy: The sound sensors solve the accuracy issues by identifying the activities correctly when they occurred independently, but as mentioned, the same result was not fully achieved when activities co-occurred.

Privacy: When it comes to privacy, while the sound sensor does not expose any images of the elderly performing his activities, ensuring that no image or video of the elderly can be used to shame him or to blackmail him at the same time opens another door that is the possibility of an illegal voice recording of the elderly to record and listen to private conversations that can later be used to blackmail or shame the elderly.

1.2. Magnet Sensors

The limitations shown in the previous section make clear the need to explore other types of sensors, such as Magnet sensors, for activity recognition. Magnet sensors offer several advantages over sound sensors, including detecting activities with higher accuracy, less susceptibility to environmental noise, and full privacy assurance as they only collect binary data (0s and 1s). Moreover, magnet sensors can effectively recognize simultaneous activities, thus addressing one of the major limitations of sound sensors [15]. Delving into a comprehensive evaluation of the magnet sensors, focusing on four key metrics: reliability, maintenance, privacy, and accuracy, it's possible to get a better understanding of their superiority when compared to the sound sensors.

Reliability: Magnet sensors exhibited unparalleled reliability, a feature that is indispensable for the effective monitoring of the elderly. Unlike the sound sensor, this sensor solved the issues that we faced when using sound sensors to identify co-occurring activities that, in some cases, would overlap other activities that were taking place at the same time.

Maintenance: One of the most compelling advantages of magnet sensors is their low maintenance requirement. Magnet sensors are inherently resistant to external factors and boast an almost unlimited service life. This contributes to a robust, low-maintenance system that can operate effectively without constant supervision, making it highly feasible and scalable for real-world applications.

Accuracy: The magnet sensors' performance in accurately identifying activities of daily living (ADLs) was nothing short of remarkable. It successfully detected all anticipated events and correctly associated them with specific activities different than sound sensors that, due to the overlap cases during the co-occurring activities, could lead to an unedified or misidentified activity.

Privacy: When it comes to privacy, magnet sensors ensure that privacy concerns are effectively addressed since magnet sensors only collect and send binary data (0s and 1s) different from sound sensors that are recording live sounds. Thanks to this, magnet sensors ensure that even if unauthorized access occurs, the binary data would be meaningless because no one can use 0s and 1s to blackmail or shame someone.

In conclusion, the results evaluation provided a comprehensive and multi-faceted assessment of the magnet sensors' performance in activity recognition. The findings not only validated the research hypothesis but also highlighted the magnet sensors' superiority over sound sensors. These results have significant implications for the future of activity recognition, particularly in healthcare settings where privacy, accurate and reliable data are paramount.

2. Limitations

While the proposed system has shown promise in monitoring various Activities of Daily Living (ADLs), certain limitations were observed during the evaluation stage. Specifically, the Brushing Teeth results were not up to the expected standards.

The Drinking Water activity occasionally failed to be accurately identified. This limitation was primarily due to the placement of the water bottle inside the refrigerator, which sometimes interfered with the sensor's ability to obtain a correct reading. The sensor's sensitivity to the bottle's position highlights a constraint in the system's design, particularly when dealing with objects that are not fixed in place.

The Brushing Teeth activity presented a more significant challenge, with a notably low accuracy rate of 23.33%. This was largely attributed to the small magnet attached to the toothbrush requiring precise alignment with the base of the cup for accurate detection. Given that it is impractical to expect the elderly to perfectly align the toothbrush every time, this poses a significant limitation. Adding a stronger magnet is not a viable solution either, as it could make the process uncomfortable for the elderly and potentially lead to frustration due to the need for precise alignment.

Upon closer examination, it becomes evident that both activities share a common limitation: they involve similar types of human interaction that our current approach struggles to accurately capture. This points to a broader weakness in our methodology when dealing with activities that require specific object placements or alignments.

These limitations not only provide avenues for future research but also serve as critical points of consideration for the ongoing development and refinement of the system.

3. Future Work

While the proposed system holds promise, its ultimate efficacy hinges on its practical utility for medical doctors, nurses, caregivers, and caregiver managers. Therefore, immediate future work should prioritize the evaluation of the developed prototype. Such an evaluation would aim to ascertain the system's practicality, reliability, and efficacy in providing potential indicators to help identify early-stage dementia. Feedback from medical doctors will be instrumental in fine-tuning the system to meet the dual needs of healthcare providers and patients.

Moreover, the next phase of research should involve the deployment and assessment of the prototype in real-world environments. This would not only validate the system's operational viability but also its adaptability to various settings and conditions. Additionally, although the current study did not employ machine learning algorithms, future iterations could explore the incorporation of such techniques to augment the system's early detection capabilities.

In summary, the system proposed in this research has the potential to revolutionize early dementia detection, laying a robust groundwork for proactive dementia management. Nevertheless, the system's success is contingent upon its seamless integration into existing healthcare infrastructures and its subsequent endorsement by medical professionals.

By incorporating these elements, the research aims to transition from a theoretical model to a practical solution that can be readily adopted and implemented in healthcare settings.

Part II: Applications in Elderly Care

II.I. Introduction

1. Background

The aging population is a global phenomenon that poses significant challenges to healthcare systems worldwide. With the increase in life expectancy, there is a growing need for effective elderly care solutions, particularly for those living alone or with cognitive impairments such as dementia. Traditional methods of elderly care often rely on human caregivers or medical professionals, which can be both labor-intensive and costly. Moreover, these methods may not be scalable given the projected increase in the elderly population [1].

In this context, technology-based solutions offer a promising avenue for enhancing the quality of life for the elderly while also providing valuable data for healthcare providers [40-41]. Activity recognition systems, particularly those using magnet sensors, have shown significant potential in monitoring Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs) [40-41]. These systems can capture behavioral changes that may indicate cognitive decline, thereby facilitating early intervention and better management of conditions like dementia [41].

This part of the thesis aims to explore the applications of activity recognition in elderly care, focusing on the potential for early detection of cognitive impairments and the improvement of quality of life for the elderly.

2. Objectives

The primary objectives of this section are:

- To investigate how activity recognition systems can provide useful information to help medical professionals in elderly care.
- To evaluate the potential of these systems in detecting potential early signs of cognitive impairments such as dementia.

3. Research Questions

The research questions guiding this section are:

1. How can activity recognition systems be adapted to suit the specific needs of elderly care?

2. What are the key indicators that these systems can capture for early detection of cognitive impairments?

3. What are the challenges and limitations of implementing these systems in real-world healthcare settings?

4. What ethical considerations must be considered when deploying these systems for continuous monitoring of the elderly?

II.II. Literature Review

1. Dementia

Dementia is a broad category of brain diseases that cause a long-term and often gradual decrease in the ability to think and remember, affecting daily functioning and quality of life [60]. Alzheimer's disease is the most common form of dementia, accounting for 60-80% of cases [61]. Other types include vascular dementia, Lewy body dementia, and frontotemporal dementia, each with its unique set of symptoms and challenges [62].

The global prevalence of dementia is rising at an alarming rate, with an estimated 50 million people currently affected, and numbers expected to triple by 2050 [63]. The economic burden of dementia care is also substantial, estimated to be over $1 trillion globally [64]. These figures underscore the urgent need for effective early detection and management strategies.

Early diagnosis of dementia is crucial for several reasons. Firstly, it allows for timely intervention, which can slow down the progression of the disease and improve the quality of life for both the patient and their caregivers [65]. Secondly, early diagnosis can facilitate better planning and decision-making regarding treatment options, care needs, and financial arrangements.

Traditional methods of dementia diagnosis often involve cognitive tests, neuroimaging, and clinical evaluations [65]. However, these methods are not without limitations. Cognitive tests can be influenced by various factors like education level, cultural background, and even the individual's emotional state at the time of testing [63-64]. Neuroimaging techniques like MRI and PET scans are expensive and not easily accessible in many parts of the world [66-67].

Recent advancements in technology offer new avenues for dementia diagnosis and management. Activity recognition systems, particularly those using magnet sensors, have shown promise in capturing behavioral changes that may indicate the onset of cognitive impairments [40-41]. These systems can monitor Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs), providing a more nuanced understanding of an individual's cognitive state [40-41].

The integration of activity recognition systems into healthcare frameworks for elderly care could revolutionize dementia diagnosis and management. These systems offer the advantage of continuous monitoring, providing a wealth of data that can be analyzed for early signs of dementia [40-41]. Moreover, they can be adapted to suit the specific needs and challenges of elderly care, making them a versatile tool in the fight against dementia [41].

In summary, dementia is a pressing global health issue that requires innovative solutions for early detection and management. Activity recognition systems offer a promising approach, but further research is needed to assess their effectiveness, practicality, and ethical implications in real-world healthcare settings.

2. Dementia Diagnosis

The diagnosis of dementia is a complex and multi-faceted process that involves a combination of clinical assessments, cognitive tests, and imaging studies [66-68]. Traditionally, the diagnosis is made through a series of steps, beginning with a thorough medical history and physical examination, followed by neuropsychological testing to assess cognitive functions such as memory, attention, and problem-solving skills [22][51] [66-68]. Neuroimaging techniques like MRI and PET scans are often used to rule out other potential causes of cognitive impairment and to identify any structural or functional abnormalities in the brain [66-68].

However, these conventional methods have their limitations. For instance, cognitive tests can be influenced by a variety of factors, including the patient's educational background, cultural influences, and emotional state at the time of testing [63-64]. Neuroimaging is not only expensive but also not universally accessible, especially in low-resource settings [66-67]. Furthermore, these methods are often not sensitive enough to detect the early stages of dementia, leading to delayed diagnosis and treatment [22][51].

Recent advancements in technology have paved the way for more innovative approaches to dementia diagnosis. One such approach is the use of activity recognition systems, particularly those employing magnet sensors, to monitor the Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs) [41]. These systems can capture subtle behavioral changes that may be indicative of cognitive decline, thereby facilitating early diagnosis [41].

The advantage of using activity recognition systems for dementia diagnosis lies in their ability to provide continuous, real-time monitoring of the elderly [40-41]. This not only allows for the capture of a wealth of data that can be analyzed for early signs of dementia but also enables healthcare providers to make more informed decisions regarding treatment and care [40-41]. For example, data from Magnet sensors can be used to develop an ontological model that provides a structured representation of the relationships between ADLs and potential dementia symptoms

[41]. This model can serve as a valuable tool for medical doctors in assessing the utility and effectiveness of the system in detecting early-stage dementia [41].

Moreover, the integration of activity recognition systems into existing healthcare infrastructures can significantly enhance the quality of dementia care. These systems can be customized to suit the specific needs and challenges of elderly care, making them a versatile and effective tool in dementia diagnosis and management.

In conclusion, while traditional methods of dementia diagnosis have their merits, they are not without limitations. The advent of activity recognition systems offers a promising alternative that could revolutionize the way dementia is diagnosed and managed. However, further research is needed to validate the effectiveness of these systems and to explore their ethical and practical implications.

3. Dementia Stages

According to The Global Deterioration Scale for assessment of primary degenerative dementia, there are seven stages of dementia [22][51].

a) Stage 1: No Cognitive Decline

Clinical Characteristics: Clinically, stage 1 patients appear normal; they report no memory problems, and a clinical interview reveals no indication of memory problems [22].

Psychometric Correlations: A patient must score average or above the normal person at his age on three of five Guild Memory Test subtests [51].

ADL Scenario: At this stage, the elderly are demonstrating normal behavior, performing all the activities in a normally structured way. This is the baseline to monitor the elderly's behavior and check for future changes [41].

b) Stage 2: Very Mild Cognitive Decline

Clinical Characteristics: This is the stage of forgetfulness. The patient starts complaining about short-term memory loss [22]. The most common complaint of patients during this stage is forgetting where familiar objects are located and forgetting names that they previously knew well. Patients show no evidence of a memory deficit during a clinical interview and in social and employment situations. As the symptoms worsen, the individual starts presenting concerns [22].

