A Review of the Technology of Activity Recognition for Dementia

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Abstract Technology can help and provide support to people with dementia stay safe in their daily activity. In this paper, we summarize information about activity recognition for dementia sufferers. The purpose of this paper is to understand the uses and type of applications, the kind of sensors/systems, methods, and data used within the scope of human activity recognition to monitor, detect symptoms or help with dementia. As a result, 447 abstracts were collected from a scopus database, yielding 127 relevant papers, and 102 papers that were considered in detail based on 4 categories of assessment (application, system/sensors, methods, data). This paper shows the trend of smart environment technology is most widely used for monitoring dementia sufferers with the classification of machine learning techniques as a method in activity recognition to get the results of testing or implementing the system. This review concludes that the combining of sensor devices and the addition of smartphone devices in one system is good for implementation because it can be used as an identity so that it distinguishes the object under study with other objects. During the monitoring process simultaneously prevention can be done by adding a warning alarm in the smartphone when people with dementia perform abnormal activities, and the results need to be further analyzed to get the best pattern of activities for people with dementia. After that, the type of application that was

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originally in the form of monitoring can develop into an assistant in people with dementia. Because they are really need a system that can be his assistant for helping to make decisions in their daily lives.

1 Introduction

Advances in technology have produced a number of new devices and transferred the power of computers to aspects of daily life. This also drives the transformation of how the community deals with computer science. Systems are being designed more sophisticated so that community do not need to be a computer specialists to have benefit from computing resources. Systems in this area are called ambient intelligence (AMI) where making computational applications available to the society by not interfering with their routine, minimizing explicit interactions is at the core of its value [11].

At the same time, alzheimer's disease and related dementia (ADRD) has reached around 50 million sufferers worldwide. This amount is nowadays increasing due to the growing population which is also aging with a global prevalence which is expected to reach 152 million in 2050 [85]. Although many dementia diagnostic tools are available, 62% of ADRD cases worldwide are undiagnosed, while 91% of cases are diagnosed very late[94]. Missed or delayed diagnosis will result in increase socioeconomic burden a relative and the health care system through large expenditures on unnecessary investigations, treatments that are driven by under symptoms, and lack of family and caregiver counseling [57].

Ubiquitous computing and intelligent data analysis can provide innovative methods and tools for detecting quickly symptoms of the arise of cognitive impairment and for monitoring its evolution [98]. In this paper, we review solutions based on activity recognition offered to overcome the problem of dementia. We perform a systematic review process to identify the main solutions proposed for dementia classifying them by their application, the system and sensors used and the methods used (Section 2). After a short summary of the dementia disease presented in Section 3 for completeness, we analyze the main technological solutions proposed in Section 4. As a result of our review,we find that monitoring is the most common type of application to help people with dementia in their daily lives. However, other applications such as early symptom detection, identification and prediction have fewer research. In terms of technology, there are few datasets for this problem which difficults the development of such technology. In the papers reviewed, usually a small dataset is collected that makes the development of research difficult. Finally, we conclude that increased monitoring needs to prevent the activity of people with dementia outside the rules. This will be hard work for the future.

2 Review Method

The purpose of this review is to understand the uses and type of applications, the kind of sensors/systems, methods, and data used within the scope of human activity recognition to monitor, detect symptoms or help with dementia.

We do a systematic review process [97] to analyze the papers. All available papers are evaluated based on predetermined criteria. Then, the results will be classified based on their relevance. The population of the systematic review contains research-papers related to human activities and dementia.

Furthermore, we conducted the search from Scopus database [1]. We searched for papers related to the area of "human activity recognition" and the area of "dementia". We designed a list of keywords for each area (Tables I and II) by consulting dementia experts and activity recognition experts.