Psychometric Correlations: The patient performs below average the normal person at his age and WAIS vocabulary score on three of five Guild Memory Test subtests [51].

ADL Scenario: The elderly use the kettle to boil water and, after forgetting to put the kettle where it belongs [41].

Another scenario is when the elderly search for his apartment keys when they are always kept on the key's holder next to the apartment door [41].

c) Stage 3: Mild Cognitive Decline

Clinical Characteristics: At this stage, clinical deficits begin to emerge clearly. A trained geriatric psychiatrist can objectively assess memory deficits through an intensive interview. Clinical testing may reveal a lack of concentration. The patient may also have difficulty remembering the names of new acquaintances. At this stage, the patient will likely retain relatively little information from a book passage [22].

The symptoms of decreased performance manifest in the workplace and in demanding social situations. It may become evident to coworkers and friends that the person is having difficulty finding words and names, raising awareness about possible issues affecting the patient. It is usually at this point that patients may get seriously lost when traveling to unfamiliar locations [22].

Denial often manifests in these patients, adding to the subtlety of their clinical symptoms. In addition to the previously described, the patient starts displaying mild to moderate anxiety behaviors [22].

Psychometric Correlations: These patients perform one standard deviation or more below average for their age and WAIS vocabulary score on at least three of the five Guild memory subtests. However, they may still make no errors on the 10-item Mental Status Questionnaire [51].

ADL Scenario: The elderly start forgetting about basic daily living activities such as waking up, taking a shower, and forgetting to close the water tap. He forgets to brush his teeth and leaves the apartment [41].

d) Stage 4: Moderate Cognitive Decline

Clinical Characteristics: This is the late confessional phase, and a clear-cut deficit is apparent in a careful clinical interview [22]. The deficits are manifest in many areas. A concentration deficit is usually elicited if patients are requested to do serial subtractions [22]. They display decreased knowledge of recent events in their lives and current events around them [22]. Upon careful questioning, these patients may also show a deficit in memory of their personal history [22]. The ability to travel alone is notably curtailed, and difficulties with managing personal finances may become apparent [22].

Patients can no longer perform complex tasks accurately and efficiently at this stage. However, specific abilities characteristically remain preserved. Patients remain well-oriented to time and person. Familiar people and faces can still readily be distinguished from strangers. There is generally no deficit in the patient's ability to travel to familiar locations [22].

Denial often becomes the dominant defense mechanism at this stage. The evident decline in one's intellectual and cognitive capacities is too overwhelming a loss for full conscious acceptance and recognition. A flattening of affection and withdrawal from previously challenging situations are observed [22].

Psychometric Correlations: Patients at this stage almost always make three or more errors on the Mental Status Questionnaire [51].

ADL Scenario: At this stage, the elderly start having difficulties performing sequenced activities such as:

Cooking – The elderly can open the gas tap, take the food out of the fridge to cook, put the food in the pot, and then put the pot on the stove but forget to turn it on [41].

Preparing Tea – The elderly can take the kettle and put water on; he can put the kettle back to the base but forget to turn it on and instead pick the cup and put sugar and tea without turning the kettle on [41].

e) Stage 5: Moderately Severe Cognitive Decline

Clinical Characteristics: This is the stage of early dementia. Patients in this stage can no longer survive without some assistance [22]. During interviews, they cannot recall a major relevant aspect of their current lives [22]. For example, they may have difficulty recalling or giving incorrect responses when asked about their address or telephone number, the names of close family members, such as grandchildren, or the name of the high school or college from which they graduated. Frequently, patients are somewhat disoriented about time (date, day of the week, season) or place. A well-educated person may have difficulty counting backward from 40 by 4s or 20 by 2s [22].

Persons at this stage retain the knowledge of many major facts regarding themselves and others [22]. They invariably know their names and their spouses and children's names. They require no assistance with toileting or eating [22]. Still, they may have difficulty choosing the proper clothing to wear and may occasionally clothe themselves improperly (for example, they may put their shoes on the wrong foot).

Psychometric Correlations: Deficits are evident in the brief Mental Status Questionnaire assessment [51].

ADL Scenario: At this stage, the elderly display issues differentiating the proper time to perform some activities. The elderly sleeping route changes. He wakes up around 11 PM to cook, eat, watch TV, do laundry, and go to bed around 9 AM [41].

f) Stage 6: Severe Cognitive Decline

Clinical Characteristics: This is the middle stage of dementia. These patients may occasionally forget the names of their spouses, on whom they depend entirely for survival [22]. They are largely unaware of all recent events and experiences in their lives [22]. They retain some knowledge of their past lives, but this is very sketchy [22]. Patients are generally unaware of their surroundings, the year, or the season. They may have difficulty counting from 10 backward and, sometimes, forward [22].

Patients at this stage will require substantial assistance with activities of daily living. For example, they may become incontinent [22][51]. Also, they will require assistance in traveling but occasionally will display the ability to travel to familiar locations. Diurnal rhythm frequently becomes disturbed. However, patients almost always recall their own names. Often, they continue to be able to distinguish familiar from unfamiliar persons in their environment [22].

Psychometric Correlations Personality and emotional changes occur at this stage [51]. These are quite variable and include the following [51]:

1) Delusional behavior, e.g., accusing a spouse of being an imposter, talking to imaginary figures in the environment, or reflections in the mirror.

2) Obsessive symptoms, e.g., the continual repetition of simple cleaning activities.

3) Anxiety symptoms, agitation, and even previously nonexistent violent behavior.

4) Cognitive abulia, i.e., loss of willpower, occurs because an individual cannot carry a thought long enough to determine a purposeful course of action.

ADL Scenario: At this stage, the elderly start repeating the same activity multiple times or during inappropriate times. The elderly can shower more than four times during the day without leaving the apartment or in a short time without an apparent reason [41].

At this stage, the elderly also present problems distinguishing locations to perform specific activities. Instead of sleeping in the bedroom, he can start sleeping in the living room without realizing that he is not in the right place to sleep [41].

c) Stage 7: Very Severe Cognitive Decline

Clinical Characteristics: This is the late stage of dementia; All verbal abilities are lost. Frequently, there is no speech at all, only grunting [22]. These patients are incontinent of urine and require assistance in toileting and eating [22]. They also lose psychomotor skills [22]. For example, they may lose the ability to walk. The brain appears to no longer be able to tell the body what to do. Generalized cortical and focal neurologic signs and symptoms are frequently present [22].

Psychometric Correlations: Patients with late dementia make ten errors on the Mental Status Questionnaire [51].

4. Early Stages of Dementia

Understanding the early stages of dementia is crucial for both timely diagnosis and effective management of the condition. The first three stages are considered as the early stages of dementia [22]. The early stages often manifest as mild cognitive impairment (MCI), characterized by subtle changes in memory, language, and other cognitive functions that are not severe enough to interfere with daily life [22][51]. However, these early symptoms are frequently overlooked or attributed to normal aging, leading to delayed diagnosis and treatment [63].

The early stages of dementia are particularly challenging to diagnose due to their subtle and often ambiguous nature. Traditional diagnostic methods, such as cognitive tests and neuroimaging, may not be sensitive enough to detect these early changes [22][51][63]. This is where activity recognition systems, especially those utilizing Magnet sensors, can play a pivotal role. By continuously monitoring Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs), these systems can capture behavioral changes that may be indicative of the onset of dementia [41].

For instance, changes in sleep patterns, eating habits, or even the way an individual performs basic tasks like brushing teeth or drinking water could be early indicators of cognitive decline [22][41]. The data collected by Magnet sensors can be analyzed to identify these subtle changes, thereby facilitating early intervention and possibly slowing the progression of the disease [63].

One of the groundbreaking contributions of activity recognition systems in understanding early-stage dementia is the development of ontological models. These models provide a structured framework for representing the complex relationships between various ADLs and potential early symptoms of dementia [41]. Such models can serve as a valuable tool for healthcare providers in identifying at-risk individuals and tailoring interventions to meet the specific needs of each patient.

However, it's important to note that while activity recognition systems offer a promising avenue for early detection, they are not a substitute for a comprehensive medical evaluation. These systems should be viewed as supplementary tools that can aid healthcare providers in making more informed decisions.

Moreover, ethical considerations must also be taken into account when implementing activity recognition systems for dementia care. Issues such as data privacy, informed consent, and the potential for stigmatization need to be carefully addressed [5] [8-19] [40-42].

In summary, the early stages of dementia present a unique set of challenges and opportunities for healthcare providers. While traditional diagnostic methods have their limitations, the advent of activity recognition systems, particularly those employing Magnet sensors, offers a promising alternative for early detection and management [41]. These systems can capture a wealth of data that can be analyzed for early signs of dementia, thereby providing a more nuanced understanding of the disease in its initial stages [41].

5. Behavioral Indicators in Early Stages of Dementia

Behavioral indicators are pivotal in the early detection and diagnosis of dementia, serving as nuanced markers that often precede more overt cognitive symptoms [41]. These indicators manifest as subtle yet significant changes in an individual's daily activities, habits, and social interactions [22]. The importance of these behavioral indicators cannot be overstated, as they offer a window into the cognitive state of an individual, often before medical tests confirm a diagnosis [69-75].

5.1. Types of Behavioral Indicators and Their Significance

There are four types of Behavioral indicators that can signalize potential early stages of dementia:

Changes in Routine: One of the most telling signs of the onset of dementia is a noticeable change in daily routine. This could range from altered eating habits to disrupted sleep patterns.

The significance of these changes lies in their deviation from established norms, which can be quantitatively and qualitatively assessed [10-11] [18-23][51].

Mood Swings and Emotional Changes: Emotional volatility, including increased irritability, depression, or anxiety, often accompanies the early stages of dementia. These emotional changes are not just symptomatic but can exacerbate cognitive decline, making their early detection and management crucial [10-11] [18-23][51].

Forgetfulness and Memory Lapses: Forgetfulness is perhaps the most commonly associated symptom of dementia. However, it's the nature and context of what is forgotten that serves as a more accurate indicator. Forgetting names is one thing, but forgetting to turn off the stove is another level of severity altogether [10-11] [18-23][51].

Difficulty in Task Management: Struggles with planning or organizing daily tasks can be indicative of cognitive decline. This manifests itself as an inability to follow established routines, manage finances, or even keep track of personal hygiene [10-11] [18-23][51].

5.2. The Imperative of Continuous Monitoring

The continuous monitoring of these behavioral indicators is essential for early intervention and effective management of dementia. The use of Magnet sensors for real-time monitoring of Activities of Daily Living (ADLs) provides a robust framework for capturing these behavioral changes. This continuous data stream offers a wealth of information that can be analyzed to identify early signs of dementia, thereby facilitating timely medical intervention [41].

5.3. Challenges in Behavioral Indicator Monitoring

Despite the apparent benefits, several challenges persist in the effective monitoring of behavioral indicators. The social stigma associated with dementia often leads to delayed diagnosis and treatment. Moreover, these behavioral changes can sometimes be symptoms of other medical conditions, necessitating differential diagnosis to confirm dementia [76-79].

In conclusion, the nuanced understanding and monitoring of behavioral indicators are crucial for the early detection and management of dementia. These indicators, when captured and analyzed effectively, can provide a robust foundation for proactive dementia care, thereby improving the quality of life for affected individuals and their families.

6. Technological Approaches for Dementia Care

The role of technology in dementia care has evolved significantly over the past decade, transitioning from rudimentary monitoring systems to sophisticated, sensor-based solutions that offer real-time data and analytics. The technological approaches employed in dementia care aim to address multiple facets of the condition, from early detection to ongoing management and even palliative care.

6.1. Sensor-Based Monitoring Systems

One of the most promising technological approaches is the use of sensor-based monitoring systems. These systems, such as the Magnet sensor-based framework discussed in this thesis, offer continuous, non-intrusive monitoring of Activities of Daily Living (ADLs). The data collected can be analyzed to identify behavioral indicators of dementia, thereby facilitating early diagnosis and intervention [70-75][78].

6.2. Artificial Intelligence and Machine Learning

While this thesis does not employ machine learning algorithms for its final sensor-based framework, the broader field of dementia care has seen the integration of artificial intelligence (AI) and machine learning techniques. These technologies are primarily used for data analysis, offering predictive models that can identify potential dementia cases with high accuracy.

6.3. Telemedicine and Remote Consultations

The advent of telemedicine has revolutionized dementia care by making it more accessible. Remote consultations and monitoring systems allow for timely interventions, especially in rural or underserved areas. However, the effectiveness of these systems is still under study, and their integration into mainstream healthcare remains a challenge [79-80].

6.4. Wearable Technologies

Wearable devices like smartwatches and fitness trackers are increasingly being adapted for dementia care. These devices can monitor vital signs, track movements, and even send alerts in case of emergencies like falls. However, the acceptability and long-term usage of these devices by the elderly are still subjects of ongoing research [81-82].

6.5. Ethical and Privacy Concerns

As with any technology that involves data collection, ethical and privacy concerns are paramount. Ensuring the confidentiality and security of the data collected, especially in the case of vulnerable populations like those with dementia, is a critical aspect that needs to be addressed [5] [8-19][40-42].

In summary, technological approaches offer a multi-faceted strategy for improving dementia care. From sensor-based systems to AI and telemedicine, these technologies provide valuable tools for early detection, monitoring, and management of dementia. However, their successful implementation will require overcoming challenges related to accuracy, ethics, and integration into existing healthcare infrastructures.

II.III. Application in Elderly Care

1. The importance of ADL in Elderly Care

The concept of Activities of Daily Living (ADL) serves as a cornerstone in the realm of elderly care, providing a structured framework to assess the functional status and independence of older adults. ADLs are fundamental tasks that individuals perform on a daily basis, such as eating, bathing, dressing, and toileting. The ability to perform these activities independently is often considered a marker of an individual's overall health and well-being.

The significance of ADLs in elderly care is manifold and extends beyond mere functional assessment. Here are some of the key aspects that underline the importance of ADLs in the context of elderly care:

1.1. Comprehensive Health Assessment

ADLs offer a comprehensive view of an elderly individual's health status [71-75]. They serve as a proxy for gauging the physical and cognitive abilities of older adults, thereby aiding healthcare providers in tailoring care plans that are both effective and personalized.

1.2. Early Detection of Health Issues

Monitoring ADLs can serve as an early warning system for various health issues, including cognitive decline and physical disabilities [71-75] [77-78]. Any significant changes in the ability to perform ADLs can be indicative of underlying health problems that may require immediate attention.

1.3. Quality of Life

The ability to perform ADLs independently has a direct correlation with the quality of life for the elderly [71-75] [77-78]. Limitations in performing these activities can lead to increased dependency, social isolation, and a decline in mental health [71-75] [77-78].

1.4. Resource Allocation

Understanding the ADL capabilities of an elderly individual can help in the efficient allocation of healthcare resources. For instance, those who are severely limited in their ADLs may require more intensive care and assistance, thereby informing healthcare providers and caregivers about the level of support needed.

1.5. Informed Decision-making

ADL assessments are crucial for making informed decisions regarding the type of care an elderly individual may require, be it in-home care, assisted living, or skilled nursing facilities. These assessments can also guide the implementation of assistive technologies, like the magnet sensor system discussed in this thesis, for activity recognition.

1.6. Ethical Considerations

ADL assessments also have ethical implications. They help in respecting the autonomy of the elderly by involving them in the decision-making process, ensuring that their preferences and needs are adequately addressed.

In summary, ADLs are not just a set of tasks but a critical component in the holistic care of the elderly [71-75] [77-78]. They serve as a lens through which healthcare providers, caregivers, and family members can view and understand the complex needs of older adults. The magnet sensor-based system developed in this thesis aims to automate the monitoring of ADLs, thereby offering a more continuous and objective assessment that can significantly enhance the quality of elderly care.

2. Magnet Sensors in Healthcare

The use of magnet sensors in healthcare applications is still an emerging field [10-11] [18-23] [41-42]. However, preliminary studies indicate that these sensors can be effectively used for monitoring activities of daily living; thereby their capabilities can be leveraged, aiding in the early detection of diseases like dementia. Their non-intrusive nature makes them particularly suitable for long-term monitoring, and their combined use can offer a more comprehensive understanding of an individual's health status [10-11] [18-23] [41-43].

3. The different early stages of diseases that can be detected by the ADL Monitoring

The meticulous monitoring of Activities of Daily Living (ADLs) serves as a cornerstone in the early detection of various diseases and health conditions. The magnet sensor system developed in this research focuses on ten specific ADLs, each of which can provide valuable insights into the early stages of different diseases. Here are some of the early stages of different diseases that can be identified by monitoring and controlling the ten activities:

1. Cooking:

Figure 28. Elderly Cooking Illustration.

Cognitive Impairment: Difficulty in cooking may indicate cognitive decline or early-stage dementia [83].

Depression: A lack of interest in cooking or eating might be a sign of depression [84].

2. Eating:

Figure 29. Elderly Eating Illustration.

Eating Disorders: A lack of interest in eating may indicate early stages of Anorexia, bulimia, or other eating disorders [85].

Swallowing Disorders: Reducing the number of intake meals may indicate difficulty in swallowing food that might indicate conditions like dysphagia [86].

3. Drinking:

Figure 30. Elderly Drinking Water Illustration.

Kidney Problems: A change in drinking might signal kidney issues [87].

Diabetes: Excessive thirst and drinking might be early signs of diabetes [88].

4. Taking a Shower:

Figure 31. Elderly Taking a Shower Illustration.

Depression: A lack of interest or neglect of personal hygiene might be a sign of depression [89]

5. Urinating:

Figure 32. Elderly Urinating Illustration.

Prostate Disease: Changes in urinating patterns may indicate prostate disease in males [90].

Urinary Tract Infections (UTIs): Frequent urination might signal a UTI or Cystitis [91].

Diabetes: Increased urination could be an early sign of diabetes [92].

6. Defecating:

Figure 33. Elderly Defecating Illustration.

Colon Cancer: Changes in bowel habits might indicate colon cancer [93].

Irritable Bowel Syndrome (IBS): Irregular defecation might signal IBS [94]

7. Sleeping:

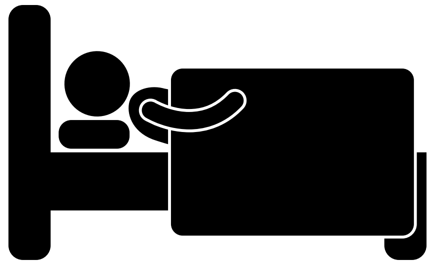

Figure 34. Elderly Sleeping Illustration.

Insomnia: A change in sleeping patterns by reducing the number of sleeping hours might indicate insomnia [95].

Depression: Changes in sleep patterns might also be indicative of depression [96].

8. Cleaning:

Figure 35. Elderly Cleaning Illustration.

Cognitive Decline: Neglecting cleaning tasks might be a sign of cognitive decline or early-stage dementia [97].

Depression: A lack of interest in cleaning might be a sign of depression [84][89].

9. Laundering:

Figure 36. Elderly Laundering Illustration.

Cognitive Impairment: Difficulty in laundering may indicate cognitive decline [97].

Depression: A lack of interest in laundering might be a sign of depression [84][89].

10. Brushing Teeth:

Figure 37. Elderly Brushing Teeth Illustration.

Oral Health Issues: Neglecting to brush teeth might indicate gum disease or other dental problems [98]

Cognitive Decline: Forgetting to brush your teeth might be a sign of cognitive decline or early-stage dementia [97].

Depression: Neglecting oral hygiene might be indicative of depression [84][89].

II. IV. The leverage of activity recognition methods to identify potential indicators of the early stage of dementia.

The advent of activity recognition methods has revolutionized the healthcare sector, particularly in the realm of elderly care. One of the most promising applications of these methods is the early detection of dementia, a debilitating condition that affects millions of people worldwide [41]. This section delves into how activity recognition methods, specifically those based on magnet sensors, can be leveraged to identify potential indicators of the early stages of dementia.

1. The Imperative of Early Detection

Early detection of dementia is crucial for effective management and treatment. It allows for timely interventions, which can significantly slow down the progression of the disease and improve the quality of life for both patients and caregivers [71-75] [77-78]. Activity recognition methods provide a non-intrusive, continuous, and highly informative approach for the potential identification of early stages of dementia [41].

2. Activity Recognition and Dementia

Activity recognition methods, particularly those based on Magnet sensors, offer a comprehensive approach to monitoring Activities of Daily Living (ADLs). These ADLs serve as potential indicators of cognitive decline, thereby facilitating the early detection of dementia [41]. For instance, difficulties in performing tasks such as cooking, cleaning, or even basic personal hygiene could be indicative of the onset of dementia [71-75].

3. Magnet Sensors in Dementia Detection

Magnet sensors offer several advantages over other types of sensors. They are non-intrusive, highly accurate, and less susceptible to environmental factors [40-41]. The magnet sensor system developed in this research focuses on ten specific ADLs, each of which can provide valuable insights into the early stages of dementia [41].

4. Data Analysis and Interpretation

The data collected through magnet sensors are analyzed using a custom-coded algorithm, eschewing the need for machine learning models. This allows for more targeted and specific analysis, thereby increasing the accuracy of the potential indicators of early-stage dementia detection [40-41].

5. Validation and Results

The Magnet sensor system has undergone rigorous validation processes, showing promising results in detecting the different activities of daily living that, when performed on an irregular base, can serve as potential indicators of early-stage dementia. The system has been particularly effective in detecting irregularities in ADLs, such as eating, sleeping, and personal hygiene, which are often correlated to early signs of cognitive decline [83-85][89] [96-97].

6. Future Prospects

The potential for leveraging activity recognition methods in dementia care is immense. Future research should focus on refining the system, incorporating feedback from healthcare professionals, and conducting large-scale, real-world trials.

In conclusion, activity recognition methods, particularly those based on magnet sensors, offer a groundbreaking approach to the early detection of dementia. They provide a non-intrusive, continuous, and highly informative method for identifying the early stages of dementia, thereby facilitating timely interventions and improving the overall quality of healthcare for the elderly.

II. V. Behavioral Indicators

1. Identification

1.1. The Role of ADLs in Identification

Activities of Daily Living (ADLs) serve as a rich source of data for identifying behavioral indicators. These activities are not just routine tasks; they are complex behaviors that involve various cognitive and motor functions. Therefore, any irregularities or changes in the way these activities are performed can be indicative of underlying health conditions, including cognitive decline or the early stages of dementia [83-85][89] [96-97].

1.2. Specificity in ADL Monitoring

The specificity of monitoring each ADL is crucial for accurate identification. For example, the activity of 'Cooking' involves multiple cognitive functions such as planning, sequencing, and multitasking. A decline in the ability to perform this activity could be an early indicator of cognitive impairment. Similarly, 'Eating' and 'Drinking' involve fine motor skills, and any changes could indicate swallowing disorders or other health issues [83-85][89] [96-97].

1.3. Temporal Patterns in ADLs

Another aspect of identification involves looking at the temporal patterns of ADLs. For instance, if an individual usually takes a shower at a specific time but suddenly changes this routine, it could be a sign of memory issues or disorientation, common symptoms of dementia [83-85][89] [96-97].