Table 1 Keyword of search for activity recognition areas

Keywords: activity recognition	AND
• information systems • cognitive impairment • physically active • talking • assessment methods • prediction methods • multilayer perceptron • LSVM • ICC • equal error rate • linear regression • radio frequency	• support vector regression • radial basis function • k-nearest neighbors • mean absolute error • naïve bayes • hidden semi-markov model • conditional random fields • long short term memory • graph convolutional network • prevention

In the activity recognition area, the highest keyword is activity recognition AND memory with 281 articles, then activity recognition AND assessment with 240 and activity recognition AND language with 160 articles. Meanwhile, for dementia area, the highest keyword is dementia AND prediction with 193 articles, then dementia AND drug as many as 156 and dementia AND support vector machine with 160 articles.

The selected papers are then classified into four main subjects: application types, sensor/system types, methods, and datasets. Hereinafter, related types regarding application types are further divided into eight categories, namely algorithm comparison, analysis, diagnosis, guidance, identification, monitoring, prediction, and prevention.

[1] https://www.scopus.com

Table 2 Keyword of search for dementia areas

Keywords: dementia	AND	
• behavioral and psychological symptoms of dementia • mini-mental state examination • montreal cognitive assessment • assessment • eating • language • memory • prediction • prevention • acupuncture • alcohol • APOE	• apolipoprotein E • behavior recognition • diet • drug • eating • herbal • lewy bodies • light therapy • massage • mathematical • mentally • aromatherapy • age • genetic	• multilayer perceptron • music therapy • smoking • smoteBOOST • talking • temporal • urine • vascular • wRACOG • alzheimer • frontotemporal • lifestyle

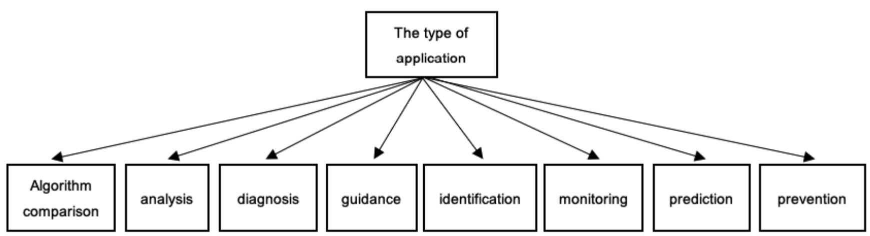

Fig. 1 Classification based on application type

Then, for the type of sensor/system used in each paper is divided into ten categories, audio, design, electroencephalogram (EEG), framework, MRI, sensor, smart environment, speech, video, wearable.

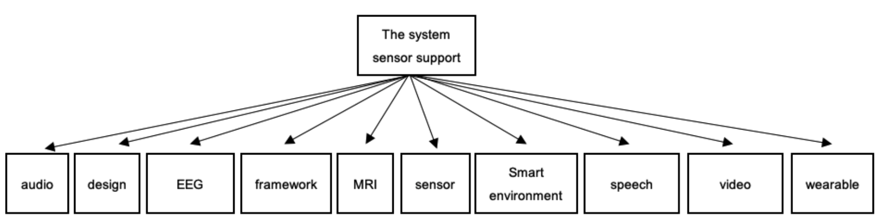

Fig. 2 Classification by system sensor support

Meanwhile, the method/algorithm support to used in processing data in each article are nine categories, there are: support vector machine (SVM), Naive Bayes, K-Nearest Neighbors, Hidden Markov Model (HMM), Bayesian Network, Decision Tree (C4.5), and Random Forest (RF).

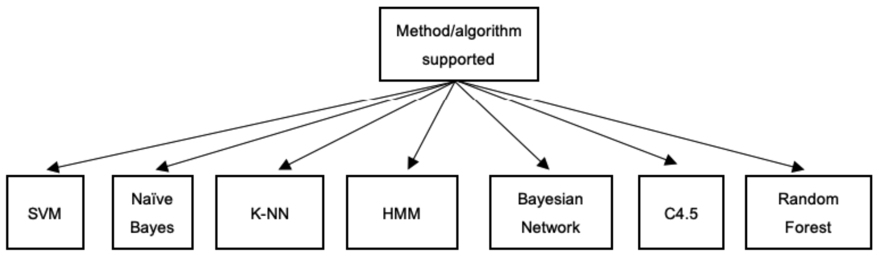

Fig. 3 Method/Algorithm support

And the last is the dataset category used, there are: real data, simulated data, Liara, Activities of Daily Living (ADL) datasets, sensor data, smartphone, Alzheimer's Disease Neuroimaging Initiative (ADNI).