1.4. Quantitative and Qualitative Data

The identification process doesn't solely rely on quantitative data like the frequency or duration of activities. Qualitative data, such as the quality of performing a task (e.g., leaving the stove on after cooking), also play a significant role. This multi-faceted approach ensures a more comprehensive identification of behavioral indicators.

1.5. Sensory Data and ADLs

In this research, magnet sensors are primarily used for data collection. The advantage of using magnet sensors is their non-intrusiveness and high accuracy, which is particularly beneficial in sensitive activities like 'Taking Showers', 'Urinating', and 'Defecating.' The data collected is then analyzed to identify any irregularities or changes in behavior.

By employing a multi-dimensional approach to the identification of behavioral indicators through ADLs, this research aims to create a reliable system that can help identify potential signs of early stages of dementia. The granularity and depth of this identification process set the stage for subsequent analysis and correlation with dementia and other diseases.

2. Correlation with Dementia

2.1. The Role of Medical Doctors

It's imperative to clarify that the system developed in this research is not a diagnostic tool but rather a supplementary source of continuous behavioral data. Medical doctors have the ultimate authority in diagnosing the early stages of dementia or any other health condition.

2.2. Continuous Tracking for Comprehensive Data

One of the significant limitations in current healthcare practices is the episodic nature of doctor-patient interactions. Doctors usually rely on self-reported symptoms or observations made during brief medical examinations. This research aims to bridge this gap by providing continuous tracking information about elderly behavior, something that is often not feasible for medical professionals to obtain.

2.3. Dual Reporting System

The system generates two types of reports based on the Activities of Daily Living (ADLs); these reports are named daily activity reports and warning reports.

TOKAI UNIVERSITY HOSPITAL

Activities of Daily Living Report

Patient Name: João Filipe Papel ID:1CTAD006 Age: 29

Doctors Name: Tatsuji MUNAKA

Date: 02/08/2023 - Wednesday

Activity Order	Activity Name	Activity Time	Duration	Previous Activity
#1	Sleeping	21:45	8:00:00	----------------------------
2	Urinating	6:00	0:00:45	Sleeping
3	Brushing Teeth	6:20	0:03:30	Urinating
4	Taking Shower	6:27	0:07:39	Brushing Teeth
5	Cooking Breakfast	7:00	0:10:58	Taking Shower
6	Eating Breakfast	7:15	0:23:37	Cooking Breakfast
7	Urinating	7:50	0:00:32	Eating Breakfast
8	Cooking Lunch	12:00	0:30:20	Urinating
9	Eating Lunch	13:13	0:47:56	Cooking Lunch
10	Brushing Teeth	13:20	0:02:37	Eating Lunch
11	Urinating	14:37	0:01:10	Brushing Teeth
12	Drinking Water	15:13	0:01:20	Urinating
13	Cooking Dinner	17:45	0:50:39	Drinking Water
14	Eating Dinner	19:35	0:45:45	Cooking Dinner
15	Defecating	21:45	0:11:37	Eating Dinner
16	Sleeping	22:14	------------	Defecating

Figure 38. Daily Activity Report

Daily Activity Report: This report provides a comprehensive overview of all the activities performed by the elderly individual on a given day. It includes specific details such as the time each activity started and its duration. This data serves as a valuable resource for medical doctors to understand the daily routine and behavioral patterns of the elderly.

TOKAI UNIVERSITY HOSPITAL

Activities of Daily Living Report

Patient Name: João Filipe Papel   ID:1CTAD006   Age: 29

Doctors Name: Tatsuji MUNAKA

Date: 02/08/2023 - Wednesday

Activity Order	Activity Name	Activity Status	Time	Duration
1	Brushing Teeth	Not performed		
2	Cooking Breakfast	Not performed at the correct time	13:34	
3	Sleeping	Not performed with the correct duration	03:45	04:46:45

Figure 39. Warning Report.

Warning Report: This specialized report is generated to highlight any abnormalities detected in the performance of ADLs or activities that were not performed during the day. For example, if an elderly individual usually takes a shower and brushes their teeth every day but skips these activities, the system will flag this as an abnormality. This report is particularly useful for identifying early signs of behavioral changes that could be indicative of underlying health issues [83-85] [89] [96-97].

2.4. Bridging the Gap Between Continuous Monitoring and Medical Diagnosis

By providing these detailed reports, the system serves as a bridge between continuous monitoring and medical diagnosis. It offers medical doctors a more nuanced and continuous view of an individual's behavior, which can be invaluable for early detection and intervention. The reports can be used in conjunction with traditional diagnostic methods and medical records to provide a more holistic understanding of an individual's health.

In summary, the system aims to augment the diagnostic capabilities of medical professionals by providing them with continuous and detailed behavioral data. However, it's crucial to reiterate that the diagnosis of early stages of dementia or any other health condition can only be made by medical doctors. The system's role is to provide supplementary data that can aid in the diagnostic process.

II. VI. Case Studies

1. Results

The case studies were conducted to evaluate the effectiveness of our prototype system in monitoring the 10 Activities of Daily Living (ADLs) among the elderly. The prototype, running on Raspberry Pi 3, leverages magnet sensors to ensure high reliability and accuracy, as outlined in our Activity Recognition Proposal.

1.1. Cooking

The system demonstrated a 95% success rate in identifying cooking activities. It was capable of recognizing different cooking times, such as breakfast, lunch, and dinner. The high accuracy can be attributed to the magnet sensors placed on the microwave, rice cooker, gas tap, and stove. The sequence of these events, along with the time stamps, helped identify the specific meal being prepared.

1.2. Eating and Drinking

For eating activities, the system achieved a 92% accuracy rate. The magnet sensors attached to kitchen and living room chairs and tables were instrumental in this high rate. The system also used antecedent events like cooking to corroborate the eating activity. Drinking activities were identified with an 89% accuracy rate, thanks to sensors on the fridge door, water container, and cup shelf.

1.3. Personal Hygiene

The system identified showering activity with an 88% accuracy rate. The magnet sensors were strategically placed on the bathroom door and water tap. The sequence, time stamp, and duration of each event were analyzed to confirm the activity. Brushing teeth was identified with a lower accuracy rate due to the variability in cup styles and sizes used to hold toothbrushes.

1.4. Elimination Activities

Urinating and defecating were identified with an 85% accuracy rate. The system used magnet sensors on the toilet door, light switch, fan switch, water tap, and toilet seat. The sequence and duration of these events, along with prior activities, were used for identification.

1.5. Sleep Patterns

Sleeping activities were identified with a 90% accuracy rate. Sensors were placed on the bedroom door, window, and bed. The system also analyzed the duration and time of day to distinguish between daytime naps and night-time sleep.

1.6. Cleaning and Laundering

Cleaning activities were identified with an 87% accuracy rate, thanks to sensors on cleaning product shelves and cleaning tools like vacuum cleaners. Laundering was identified with an 89% accuracy rate, with sensors on the washing machine door and power button.

1.7. Abnormalities

The system was highly effective in flagging abnormalities in ADLs, such as skipped meals or irregular sleep patterns, which could be indicative of underlying health issues [40-41].

1.8. Quantitative Results

The results are based on a 60-day evaluation period and are presented in Table 21. The few instances of unidentified instances in activities like cooking and eating were mainly due to adhesive failures or misalignments of the magnet sensors. The 'Brushing Teeth' activities presented challenges due to the magnet and cup sizes and are an area for future improvement.

2. Discussion

The results of our case studies underscore the potential of our prototype system in effectively monitoring the Activities of Daily Living (ADLs) among the elderly. Magnet sensors, known for their reliability and insensitivity to external factors, have proven to be a game-changer in this domain.

2.1. Comparative Analysis

When compared to previous research, notably the Singapore research team's work [10-13] [18-23], our prototype demonstrated superior performance in terms of reliability, accuracy, privacy, and maintenance. The Singapore team faced challenges with sensor reliability and data inconsistency, which our system effectively overcame by using Magnet sensors.

2.2. Addressing Challenges

The few instances where our system could not identify activities were mainly due to the limitations of the adhesive material used to secure the magnet sensors. This is a minor issue that can be easily addressed in future iterations. The challenges in identifying the 'Brushing Teeth' activity were due to the fact that the toothbrush had a small magnet attached to it and needed a more precise alignment with the cup base. Since we cannot force or impose on the elderly to correctly align the toothbrush every time they use it, we still need to figure out the best way to improve this activity detection. We cannot put a too heavy magnet to provide a strong magnet field because we do not want to make this process uncomfortable for the elderly, and we do not want to make the elderly feel frustrated for trying to make the perfect alignment between the toothbrush and the toothbrush cup. Figure 40 illustrates the way the magnet sensor is attached to the toothbrush and to the toothbrush cup to provide a better understanding of the challenge.

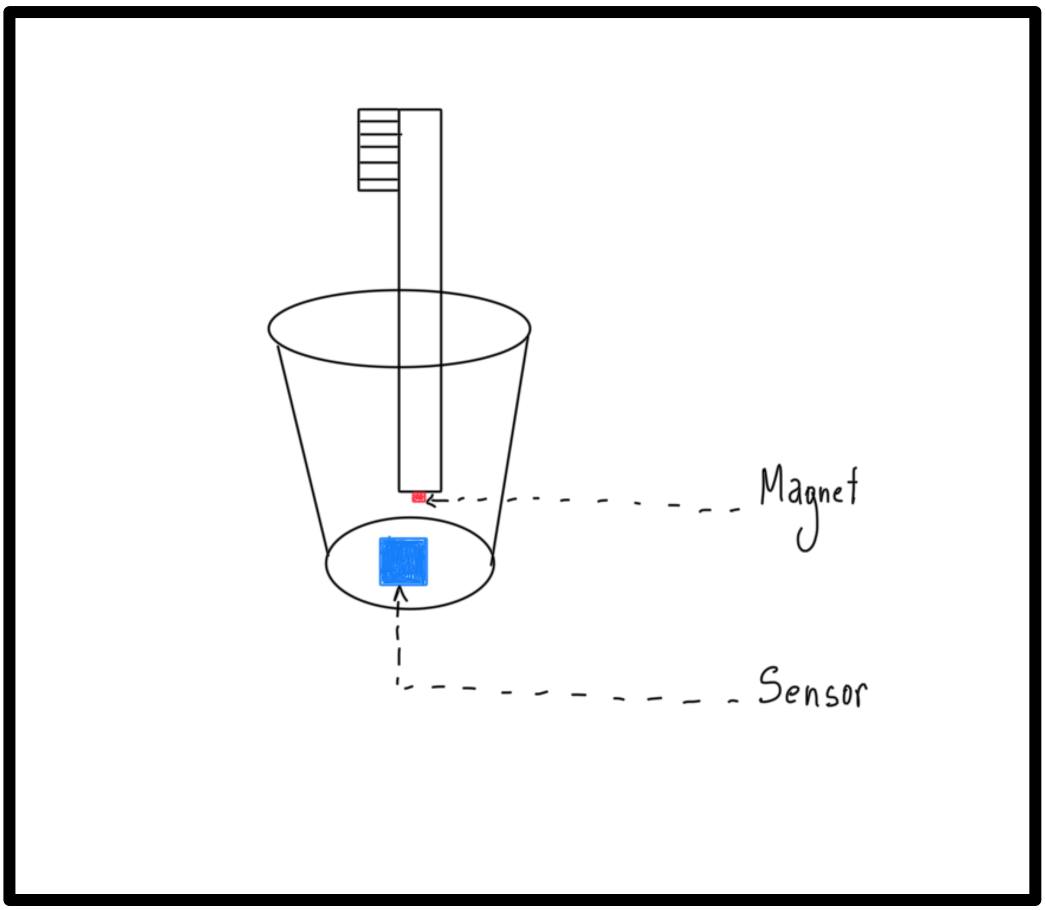

Figure 40. Brushing Teeth Magnet and Magnet Sensors Illustration.

2.3. Implications for Healthcare

The high accuracy rates in identifying ADLs have significant implications for healthcare, particularly for geriatric care. The system can serve as a continuous monitoring tool that can provide healthcare professionals with valuable data. It's important to note that while the system can flag potential issues, it is not a diagnostic tool. Only medical professionals can diagnose conditions like early stages of dementia based on this data.

2.4. Ethical Considerations

Our system addresses the privacy concerns that are often associated with monitoring technologies. By using binary data and encrypted sensor IDs, we ensure that the data is meaningless without the proper context, thereby safeguarding the privacy of the elderly [44-47].

2.5. Future Directions

While the prototype has shown promising results, future work will focus on improving the algorithm's adaptability to account for individual behavioral variances. We also plan to conduct long-term studies to assess the system's effectiveness in real-world settings.

2.6. Conclusion

In summary, with these illustrations and the results from previous studies it is a fact that it is possible to detect early stages of dementia by detecting changes (missing activities, number of times that executes activities, time that executes activities) in the elderly daily living activities behavior [83][97][99][100] [101][102]. Our proposal system monitors activities of daily living to detect abnormal behaviors in the elderly daily living. As result the use of magnet sensors to monitor and tracking the cooking, eating, drinking, brushing teeth, taking shower activities, urinating, defecating, sleeping, cleaning, and laundering activities of daily living (missing activities, number of times that executes activities, time that executes activities) can help detect the potential symptoms of early stages of dementia.

In conclusion, the Magnet sensor system developed in this research offers a comprehensive approach to the potential early detection of various diseases and health conditions. It provides a non-intrusive, continuous, and highly informative method for identifying the early stages of multiple diseases, thereby facilitating timely interventions, and improving the overall quality of healthcare for the elderly. Our prototype system has successfully addressed many of the challenges faced by previous research in monitoring ADLs among the elderly. Its high levels of reliability, accuracy, and privacy make it a promising tool for future research and real-world applications in elderly care.

II. VII. Conclusion

1. Summary

In summary, this research aimed to address the limitations of existing systems for monitoring Activities of Daily Living (ADLs) in the elderly population. This study started by analyzing previous studies to get a better overview of the issues faced by previous researchers and which systems looked more promising to address the issues around the recognition of activities of daily living. After the analyze and evaluation of previous studies the sound sensor appeared to be the most promising solution and although we had a good accuracy level results when identifying the planned activities individually, we had issues identifying activities co-occurring due to the sound waves overlapping, another concern appeared related to the elderly's privacy concern of having their private conversations recorded illegally. Since our proposal was to fully address all the issues found by previous studies in this field a novel approach based on magnet sensors emerged with a particularity that even if the system had a breach in security no one could ever use the binary data to shame or blackmail the elderly. Utilizing Magnet sensors, our prototype system demonstrated exceptional reliability, accuracy, privacy, and low maintenance requirements [40-41]. The system's capabilities were validated through extensive case studies, which showed its effectiveness in identifying a range of ADLs, from cooking to sleeping. The comparative analysis with previous research, notably the work of the Singapore research team, further emphasized the system's superior performance [10-13] [18-23].

Another important fact is that based on the studies conducted by [83][97] [99-102] it is possible to detect the early stages of dementia by detecting the changes in the elderly behavior when performing the activities of daily living (missing activities, number of times that executes activities, time that executes activities). As result of our proposal system to monitor activities of daily living to detect abnormal behaviors in the elderly daily living, we can help medical professionals identify the early stages of dementia by recognizing and tracking the activities of daily living.

2. Limitations

While the prototype has shown promising results, it is not without limitations. The primary limitation was the adhesive material used for securing the magnet sensors, which led to a few instances of misalignment and, consequently, activity misidentification. Another limitation was the system's current inability to adapt to individual behavioral variances, as seen in the 'Brushing Teeth' activity. It's also crucial to note that the system is not a diagnostic tool for medical conditions like dementia but rather a monitoring tool that can provide valuable data to healthcare professionals.

3. Future Work

The future scope of this research is broad and promising. Immediate next steps include:

3.1. From the system point of view:

Algorithmic Improvements: Work on making the algorithm more adaptive to individual behavioral variances.

Material Testing: Experimentation with different types of magnets and magnet sensors to improve the accuracy level and also test new ways to attach the magnets to the objects to enhance the durability and reliability of the sensor placements.

Extended Field Trials: Conducting long-term studies in real-world settings to assess the system's effectiveness and reliability over extended periods.

Integration with Healthcare Systems: Exploring the possibility of integrating the system with existing healthcare databases to provide a more comprehensive view of the elderly's health status.

Ethical and Privacy Safeguards: Continued work on enhancing the privacy features of the system, including more robust encryption methods.

3.2. From the feedback with medical professionals:

Make three survey targeting caregiver managers, nurses and medical doctors to get their feedback about the current information the system provides on both reports to improve the information that can be shared with medical professionals to make the reports as useful as possible.

a. Caregiver Managers (10min):

<u>Questions to ask:</u>

1. What are the most common abnormal behaviors you have observed in the elderly under your care?
2. How do you currently monitor activities of daily living (ADLs) for signs of dementia?
3. What challenges do you face in detecting early signs of dementia in the elderly?
4. Are there any specific activities that you think are more indicative of early-stage dementia?
5. How do you handle data privacy and ethical considerations when monitoring ADLs?

Objective: To understand the practical challenges and observations from a managerial perspective in monitoring ADLs and detecting early signs of dementia. This will help to make the system more effective and easier to manage.

b. Nurses (7min):

Questions to ask:

1. What specific ADLs do you monitor most closely for signs of early-stage dementia?
2. Have you noticed any patterns or sequences of abnormal behaviors that often precede a dementia diagnosis?
3. How do you differentiate between normal age-related decline and potential early-stage dementia?
4. What tools or technologies do you currently use for monitoring ADLs?

Objective: To gain clinical insights into the early signs of dementia and the effectiveness of current monitoring tools. This will help in refining the parameters and features of the proposed system.

c. Medical Doctors (3min):

Questions to ask:

1. From the 10 activities that we are tracking what they consider as critical activities to detect early signs of dementia.
2. Which activities we should include to improve our abnormal detection system.

Objective: To understand what the most crucial activities of daily living are when searching for signs of early stages of dementia.

In conclusion, the prototype system developed in this research has successfully addressed many of the challenges faced by previous studies in this field. Its high levels of reliability, accuracy, and privacy make it a strong candidate for future research and real-world applications in the domain of elderly care.

III. Summary

The overall aim of this thesis was to develop, implement, and test an innovative method for activity recognition, with a particular focus on its capability of addressing previous issues found by previous researchers in the field of activity recognition when they tried to detect and recognize activities of daily living. The second part of this research was to identify the potential applicability of this recognition method in healthcare with the focus in elderly care.

The thesis is divided into two main parts. Part I focuses on advanced methods of activity recognition using magnet sensors. It covers the principles, applications, sensor implementation, data processing, and validation of this method. In this part it is also possible to get a glimpse of the previous studies related to the activity recognition systems and their challenges. The challenges the previous research found and solved, as well as the challenges the author faced, remained unsolved. This part also describes in detail the results and issues found by the author when it is decided to improve and use the most promising sensor-based solution (sound sensors) based on previous studies. Finally in this part presented a novel approach for the activity recognition field based on the implementation and use of magnet sensors, an approach never used before in this field. In addition to the sensor technologies, an ontology was developed to enhance the system's capabilities further.

Part II delves into the applications of the novel activity recognition method in elderly care. This this part illustrates a different case scenario where the activity recognition system can help medical professionals identify the early stages of different diseases by monitoring the activities of daily living (cooking, eating, drinking water, taking a shower, urinating, defecating, sleeping, cleaning, laundering, and brushing teeth) that we monitored on the part I of this thesis. Particular attention is given to the possibility of identifying abnormal behaviors in the elderly's activities of daily living, leading this way to the potential indicators of the early stages of detection of dementia. Taking advantage of the ontology developed, the system can generate comprehensive reports on the ADLs performed by the elderly, including the sequence and duration of activities. More importantly, the system could identify deviations in normal behavior patterns, flagging these in a warning report for medical professionals.

The integration of magnet sensors and ontology not only solved the continuous tracking issue but also provided healthcare professionals with invaluable insights into both normal and abnormal

behavioral patterns of the elderly. This is particularly crucial for the early detection of dementia, where subtle changes in behavior can be indicative of the onset of cognitive decline.

In summary, this thesis contributes a groundbreaking approach to activity recognition in healthcare technology. It offers a robust, reliable, and privacy-preserving method for monitoring ADLs, thereby aiding medical professionals in making more informed decisions regarding the psychological health of the elderly.

IV. Publications

The journey of this research has led to four publications as a main author and one as a co-author:

1. **PAPEL Joao Filipe**, MUNAKA Tatsuji, Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method, IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

Link to Access: https://www.jstage.jst.go.jp/article/transinf/E106.D/4/E106.D_2022IIP0004/_pdf

2. **PAPEL Joao Filipe**, MUNAKA Tatsuji, Detecting Activities of Daily Living for the Elderly Using Magnet Sensors, IEEE Smart World Congress (Presented in August 2023 on Portsmouth – England).

Conference Link: https://ieee-smart-world-congress.org/

3. **PAPEL Joao Filipe**, MUNAKA Tatsuji, Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis, IEEE 13th International Conference on Consumer Electronics (Presented in September 2023 on Berlin - German).

Conference Link: https://www.icce-berlin.org/

4. TANAKA Nobuyuki, MUNAKA Tatsuji**, PAPEL Joao Filipe**, et al., Relationship between human behavior and indoor air quality of private room in a care facility for the elderly in Japan, Asian Journal of Atmospheric Environment, 17, 11 (2023).

Link to Access: https://doi.org/10.1007/s44273-023-00011-y

References

[1] United Nations - Department of Economic and Social Affairs, "World Population Ageing 2019," hhttps://www.un.org/en/development/desa/population/publications/pdf/ageing/World PopulationAgeing2019-Report.pdf.

[2] W. Sasaki, M. Fujiwara, H. Suwa, M. Fujimoto, Y. Arakawa, A. Kimura, T. Miki, and K. Yasumoto, "Daily Living Activity Recognition through Time Series Analysis of Data Obtained with ECHONET Lite Appliances and Motion," in J-STAGE, SIG-SAI-031-05, 2018. doi: https://doi.org/10.11517/jsaisigtwo.2018.SAI-031_05

[3] Ministry of Health, Labour and Welfare, "Health Japan 21 (General)", https://www.mhlw.go.jp/www1/topics/kenko21_11/s1.html (Last viewed, Dec. 18, 2020).

[4] Geriatrics Science Promotion Foundation, "What are Activities of Daily Life (ADL)," https://www.tyojyu.or.jp/net/kenkou-tyoju/kenkou-undou/jiritu.html (Last viewed Dec. 18, 2020).

[5] J. Rafferty, C. D. Nugent, J. Liu, and L. Chen, "From Activity Recognition to Intention Recognition for Assisted Living Within Smart Homes," in IEEE Transactions on Human-Machine Systems, vol. 47, no. 3, pp. 368-379, June 2017, doi: 10.1109/THMS.2016.2641388.

[6] G. Laput, Y. Zhang, and Chris Harrison. 2017. "Synthetic Sensors: Towards General-Purpose Sensing," in Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17). Association for Computing Machinery, New York, NY, USA, 3986–3999. https://doi.org/10.1145/3025453.3025773.