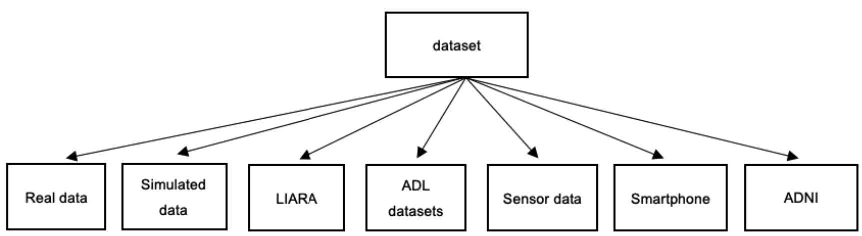

Fig. 4 Dataset of dementia

3 Dementia(Overview)

3.1 Types of Dementia

Dementia is a chronic brain disorder divided by four different diseases that effect into cognition and mental degeneration. Every subgroup exhibits similar brain deficiencies and mutations [66]. Dementia causes a decrease in memory and ways of thinking. This condition affects the lifestyle, ability to socialize, to the daily activities of the sufferer. Dementia is not the same as senile. Senile is a decrease in the ability to remember and think that usually occurs with age. This change can affect memory, but it is not significant and does not affect someone depends on others. Alzheimer's disease and vascular dementia are the most common types of dementia. Alzheimer is the most common neurodegenerative disease for dementia, consist of 60% to 80% of cases and vascular dementia is the second most common form of dementia (20%)[34]. Alzheimer's is dementia related to genetic changes and protein changes in the brain. Meanwhile, vascular dementia is a type of dementia that causes disturbance with the blood vessels of the brain.

Lewy body dementia (LBD) is a form of dementia caused by abnormal deposits of alpha-synuclein protein (lewy bodies) inside neurons. It contributes for 5% to 15% of all dementias [20]. Besides, Frontotemporal dementia (FTD) is a type of dementia that can affect behavior and personality and language function, that affect the frontal and temporal lobes of the brain. The brief explanation is available on Table III.

Table 3 Distinguishing features of subtypes of dementia [79]

Dementia subtype	Clinical presentation*
Alzheimer's disease	• Insidious onset and slow progressive decline • Short-term memory impairment in early stage; deficit on 3-word or 5-word recall; executive function impairment in later stages
Vascular dementia	• Sudden or gradual onset • Usually correlated with cerebrovascular disease (stroke, lacunar infarcts) and atherosclerotic comorbidities (diabetes, hypertension, coronary heart disease) • Mild memory impairment in early stage • Possible gait difficulties and falls (depending on the extent of the stroke)
Lewy body dementia	• Fluctuating cognition associated with parkinsonism • Poor executive function and visual hallucinations in early stage; deficits on tests designed to examine visual perception (pentagons, cube, trails, clock face)
Frontotemporal dementia	• More prominent personality changes (disinhibition) and behavioral disturbances (apathy, aggression, agitation with less memory impairment in early stage)

Unfortunately, there is no medicine that can heal dementia exactly [123]. However, some therapies are available to deal with dementia symptoms and behaviors. Here are the following therapies:

- Cognitive stimulation therapy, good for opening memory, problem solving skills, and ability to support, by doing group activities or sports.
- Occupational therapy aimed at teaching sufferers how to do their daily activities safely based on their conditions and also how to control emotions in dealing with the development of symptoms.
- Memory therapy works to help sufferers remember their life journey, such as childhood memory, school period, work, hobbies, etc.
- Cognitive rehabilitation intent to train non-functioning parts of the brain, using parts of the brain which are still healthy.