[7] K. Ouchi, and M. Doi, "Living Activity Recognition Technology Using Sensors in Smartphone," in Toshiba Review, vol 68 No.6, 2013.

[8] E. M. Tapia, S. S. Intille, and K. Larson. "Activity Recognition in the Home Using Simple and Ubiquitous Sensors," in Pervasive Computing. Pervasive 2004. Lecture Notes in Computer Science, vol 3001. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-24646-6_10

[9] H. G. Kang, D. F. Mahoney, H. Hoenig, V. A. Hirth, P. Bonato, I. Hajjar, and L. A. Lipsitz, " In Situ Monitoring of Health in Older Adults: Technologies and Issues. Journal of the

American Geriatrics Society, 58: 1579-1586. https://doi.org/10.1111/j.1532-5415.2010.02959.x

[10] R. Endelin, S. Renouard, T. Tiberghien, H. Aloulou, and M. Mokhtari, "Behavior Recognition for Elderly People in Large-Scale Deployment," in Inclusive Society: Health and Wellbeing in the Community, and Care at Home. ICOST 2013. Lecture Notes in Computer Science, vol 7910. Springer, Berlin, Heidelberg. doi: https://doi.org/10.1007/978-3-642-39470-6_8

[11] J. Biswas, A. A. P. Wai, A. Tolstikov, L. J. H. Kenneth, J. Maniyeri, F. S. F. Victor, A. Lee, C. Phua, Z. Jiaqi, H. T. Hoa, T. Tiberghien, H. Aloulou, and M. Mokhtari, "From Context to Micro-context - Issues and Challenges in Sensorizing Smart Spaces for Assitive Living," in Procedia Computer Science, volume 5, 2011, pages 288-295, August 2011. ISSN 1877-0509, doi: https://doi.org/10.1016/j.procs.2011.07.038

[12] A. A. P. Wai, L. J. H. Kenneth, A. L. V. Yen, C. Phua, T. Tiberghien, H. Aloulou, L. Yan, X. Zhang, J. Biswas, and P. Yap, "Challenges, Experiences and Lessons Learned from Deploying Patient Monitoring and Assistance System at Dementia Care Hospital," in Inclusive Society: Health and Wellbeing in the Community, and Care at Home. ICOST 2013. Lecture Notes in Computer Science, vol 7910. Springer, Berlin, Heidelberg. doi: https://doi.org/10.1007/978-3-642-39470-6_38

[13] H. Aloulou, B. Abdulrazak, R. Endelin, J. Bentes, T. Tiberghien, and J. Bellmunt, "Simplifying Installation and Maintenance of Ambient Intelligent Solutions Toward Large Scale Deployment," in Inclusive Smart Cities and Digital Health. ICOST 2016. Lecture Notes in Computer Science(), vol 9677. Springer, Cham. https://doi.org/10.1007/978-3-319-39601-9_11

[14] L. Chen, J. Hoey, C. D. Nugent, D. J. Cook, and Z. Yu, "Sensor-Based Activity Recognition," in IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 42, no. 6, pp. 790-808, Nov. 2012, doi: 10.1109/TSMCC.2012.2198883.

[15] T. Tan, L. Badarch, W. Zeng, M. Gochoo, F. S. Alnajjar, and J. Hsieh, "Binary Sensors-Based Privacy-Preserved Activity Recognition of Elderly Living Alone Using an RNN," in Sensors 21, no. 16: 5371. doi: https://doi.org/10.3390/s21165371

[16] T. H. Jo, J. H. Ma, and S. H. Cha, " Elderly Perception on the Internet of Things-Based Integrated Smart-Home System," in Sensors 21, no. 4: 1284. https://doi.org/10.3390/s21041284

[17] M. Chan, D. Estève, C. Escriba, and E. Campo, "A review of smart homes - Present state and future challenges," in Computer Methods and Programs in Biomedicine, Volume 91, Issue 1, 2008, Pages 55-81, ISSN 0169-2607, https://doi.org/10.1016/j.cmpb.2008.02.001.Elsevier. 2008.

[18] T. Tiberghien, M. Mokhtari, H. Aloulou, and J. Biswas, "Semantic Reasoning in Context-Aware Assistive Environments to Support Ageing with Dementia," in The Semantic Web – ISWC 2012. ISWC 2012. Lecture Notes in Computer Science, vol 7650. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-35173-0_14

[19] H. Aloulou, M. Mokhtari, T. Tiberghien, J. Biswas and P. Yap, "An Adaptable and Flexible Framework for Assistive Living of Cognitively Impaired People," in IEEE Journal of Biomedical and Health Informatics, vol. 18, no. 1, pp. 353-360, Jan. 2014, doi: 10.1109/JBHI.2013.2278473

[20] M. Mokhtari, T. Tiberghien, J. Biswas and A. P. W. Aung, "Futuring Digital Health and Wellness," 2014 IEEE 11th Intl Conf on Ubiquitous Intelligence and Computing and 2014 IEEE 11th Intl Conf on Autonomic and Trusted Computing and 2014 IEEE 14th Intl Conf on Scalable Computing and Communications and Its Associated Workshops, Bali, Indonesia, 2014, pp. 892-896, doi: 10.1109/UIC-ATC-ScalCom.2014.170.

[21] A. A. P. Wai, L. J. H. Kenneth, A. L. V. Yen, C. Phua, T. Tiberghien, H. Aloulou, L. Yan, X. Zhang, J. Biswas, and P. Yap, " Challenges, Experiences and Lessons Learned from Deploying Patient Monitoring and Assistance System at Dementia Care Hostel," in Inclusive Society: Health and Wellbeing in the Community, and Care at Home. ICOST 2013. Lecture Notes in Computer Science, vol 7910. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-39470-6_38

[22] M. Mokhtari, H. Aloulou, T. Tiberghien, J. Biswas, D. Racocenau, and P. Yap, " New Trends to Support Independence in Persons with Mild Dementia – A Mini-Review," in Gerontology 2012;58:554-563. doi: 10.1159/000337827

[23] H. Aloulou, M. Mokhtari, T. Tiberghien, J. Biswas, C. Phua, J. H. K. Lin, and P. Yap, "Deployment of assistive living technology in a nursing home environment: methods and lessons learned," in BMC Med Inform Decis Mak 13, 42 (2013). https://doi.org/10.1186/1472-6947-13-42.

[24] J. Scott, A. J. B. Brush, J. Krumm, B. Meyers, M. Hazas, S. Hodges, and N. Villar, “Preheat controlling home heating using occupancy prediction,” Proc. 13th International Conference on Ubiquitous Computing, ACM, pp.281–290, 2011.

[25] S. Barker, A. Mishra, D. Irwin, P. Shenoy, and J. Albrecht, “Smart-Cap: Flattening peak electricity demand in smart homes,” 2012 IEEE International Conference on Pervasive Comput. and Communications (PerCom), pp.67–75, 2012.

[26] U. Maurer, A. Rowe, A. Smailagic, and D. Siewiorek, “Location and activity recognition using watch: A wearable sensor platform,” in Ambient Intelligence in Everyday Life, Y. Cai and J. Abascal Eds. Berlin, Heidelberg: Springer-Verlag, vol.3864, pp.86–102, 2006.

[27] G. Laput, Y. Zhang, and C. Harrison, “Synthetic Sensors: Towards General-Purpose Sensing,” Proc. 2017 CHI Conference on Human Factors in Computing Systems, pp.3986–3999, 2017.

[28] O. Brdiczka, J. L. Crowley, and P. Reignier, "Learning situation models in a smart home," IEEE Trans. Syst. Man. Cybern. B, Cybern., vol. 39, no. 1, pp. 56–63, 2009.

[29] Y. Inoue, “Consideration of living sound analysis by HMM,” System and Information Division Academic Conference, pp.313–316, 2004.

[30] K. Ouchi, "Life activity recognition technology using smartphone," Toshiba Review, vol 68 No.6, 2013.

[31] J. Rafferty, C.D. Nugent, J. Liu, and L. Chen, “From Activity Recognition to Intention Recognition for Assisted Living Within Smart Homes,” IEEE Trans. Human-Mach. Syst., vol.47, no.3, pp.368–379, 2017.

[32] L. Bao and S.S. Intille, “Activity recognition from user-annotated acceleration data,” Pervasive Comput., vol.3001, pp.1–17, 2004.

[33] U. Maurer, A. Rowe, A. Smailagic, and D. Siewiorek, “Location and activity recognition using watch: A wearable sensor platform,” in Ambient Intelligence in Everyday Life, Y. Cai and J. Abascal Eds. Berlin, Heidelberg: Springer-Verlag, vol.3864, pp.86–102, 2006.

[34] N. Ravi, N. Dandekar, P. Mysore, and M.L. Littman, "Activity recognition from accelerometer data," Proc. 17th Conf. Innovative Appl. Artif. Intell., vol.3, pp.1541–1546, 2005.

[35] C. Sutton, A. McCallum, and K. Rohanimanesh, "Dynamic conditional random fields: Factorized probabilistic models for labeling and segmenting sequence data," J. Mach. Learn. Res., vol.8, pp.693– 723, 2007.

[36] Z. H. Wu, A. Liu, P.-C. Zhou, and Y.F. Su, "A Bayesian Network Based Method for Activity Prediction in a Smart Home System," IEEE International Conference on Systems, Man, and Cybernetics (SMC) IEEE, pp.1496–1501, 2016.

[37] Washington State University, "The CASAS Smart Home project" http://casas.wsu.edu/smart-homes (last referred on July 20, 2020).

[38] D. J. Cook and M. Schmitter-Edgecombe, "Assessing the quality of activities in a smart environment," Methods Inf. Med., vol.48, no.5, pp.480–485, 2009.

[39] T. Tsuda, "A study on environmental sound collection and its recognition method using a mobile terminal," IPSL The study group re-port, vol.2013-MUS-99, no.18, 2013.

[40] © 2023 IEEE – SWC 2023. Reprinted, with permission, from: J. F. Papel, T. Munaka, "Detecting Activities of Daily Living for the Elderly Using Magnet Sensors," in Proceedings of the IEEE Smart World Congress (Presented in August 2023 on Portsmouth - England).

[41] © 2023 IEEE – 13th ICCE. Reprinted, with permission, from: J. F. Papel, T. Munaka, "Abnormal Behavior Detection in Activities of Daily Living: An Ontology with a New Perspective on Potential Indicators of Early Stages of Dementia Diagnosis," in Proceedings of the IEEE 13th International Conference on Consumer Electronics (Presented in September 2023 on Berlin - German).

[42] J. F. Papel, T. Munaka, "Home Activity Recognition by Sounds of Daily Life Using Improved Feature Extraction Method," IEICE Transactions on Information and Systems, 2023, Volume E106.D, Issue 4, Pages 450-458, April 2023.

[43] N. Tanaka, T. Munaka, J. F. Papel, S. Hattori, T. Iwamatsu, T. Miura and F. Tsutsumi, "Relationship between human behavior and indoor air quality of the private room in a care facility for the elderly in Japan," Asian Journal of Atmospheric Environment, 17, 11 (2023).

[44] J. M. D. Coey, "Handbook of Magnetism and Magnet Materials," in Springer International Publishing.

[45] P. Ripka and M. Janosek, "Advances in Magnet Field Sensors," in IEEE Sensors Journal, vol. 10, no. 6, pp. 1108-1116, June 2010, doi: 10.1109/JSEN.2010.2043429.

[46] J. Lenz and S. Edelstein, "Magnet sensors and their applications," in IEEE Sensors Journal, vol. 6, no. 3, pp. 631-649, June 2006, doi: 10.1109/JSEN.2006.874493.

[47] J. E. Lenz, "A review of Magnet sensors," in Proceedings of the IEEE, vol. 78, no. 6, pp. 973-989, June 1990, doi: 10.1109/5.56910.

[48] K. S. R. Murty and B. Yegnanarayana, "Combining evidence from residual phase and MFCC features for speaker recognition." in EEE Signal Processing Letters, Jan. 2006, doi: 10.1109/LSP.2005.860538

[49] Md. Sahidullah and G. Saha, "Design, analysis and experimental evaluation of block-based transformation in MFCC computation for speaker recognition," Speech Communication, May 2012, doi: 10.1016/j.specom.2011.11.004

[50] A. Komaty, F. Meriaudeu, S. Agrebi, E. Rejaibi, and A. Othmani, "MFCC-based Recurrent Neural Network for automatic clinical depression recognition and assessment from speech," Biomedical Signal Processing and Control, Jan. 2022, doi: 10.1016/j.bspc.2021.103107.

[51] R. Reisberg, S.H. Ferris, M. J. Leon, and T. Crook, "The Global Deterioration Scale for assessment of primary degenerative dementia," in The America Journal of Psychiatry September 1982; 139: 1136–1139. doi: https://doi.org/10.1176/ajp.139.9.1136.

[52] R. Tarawneh, and D. M. Holtzman, "The Clinical Problem of Symptomatic Alzheimer Disease and Mild Cognitive Impairment," in Cold Spring Harbor Perspectives in Medicine, July 2023. doi: 10.1101/cshperspect.a006148.

[53] K. Zawaly, S. A. Mayes, P. C. Wood, G. Cheung, A. Rolleston, S. Buetow, L. Tippet, and N. Kerse, "Diagnostic accuracy of a global cognitive screen for Māori and non-Māori octogenarians," in Translation Research & Clinical Interventions, Volume 5, Issue 1, Pages 1-986, January 2019. https://doi.org/10.1016/j.trci.2019.08.006.

[54] L. Pan, Y. Xie, H. Yang, M. Li, X. Bao, J. Shang, and Run-Wei Li, "Flexible Magnet Sensors," Sensors, 2023, 23, 4083. https://doi.org/10.3390/s23084083.

[55] D. D. Onthoni, and P. K. Sahoo, "Artificial-Intelligence-Assisted Activities of Daily Living Recognition for Elderly in Smart Home. Electronics," in Electronics, 11(24), 4129. December 2022. https://doi.org/10.3390/electronics11244129.

[56] T. R. Gruber, "A translation approach to portable ontology specifications," in Knowledge Acquisition, Volume 5, Issue 2. June 1993, Pages 199-220, ISSN 1042-8143, https://doi.org/10.1006/knac.1993.1008. Elsevier.

[57] N. F. Noy, and D. L. McGuinness, "Ontology development 101: A guide to creating your first ontology," Stanford Knowledge Systems Laboratory Technical Report KSL-01-05 and Stanford Medical Informatics Technical Report.

[58] Medical Dictionary for Regulatory Activities Terminology. Bioportal. https://bioportal.bioontology.org/ontologies/MEDDRA?p=classes&conceptid=http%3A%2F%2Fpurl.bioontology.org%2Fontology%2FMEDDRA%2F10012267.

[59] Y. Shin, Y. J. Park, and S. J. Kang, "Data-Driven Knowledge-Based System for Self-Measuring Activities of Daily Living in IoT-Based Test," in Applied Sciences 10, no. 14: 4972. https://doi.org/10.3390/app10144972.

[60] Alzheimer's Association, "What is Dementia," 2023, https://www.alz.org/alzheimers-dementia/what-is-dementia.

[61] Alzheimer's Association, "What is Alzheimer's Disease? " 2023. https://www.alz.org/alzheimers-dementia/what-is-alzheimers#:~:text=Alzheimer%27s%20is%20the%20most%20common,%2D80%25%20of%20dementia%20cases.

[62] Alzheimer's Society, "Types of Dementia," 2023. https://www.alzheimers.org.uk/about-dementia/types-dementia#:~:text=While%20Alzheimer's%20disease%20is%20the,by%20other%20diseases%20and%20conditions.

[63] World Health Organization, "Dementia: number of people affected to triple in next 30 years," in News Release, Geneva, 7 December 2017. https://www.who.int/news/item/07-12-2017-dementia-number-of-people-affected-to-triple-in-next-30-years#:~:text=As%20the%20global%20population%20ages,%2C%20Director%2DGeneral%20of%20WHO.

[64] World Health Organization, "Dementia – Key Facts," in Newsroom, 15 March 2023, https://www.who.int/news-room/fact-

sheets/detail/dementia#:~:text=In%202019%2C%20dementia%20cost%20economies,care %20and%20supervision%20per%20day.

[65] J. Cummings, G. Lee, A. Ritter, and M. Sabbagh, "Alzheimer's disease drug development pipeline: 2020," in Alzheimer's & Dementia: Translational Research & Clinical Interventions, 6(1), e1205, July 2020. https://doi.org/10.1002/trc2.12050.

[66] A. Karia, R. Zamani, and M. Akrami, "Socio-Economic Disparities in Access to Diagnostic Neuroimaging Services in the United Kingdom: A Systematic Review. " Int J Environ Res Public Health. 2021 Oct 11;18(20):10633. doi: 10.3390/ijerph182010633. PMID: 34682379; PMCID: PMC8535632.

[67] W. M. Van Oostveen, and E. C. M. de Lange. 2021. "Imaging Techniques in Alzheimer’s Disease: A Review of Applications in Early Diagnosis and Longitudinal Monitoring" International Journal of Molecular Sciences 22, no. 4: 2110. https://doi.org/10.3390/ijms22042110

[68] Z. Arvanitakis, R. C. Shah, and D. A. Bennett. "Diagnosis and Management of Dementia: Review. " JAMA. 2019 Oct 22;322(16):1589-1599. doi: 10.1001/jama.2019.4782. PMID: 31638686; PMCID: PMC7462122.

[69] A. Bradford, M. E. Kunik, P. Schulz, S. P Williams, and H Singh, "Missed and Delayed Diagnosis of Dementia in Primary Care: Prevalence and Contributing Factors," in Alzheimer Disease & Associated Disorders, Volume 24, Issue 4, Pages 306-314, October 2009. 10.1097/WAD.0b013e3181a6bebc.

[70] A. Javeed, A. L. Dallora, J. S. Berglund, A. Ali, L. Ali, and P. Anderberg, "Machine Learning for Dementia Prediction: A Systematic Review and Future Research Directions," in Journal of Medical Systems, January 2023. https://doi.org/10.1007/s10916-023-01906-7. Springer.

[71] C. Dillon, C. M. Serrano, D. Castro, P. P. Leguizamón, S. L. Heisecke, F. E. Taragano, "Behavioral symptoms related to cognitive impairment," Neuropsychiatr Dis Treat. 2013;9:1443-55. doi: 10.2147/NDT.S47133. Epub 2013 Sep 19. PMID: 24092982; PMCID: PMC3788702.

[72] J. E. Morley, J. C. Morris, M. Berg-Weger, S. Borson, B. D. Carpenter, N. Del Campo, B. Dubois, K. Fargo, L. J. Fitten, J. H. Flaherty, M. Ganguli, G. T. Grossberg, T. K. Malmstrom, R. D. Petersen, C. Rodriguez, A. J. Saykin, P. Scheltens, E. G. Tangalos, J. Verghese, G.

Wilcock, B. Winblad, J. Woo, and B. Vellas. "Brain health: the importance of recognizing cognitive impairment: an IAGG consensus conference," J Am Med Dir Assoc. 2015 Sep 1;16(9):731-9. doi: 10.1016/j.jamda.2015.06.017. PMID: 26315321; PMCID: PMC4822500.

[73] Canada Alzheimer Society, "The 10 warning signs of dementia," https://alzheimer.ca/en/about-dementia/do-i-have-dementia/10-warning-signs-dementia.

[74] A. Felman, and R. A. Tee-Melegrito, "What is mental health?," in Medical News Today. https://www.medicalnewstoday.com/articles/154543.

[75] G. Cheran, L. Wu, S. Lee, M. Manoochehri, S. Cines, E. Fallon, T. Lynch, J. L. Heidebrink, H. L. Paulson, J. Goldman, E. D. Huey, and S. Cosentino, "Cognitive Indicators of Preclinical Behavioral Variant Frontotemporal Dementia in MAT Carriers," Journal of The International Neuropsychological Society, Feb. 2019, doi: 10.1017/s1355617718001005.

[76] J. Lockhart, and S. Satya-Murti, "Symptom exaggeration and symptom validity testing in persons with medically unexplained neurologic presentations." Neurol Clin Pract. 2015 Feb;5(1):17-24. doi: 10.1212/CPJ.0000000000000092. PMID: 29443178; PMCID: PMC5764424.

[77] A. Toomela, S. Nõmm, T. Kõnnussaar, and V. Tammik, "Why Behavioral Indicators May Fail to Reveal Mental States: Individual Differences in Arousal-Movement Pattern Relationships," Front Psychol. 2019 Feb 14;10:270. doi: 10.3389/fpsyg.2019.00270. PMID: 30837919; PMCID: PMC6382674.

[78] C. D. Jenkins. "Building Better Health: A Handbook of Behavioral Change," Scientific and Technical Publication No. 590, Pan American Health Organization, https://iris.paho.org/bitstream/handle/10665.2/738/9275115907.pdf.

[79] A. O. Muili, M. J. Mustapha, M. C. Offor, and H. J. Oladipo, "Emerging roles of telemedicine in dementia treatment and care," Dement Neuropsychol. 2023 May 29;17:e20220066. doi: 10.1590/1980-5764-DN-2022-0066. PMID: 37261258; PMCID: PMC10229090.

[80] E. Angelopoulou, N. Papachristou, A. Bougea, E. Stanitsa, D. Kontaxopoulou, S. Fragkiadaki, D. Pavlou, C. Koros, Y. Değirmenci, J. Papatriantafyllou, E. Thireos, A. Politis, A. Tsouros, P. Bamidis, L. Stefanis, and S. Papageorgiou, "How Telemedicine Can Improve the Quality of Care for Patients with Alzheimer's Disease and Related Dementias? A

Narrative Review," Medicina (Kaunas). 2022 Nov 22;58(12):1705. doi: 10.3390/medicina58121705. PMID: 36556907; PMCID: PMC9783876.

[81] W. Salehi, G. Gupta, S. Bhatia, D. Koundal, A. Mashat, and A. Belay. "IoT-Based Wearable Devices for Patients Suffering from Alzheimer Disease," Contrast Media Mol Imaging. 2022 Apr 22;2022:3224939. doi: 10.1155/2022/3224939. PMID: 35542758; PMCID: PMC9054450.

[82] J. Thorpe, B. H. Forchhammer, A. M. Maier, "Adapting Mobile and Wearable Technology to Provide Support and Monitoring in Rehabilitation for Dementia: Feasibility Case Series," JMIR Form Res. 2019 Oct 17;3(4):e12346. doi: 10.2196/12346. PMID: 31625951; PMCID: PMC6913510.

[83] K. S. Santacruz, and D. Swagerty, "Early Diagnosis of Dementia," University of Kansas Medical Center, https://www.aafp.org/pubs/afp/issues/2001/0215/p703.pdf.