3.2 Causes of Dementia

Dementia is caused by damage or loss of connection of nerve cells in parts of the brain. Moreover, age is the most risky factor for dementia [113]. In 2000, prevalence data from 11 European population-based studies were collected to gain stable estimates of dementia prevalence in the elderly (65 years) [62].

A small portion of people with dementia come from dementia families, with autosomal dominant mutations. Mutations caused by several genes have been shown to cause AD, except that the genetic form of AD accounts for less than 5% of all cases. The hypothesis of "common variance" states that common disorders such as AD are also regulated by common DNA variants. This variant significantly increases the risk of disease but not enough to actually cause certain disorders[113].

Other factors that may be the cause of dementia are vascular factors. Vascular risk factors such as diabetes mellitus, hypertension, smoking, and heart disease have been proved to be related to Alzheimer's [17]. Nowadays study, the subjects with VCD and AD share the same vascular risk factors, even though the higher prevalence of hypertension, diabetes mel- litus, hyperlipidemia, stroke and white matter change (WMC) were recorded in the group with vascular cognitive decline (VCD), but not for the coronary artery disease and atrial fibrillation [108].

3.3 Symptoms of Dementia

Each dementia patient will have a unique experiences in a different way. Different types of dementia also tend to affect people differently, especially in the early stages. Another factor that will affect the level of life quality of a dementia patient depends on how community and environment support them.

Dementia patients will have cognitive symptoms (to do with thinking or memory). They will often have problems by the following[21]:

1. day-to-day memory
2. concentrating, planning or organizing
3. language

4. visuospatial skills
5. orientation

3.4 Monitoring of Dementia

Dementia reduces one's intellectual function compared to before. It also triggers behavioural changes of the patients. Behavioral and psychological symptoms affect up to 90% of all dementia subjects [52]. These effects make abnormal behavior for parents with dementia such as repeating activities, disruption in sleeping, and confusion [8]. While psychological effects such as agitation, anxiety, elation, irritability, depression, apathy, delusions, and hallucinations [23].

Therefore, it is necessary to assess and monitor activities of dementia patients. So that, it will increase the life expectancy of Dementia patients even though it cannot be denied that the number of Dementia patients will continuously increase dramatically [91]. In this paper, we show the various tracking and assessment methods used for dementia, clearly based on the activity recognition so that it is can be recorded. In session four we present the role of the importance of dementia monitoring, followed by other applications.

4 Human Activity Recognition for Dementia

Human Activity Recognition (HAR) is using sensing technology to identify the activity of humans. Usually, HAR is integrated with other methods for obtaining additional information [46] such as demographic variables. In the case of dementia, HAR technology has an important role because dementia patients experience damage or lose the connection of nerve cells in parts of the brain. Recognizing activities can help in monitoring activities to detect abnormal situations, detecting missing activities to provide reminders (v. gr. medication reminders based on context) or provide other types of care. In this section, we analyze the articles based on the following criteria: types of applications, kind of sensors/systems, methods, and data to make the focus for analyzing needs of technologies and methods for activities dementia patients.

4.1 Application

From the review papers, we summarize the application in computer science that has a relationship with dementia in table 4. In this session, we categorize the application into eight parts, namely (1) Algorithmic Comparison, we include papers that have the main purpose of comparing the performance of algorithms into this category such as comparing a series of machine learning classification techniques for activity recognition [45], classifying aphasic and non-aphasic speakers [48]; (2) Analysis, in this category we classify papers related to the discussion of investigations, assessments, explorations or evaluations of an object with the aim of knowing the actual situation or getting the level of accuracy of the research. For example behavior analysis based on visual understanding [117], behavioral anomalies [98], activity transitions [37]; (3) Diagnosis, research on the related to find out developments and provide solutions to the problems of people with dementia we group in this section. Eg, decision support for the diagnosis of Alzheimer's disease (AD) and Mild cognitive impairment (MCI) [84], diagnosis to determine the severity of the disease [63], detecting the earliest stages of Alzheimer's disease (AD) [3]; (4) Guidance, part of the paper describes assistive technology support for people with dementia [2], or caregivers [32] and there are also studies that discuss tools for quality of life measures [28]; (5) Identification, in this category we provide information about papers discussing ongoing activities [14] to find out the characteristics of people with dementia; (6) Monitoring, we grouped papers that observe the daily activities of people with dementia, both in the home environment [74] [118] [70], hospital [72] and nursing home [114] to reduce stress due to constant patient monitoring [40]; (7) Prediction, this category contains papers that provide information about behavior probable [86] of people with dementia. For example, actions that users will take next [4] after doing an activity; (8) Prevention, in this category we group based on research that discusses actions to prevent dementia from developing worse [111] and prevent synchronization errors in applications [38]; We do grouping for that category every year.

4.2 Systems/Sensors used in Dementia Support Activity Recognition Applications

Development and experiments of the system to the analysis, diagnosis, monitoring, identifying, and preventing of dementia are carried out with the aim of alleviating the burden on the dementia sufferer's life. Various technologies develop applications related to dementia. We make categories based on (1) Audio, research by detecting existing sounds; (2) Design, research by creating new applications for sufferers of dementia; (3) EEG (Electroencephalography) is recording the electrical activity of the brain; (4) Framework is a workflow method for the initial stage of making an application so that it forms a new system; (5) MRI (Magnetic Resonance Imaging), research by examination using radio wave technology; (6) Sensors, research to motion detection using devices placed on certain body parts; (7) Smart environment, an environment of dementia patients has the presence of technology (motion sensor or camera); (8) Speech, research with the concept of dialogue or recorded conversations with dementia sufferers; (9) Video, research conducted with data derived from video; (10) Wearable, research using wearable devices or wearable software such as touchscreen interactions, Cognitive Drug Research (CDR) computerized,

Table 4 Application

Year	1	2	3	4	5	6	7	8
1999						[69]		
2003			[124]					
2004				[2]				
2005						[88]		
2006				[32]				
2008			[33]			[118] [60]		
2009				[36]		[112] [89] [81]		
2010		[1] [42]		[75] [119] [87]		[116] [70] [65]		
2011	[48]	[106] [115]	[59]	[99]				
2012			[90]	[25] [96]	[64]	[121]		
2013		[22] [24] [58]	[63] [12]			[110] [93] [92]	[83]	[111]
2014		[44] [77] [50] [5] [103] [105]	[18] [101]	[16] [28]	[14]	[30] [61]	[31] [26] [5]	
2015		[37] [80] [13]	[39]	[109]	[9]	[78] [76]		[38]
2016		[98]	[41] [55] [82]	[19] [29]		[107] [40] [72]	[43] [104]	
2017		[7] [49]	[56] [73] [35]			[120] [27] [54]	[86]	
2018		[117] [122] [15]	[95] [3]	[47]		[10] [114] [74] [71]	[4]	
2019	[45]	[67]	[84] [100]			[53]		

1: Algoritm Comparison; 2: Analysis; 3: Diagnosis; 4: Guidance; 5: Identification; 6: Monitoring; 7: Prediction; 8: Prevention

smartwatch to obtain data. We show in Table 5 various systems/sensors related to the activity recognition used in handling dementia cases.

Most monitoring applies a smart environment system for detecting activities using various sensors such as smart carpet, posture sensor, bed sensor, door sensor [40] to assess possible risks faced, RFID sensors [120] into everyday products to track functional degradation Alzheimer's disease [112] [81]. The design of monitoring also uses devices such as ambient sensors, wireless communication protocols, smart home test beds [93] for remote maintenance in smart homes. In the diagnosis also uses a variety of devices to detect people with dementia such as Magnetic Resonance Images (MRI) [33] [100], Mobile Conversational Agents [41], RFID [90] and some are making prototypes of iKnow [73] that put energy consumption sensors, motion sensors, wrist-worn sensors, sleep sensors, magnetic sensors in parts of the house. Another interesting thing is the analysis of daily life activities in videos obtained from wearable cameras [50], the activity of comparing manual annotations with hand tracking [42].