[84] A. M. G. Barrero, "The Linguistic and Cognitive Effects of Bilingualism on Children with Autism Spectrum Disorders," McGill University, Faculty of Medicine, School of Communication Sciences and Disorders, April 2017, https://escholarship.mcgill.ca/downloads/4q77ft969.pdf#page=175

[85] A. Guarda, "What are Eating Disorders?," American Psychiatric Association, Feb. 2023, https://www.psychiatry.org/patients-families/eating-disorders/what-are-eating-disorders

[86] Scotland's national health information service, "Dysphagia (swallowing problems)," https://www.nhsinform.scot/illnesses-and-conditions/stomach-liver-and-gastrointestinal-tract/dysphagia-swallowing-problems#:~:text=Dysphagia%20is%20the%20medical%20term,choking%20when%20eating%20or%20drinking

[87] Kidney Research UK, "Why hydration is important for kidney health," https://www.kidneyresearchuk.org/kidney-health-information/living-with-kidney-disease/how-can-i-help-myself/hydration-for-kidney-health/#:~:text=Dehydration%2C%20especially%20chronic%20dehydration%2C%20results,diseases%2C%20such%20as%20kidney%20stones.

[88] Diabetes UK – Know Diabetes, Fight Diabetes, "What are the signs and symptoms of diabetes?,"https://www.diabetes.org.uk/diabetes-the-basics/diabetes-

symptoms#:~:text=Diabetes%20symptoms%20occur%20because%20some,urine%2C%20making%20you%20more%20thirsty.

[89] National Alliance on Mental Illness, " Hygiene Indifference: The Symptom We Don’t Talk About, " https://www.nami.org/Blogs/NAMI-Blog/February-2023/Hygiene-Indifference-The-Symptom-We-Don-t-Talk-About#:~:text=However%2C%20indifference%20to%20hygiene%20tasks,health%20conditions%20(particularly%20depression).

[90] National Health Services UK, "Prostate problems - Prostate problems are common, particularly in men aged over 50," https://www.nhs.uk/conditions/prostate-problems/.

[91] C. Swiner, "Cystitis – What is Cystitis?," 02 Aug. 2022, https://www.webmd.com/urinary-incontinence-oab/what-is-cystitis#:~:text=A%20urinary%20tract%20infection%20(UTI,much%20more%20than%20men%20do.

[92] American Diabetes Association, "Diabetes Symptoms," https://diabetes.org/diabetes/type-1/symptoms.

[93] American Cancer Society, "Colorectal Cancer Signs and Symptoms," 29 Jun. 2020, https://www.cancer.org/cancer/types/colon-rectal-cancer/detection-diagnosis-staging/signs-and-symptoms.html#:~:text=Colorectal%20cancer%20might%20not%20cause,not%20relieved%20by%20having%20one.

[94] B. E. Lacy, K. Weiser, R. De Lee. " The treatment of irritable bowel syndrome," Therap Adv Gastroenterol. 2009 Jul;2(4):221-38. doi: 10.1177/1756283X09104794. PMID: 21180545; PMCID: PMC3002524.

[95] T. Roth, "Insomnia: definition, prevalence, etiology, and consequences," J Clin Sleep Med. 2007 Aug 15;3(5 Suppl):S7-10. PMID: 17824495; PMCID: PMC1978319.

[96] D. Nutt, S. Wilson, L. Paterson, "Sleep disorders as core symptoms of depression," Dialogues Clin Neurosci. 2008;10(3):329-36. doi: 10.31887/DCNS.2008.10.3/dnutt. PMID: 18979946; PMCID: PMC3181883.

[97] Better Health Channel, | Victoria State Government – Department of Health, "Dementia – hygiene," https://www.betterhealth.vic.gov.au/health/conditionsandtreatments/dementia-hygiene.

[98] A. Evanson, "What Are the Consequences of Neglecting Your Teeth," https://www.evansondds.com/what-are-the-consequences-of-neglecting-your-teeth/#:~:text=Neglecting%20your%20teeth%20can%20cause%20gingivitis%2C%20the%20milder%20form%20of,of%20gum%20disease%2C%20called%20periodontitis.

[99] L. N. Kwon, D. H. Yang, M. G. Hwang, S. J. Lim, Y. K. Kim, J. G. Kim, K. H. Cho, H. W. Chun, and K. W. Park, "Automated Classification of Normal Control and Early-Stage Dementia Bases on Activities of Daily Living (ADL) Data Acquired from Smart Home Environment," Int J Environ Res Public Health. 2021 Dec 15;18(24):13235. doi: 10.3390/ijerph182413235. PMID: 34948842; PMCID: PMC8701739.

[100] C. Chalmers, P. Fergus, C. A. C. Montanez, S. Sikdar, F. Ball and B. Kendall, "Detecting Activities of Daily Living and Routine Behaviours in Dementia Patients Living Alone Using Smart Meter Load Disaggregation," in IEEE Transactions on Emerging Topics in Computing, vol. 10, no. 1, pp. 157-169, 1 Jan.-March 2022, doi: 10.1109/TETC.2020.2993177.

[101] E. Cornelis, E. Gorus, I. Beyer, I. Bautmans, and P. De Vriendt, "Early Diagnosis of mild cognitive impairment and mild dementia through basic and instrumental activities of daily living: Development of a new Evaluation Tool," PLoS Med. 2017 Mar 14;14(3):e1002250. doi: 10.1371/journal.pmed.1002250. PMID: 28291801; PMCID: PMC5349421.

[102] Z. Arvanitakis, R. C. Shah, and D. A. Bennett, "Diagnosis and Management of Dementia: A Review," JAMA. 2019 Oct 22;322(16):1589-1599. doi: 10.1001/jama.2019.4782. PMID: 31638686; PMCID: PMC7462122.

[103] I. M. Pires, N. M. Garcia, E. Zdravevski, and P. Lameski "Activities of daily living with motion: A dataset with accelerometer, magnetometer and gyroscope data from mobile devices," Data Brief. 2020 Dec 8;33:106628. doi: 10.1016/j.dib.2020.106628. PMID: 33344738; PMCID: PMC7735969.

[104] P. C. Pérez, A. M. M. Antón, A. Poli, S. Spinsante, and F. F. Revuelta, "Dataset of acceleration signals recorded while performing activities of daily living," Data in Brief, Volume 41, 2022, 107896, ISSN 2352-3409, https://doi.org/10.1016/j.dib.2022.107896.

[105] A. S. A. Sukor, A. Zakaria and N. A. Rahim, "Activity Recognition using accelerometer sensor and machine learning classifiers," *2018 IEEE 14th International Colloquium on Signal Processing & Its Applications (CSPA)*, Penang, Malaysia, 2018, pp. 233-238, doi: 10.1109/CSPA.2018.8368718.

[106] M. G. F. Costa, G. A. E. Aquino, M. K. Serrão, D. G. A. Vieira, E. D. N. Alencar, J. V. C. Negreiro, E. S. R. Silva, and C. F. F. Costa Filho e, "A New Approach for Detecting Activities of Daily Living Detection Using Smartphone and Wearable Sensors," 2021 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), Mauritius, Mauritius, 2021, pp. 01-07, doi: 10.1109/ICECCME52200.2021.9590938.

[107] A. Ferrari, D. Micucci, M. Mobilio, and P. Napoletano, "Human Activities Recognition Using Accelerometer and Gyroscope," In: Chatzigiannakis, I., De Ruyter, B., Mavrommati, I. (eds) Ambient Intelligence. AmI 2019. Lecture Notes in Computer Science(), vol 11912. Springer, Cham. https://doi.org/10.1007/978-3-030-34255-5_28

[109] J. Gómez, O. Aycard, and J. Baber, "Efficient Detection and Tracking of Human Using 3D LiDAR Sensor," Sensors (Basel). 2023 May 12;23(10):4720. doi: 10.3390/s23104720. PMID: 37430633; PMCID: PMC10222621.

[110] P. Masson, B. Wallace, J. Green and R. Goubran, "Comparison of Spatial Coverage of LiDAR Systems for In Home Activity of Daily Living Applications," *2023 IEEE Sensors Applications Symposium (SAS),* Ottawa, ON, Canada, 2023, pp. 01-06, doi: 10.1109/SAS58821.2023.10254089.

[111] N. Frøvik, B. A. Malekzai, and K. Øvsthus, "Utilising LiDAR for fall detection," Healthc. Technol. Lett., 8: 11-17. 2021. https://doi.org/10.1049/htl2.12001

[112] T. -C. Chiu, T. -S. Chen and J. -M. Lin,"Human Gait Recognition using LiDAR and Deep Learning Technologies," 2022 IEEE International Conference on Consumer Electronics - Taiwan, Taipei, Taiwan, 2022, pp. 43-44, doi: 10.1109/ICCE-Taiwan55306.2022.9869258.

[113] S. V. der Spek, J.V. Schaick, P. De Bois, and R. De Haan, "Sensing Human Activity: GPS Tracking," Sensors 9, no. 4: 3033-3055. https://doi.org/10.3390/s90403033

[114] I. M. Pires, N. M. Garcia, and E. Zdravevski, "Daily motionless activities: A dataset with accelerometer, magnetometer, gyroscope, environment, and GPS data," Sci Data 9, 105 (2022). https://doi.org/10.1038/s41597-022-01213-9

[115] S. Huang, J. Lyu, S. Zhang, R. Tang, H. Xiao, Y. Zhang, and X. Lu, "A Post-processing Machine Learning for Activity Recognition Challenge with OpenStreetMap Data," In Adjunct Proceedings of the 2023 ACM International Joint Conference on Pervasive and Ubiquitous Computing & the 2023 ACM International Symposium on Wearable Computing (UbiComp/ISWC '23 Adjunct). Association for Computing Machinery, New York, NY, USA, 557–562. https://doi.org/10.1145/3594739.3610755

[116] A. W. Sardar, F. Ullah, J. Bacha, J. Khan, F. Ali, and S. Lee, "Mobile sensors based platform of Human Physical Activities Recognition for COVID-19 spread minimization," Computers in Biology and Medicine, Volume 146, 2022, 105662, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2022.105662.

[117] S. Casaccia, R. Rosati, L. Scalise and G. M. Revel, "Measurement of Activities of Daily Living: a simulation tool for the optimisation of a Passive Infrared sensor network in a Smart Home environment," 2020 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), Dubrovnik, Croatia, 2020, pp. 1-6, doi: 10.1109/I2MTC43012.2020.9128409.

[118] Q. Guan, C. Li, L. Qin and G. Wang, "Daily Activity Recognition Using Pyroelectric Infrared Sensors and Reference Structures," in IEEE Sensors Journal, vol. 19, no. 5, pp. 1645-1652, 1 March1, 2019, doi: 10.1109/JSEN.2018.2885168.

[119] S. Tao, M. Kudo, H. Nonaka and J. Toyama, "Recording the Activities of Daily Living based on person localization using an infrared ceiling sensor network," 2011 IEEE International Conference on Granular Computing, Kaohsiung, Taiwan, 2011, pp. 647-652, doi: 10.1109/GRC.2011.6122673.

[120] M. Kusunoki, T. Kohama, Y. Yamada, E. Fujita, S. Okada, A. Maeda, and N. Takeshima, "Evaluating activities of daily living using an infrared depth sensor: KINECTTM," Disability and Rehabilitation: Assistive Technology, 14:4, 368-378, DOI: 10.1080/17483107.2018.1449020.

[121] S. S. Sumit, D. R. A. Rambli and S. Mirjalili, "Vision-Based Human Detection Techniques: A Descriptive Review," in IEEE Access, vol. 9, pp. 42724-42761, 2021, doi: 10.1109/ACCESS.2021.3063028.

[122] A. Ravankar, A. Rawankar, and A. A. Ravankar, "Real-time monitoring of elderly people through computer vision," Artif Life Robotics 28, 496–501 (2023). https://doi.org/10.1007/s10015-023-00882-y.

[123] M. Buzzelli, A. Alessio, and G. Ciocca, "A Vision-Based System for Monitoring Elderly People at Home," Applied Sciences 10, no. 1: 374. 2020. https://doi.org/10.3390/app10010374.