Table 5 The Systems/Sensors support to Dementia

Systems/Sensors	
AUDIO	[48]
DESIGN	[2] [89] [87] [25] [93] [61] [77] [16] [27] [35] [54] [67] [100]
ELECTRO ENCEPHALOGRAPHY (EEG)	[106] [84]
FRAMEWORK	[65] [72] [41] [107] [73] [74]
MRI	[33] [18] [103] [44] [53]
SENSOR	[76] [49] [7]
SMART ENVIRONMENT	[88] [118] [112] [81] [1] [116] [70] [99] [115] [64] [96] [121] [90] [110] [92] [58] [14] [30] [5] [6] [37] [78] [38] [80] [39] [13] [40] [98] [102] [120] [51] [4] [117] [3] [15] [45]
SPEECH	[63] [55]
VIDEO	[60] [119] [42] [12] [50] [82]
WEARABLE	[123] [32] [19] [47]

4.3 Methods and Algorithms for Dementia Support Applications

In this section, we discuss the methods and algorithms used in dementia research. We group the methods into 9 categories. From those 9 categories, the percentage of bayesian model/networks is 13.56%, classification is 52.54%, clustering is 5.08%, correlation method is 1.69%, decision making is 5.08%, deep learning is 8.47%, fuzzy logic is 3.39%, unsupervised learning is 6.78%, and reinforcement learning is 3.39%. For the algorithm, we show it in Table 6 for the 7 most frequently used algorithms.

Apart from the algorithms in Table 6, other algorithms used in the discussion of dementia include dynamic bayesian network (DBN) [99] [14], bayesian rule lists [104], bayes net [45], naïve aggregation [98], smart aggregation [98], Self-organizing map (SOM) [48], k-means [48], adaboost [37], logistic regression [101] [37], multilayer perceptron [101], decision tree (C4.5) rules [69], decision table [101], decision stump [101], J48 decision tree [101], cart [69], metacost [83], linear discriminant analysis (LDA) [53] [103], quadratic discriminant analysis (QDA) [103], discrimi-

Table 6 The Algorithm Support to Dementia

Algorithm	
Support Vector Machine (SVM)	[33] [106] [83] [63] [103] [18] [37] [107] [86] [35] [54] [7] [74] [53] [45]
Naïve Bayes (NB)	[69] [123] [48] [83] [101] [37] [54] [7] [53] [45]
K-Nearest Neighbour	[48] [59] [35] [53] [84] [67] [45]
Hidden Markov Model (HMM)	[112] [99] [50] [14] [7]
Bayesian Network (BN)	[89] [92] [55] [56]
Decision Tree (C4.5)	[69] [48] [83] [35]
Random Forest (RF)	[98] [54] [67]

nant analysis [48], markov logic network (MLN) [39], hidden semi-markov models (HSMM) [7], multilayer perceptron (MLP) [48], artificial neural networks (ANN) [49], probabilistic neural network (PNN) [48], smoteboost [3], wracog [3], flocking [15] [58], fuzzy logic [6], fuzzy clustering [5], fuzzy c-means (FCM) [78], fuzzy conditional random field (FCRF) [25], canonical correlation analysis (CCA) [95], markov decision process (MDP) [43], partially observable markov decision process (POMDP) [42] [61], long short-term memory (LSTM) [4], conditional random field (CRF) [7], convolutional neural network (CNN) [100], gaussian mixture model (GMM) [12], fisher [12], chi-square [12], relative unconstrained least squares importance fitting (RuLSIF) [37].

In table 4 we can see that monitoring has the most frequently performed role in dementia cases using HAR, and table 5 shows that the smart environment system that can use multiple sensors becomes the most preferred choice. In this part, we have shown the details of existing algorithms, then in table 7 we show the linkages of the seven most frequently used algorithms with application monitoring and smart environment systems.

Table 7 The Algorithm Combined With Application Monitoring and Smart Environment System

SVM	NB	KNN	HMM	BN	C4.5	RF
MONITORING						
[107] [54] [74] [53]	[69] [54] [53]	[53]	[112]	[89] [92]	[69]	[54]
SMART ENVIRONMENT						
[37] [45]	[37] [45]	[45]	[112] [99] [14]	[92]		[98]

Support Vector Machine is the algorithm most often used in monitoring applications and the Hidden Markov Model is the algorithm most often used for smart environment systems. Hidden Markov Model [112] and Bayesian Network [92] algorithms are the options for monitoring using a smart environment system, and using several algorithms [54][53][37][45] in a process is also considered provide improved performance.

4.4 Datasets used in Dementia Support Activity Recognition Systems

Publicly available datasets for abnormal behavior of people with dementia do not exist. However, we try to show the source data used in conducting research on dementia. Of the 127 papers studied in more detail, we only have 44 papers that provide information about data sources even though they do not provide access to these data. We group the data to support the activities of people with dementia into real data/cases, simulated data, LIARA, Activities of Daily Living (ADL) datasets, sensor data, smartphone, Alzheimer's Disease Neuroimaging Initiative (ADNI). Fig 5 is statistical of the data usage that we have grouped.

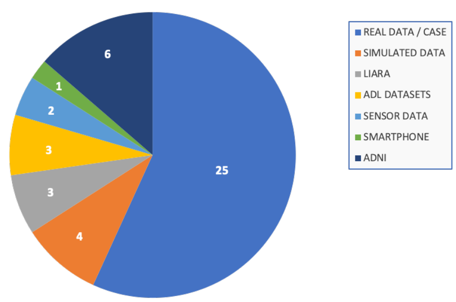

Fig. 5 Data Percentage of Activity Support

5 Discussion

In this paper, we would like to discuss the main findings and areas of future research. We have shown the systematic reviews using methodologies such as search strategy and selection criteria [97][68] we conducted regarding titles and abstracts. By observing and studying more, we can find empty spots for future research. Here monitoring type is very dominant in classification based on application applied for dementia patients from 1999 to 2019. Therefore, dementia patients will be greatly helped if the results of monitoring can prevent dementia patients from doing bad things such as forgetting their routine activities automatically and it is necessary to consider the technology used so as not to disrupt daily activities. This is important because there is no cure for people with dementia [123]. In brief, a solution to this problem is the smart environment. This supporting sensor system is the most popular system for monitoring, analyzing and diagnosing people with dementia. As the explanation of the statement, we can see the smart carpet, posture sensors, bed sensors, and door sensors [40] and RFID [81] that are placed in various places in every corner of the house or recording activities with the video cameras that are placed in the room of the house [60] provides an alternative solution to the problem. This sensor system choice has become very popular because people with dementia have cognitive disorders and irregular activities making it easy to trigger emotions. However, other problems remain because sensor applications such as smart environments or video cameras also still have limitations, if and often dementia patient does not live at home alone. So it will be a problem if the sensor detects a person who is not dementia and performs data calculations on that person, this problem results in a decrease in the level of accuracy when analyzing developing the disease in dementia and must perform activities repeatedly to get the datasets that is more. Especially if the sensor system is implemented in nursing homes or hospitals. Therefore, we need a tool that is able to provide a unique identity to the sensor so that the sensor can do its job properly.

We recommend the most likely solution to the problem is to add a new device that is assigned to identify the object precisely. For now, a smartphone or smartwatch is the right choice to send unique information to the sensor that the sensor has captured the activity of the right person. So that the process of collecting data can also be done in a mass manner and identities that are not likely to be exchanged. This is certainly a big advantage. The sensor will record the activities carried out and the identity of the nearest device to be stored in the database with a cloud system. If the patient's identity has been uniquely identified by the sensor, filtration based on the identity of each patient will be easily carried out. This is a solution that can also be applied to sensors that are used in nursing homes or hospitals. Sensors can distinguish activities performed by patients, nurses, and non-patients. To analyze data from people with dementia, we can eliminate other users than patients in the database. We can also get more data in one day if done at a nursing home or hospital because the activities of many patients are done together, the data obtained and has been stored in a database with a cloud system is also used to training data for next training.

At the same time, using algorithms in data processing becomes important to determine the level of accuracy that is processed from the system. There are SVM, NB and KNN which are the most widely used algorithms in the case of activity recognition for dementia. In our view there is no problem in the algorithm implemented, each algorithm has a good goal to get accurate results. Comparatively, we propose to use more than one algorithm in applying a comparison algorithm [45] [48] or a combination algorithm [58]. Other than the feature requirements for different algorithms, give us information that it needs to do simulations for determining the right algorithm. For example, Flocking-based Algorithms do not require the initial number of clusters, in contrast to K- means which is needed to be. But we still recommend using the classification of machine learning techniques as a method for determining the level of accuracy because it can get new knowledge by utilizing very large amounts of data, besides that machine learning can simultaneously train the activity recognition models, exploiting and recognizing activities from the sensor data [46].

After all, data is still a major problem in research related to technology for people with dementia. Session IV has given us information that there is not much data that developers can get for people with dementia. Although real data or cases are the most widely used, they still require more data [98] [3] [101] [5] the disadvantage of collecting data individually is that we have to do repeat recording of the same way to get more datasets. We recommend adding identity recognition through a smartphone or smartwatch to sensor performance. For this purpose, data recording is not done individually one by one that requires a long time but can be simultaneously in large numbers of people and storing data directly into the database. Meanwhile, smartphones and smartwatches have alarms and GPS which greatly help the system. The goal is as a reminder tool if people with dementia do activities that are not in accordance with the rules that he usually does in daily activity. For another illustration, people with dementia are often stricken with cognitive impairments that can make them confused [8]. With the help of GPS, people with dementia will be easily found and saved. This assists researchers in apprehending the technology implemented and identify the open research problems in this area. This information can be helpful in designing methods, sensors, and algorithms for dementia case solutions.

6 Conclusions

This paper presents the results of a systematic literature review to determine the technological trends used in dementia, which are mostly monitoring, focusing on smart environment applications, and using various methods and algorithms to get the best accuracy from the tests conducted. Dementia sufferers experience memory impairment and have unstable emotions, so technology with the concept of a smart environment that puts sensors, RFID, smartphone, and cameras in several places and products is the right choice to monitor the activities of patients and recognize any changes in people's behavior observed. The individual can experience dementia has symptoms and life changes that may vary resulting in the difficulty of setting fixed rules for each individual, so that it is necessary to diagnose, analyze and monitor regularly for each person. The machine learning classification technique for activity recognition is able to summarize recorded data to recognize the activities of daily life and be able to assess the performance of various algorithms to determine the decision with the best accuracy.

This work has demonstrated the development of technology to help dementia patients and provide insight into the feasibility of systems that might be used in the analysis, diagnosis, monitoring, or other needs. Improved results shown in this paper are done by gathering a lot of information and giving an idea of method solutions that might be better for handling dementia cases.

This research to further understand the benefits that can provide solutions to change the level of monitoring and analysis in more detail for people with dementia to improve quality of life using technological assistance by adding several devices to maximize system performance and warning features so as to prevent people with dementia activities beyond the rules of habit. As future work, combining the type of monitoring-based application that contains several sensors, RFID, smartphones, and data tuning rules will create a system that provides a decision to diagnose directly the level and type of dementia suffered by a patient. Therefore, an approach to the introduction of activities based on types of dementia in daily activities needs to be done and collecting real data becomes very important and helpful. It will get more optimal results if the data can be obtained from several sensor devices [40] [93], RFID [120] [90], smartphones [47], and cameras [60] [50] in one system.

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