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SURVEY

Smart Solutions for Detecting, Predicting, Monitoring, and Managing Dementia in the Elderly: A Survey

SAMPSON ADDAE[1], JUNGYOON KIM[1], ARTHUR SMITH[1], PRIYANKA RAJANA[2], AND MISUN KANG[3]

[1]Department of Computer Science, Kent State University, Kent, OH 44242, USA
[2]Department of Software Convergence, Soonchunhyang University, Asan-si, Chungcheongnam-do 31538, Republic of Korea
[3]Department of Computer Software Engineering, Soonchunhyang University, Asan-si, Chungcheongnam-do 31538, Republic of Korea

Corresponding authors: Misun Kang (ms.kang@sch.ac.kr) and Jungyoon Kim (jkim78@kent.edu)

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ABSTRACT Dementia, a syndrome which is characterized by a decline in cognitive abilities such as memory, thinking, behavior, and the ability to perform daily living activities, is prevalent in people aged 60 and above. However, detecting it early enough can possibly slow its continuous degeneration and lessen the toll on families and caregivers alike. Due to its mortality within 10 years of onset as well as its enormous socioeconomic burden, there have been active efforts by researchers to find smart and innovative solutions for its early detection, prediction, monitoring, and management. These efforts are driven by the recent advancements in the Internet of Things (IoT), wearable technologies, and machine learning algorithms. The solutions are modeled around the modifiable risk factors of dementia. In this study, we conducted a survey of smart solutions developed or implemented to assist caregivers and clinicians in managing the health of these affected individuals. We then looked at the issues and limitations of these solutions, and argued that integrated solutions comprising wearable and non-wearable technologies modeled around multiple risk factors of dementia are necessary and should be the direction of future studies.

INDEX TERMS Dementia, wearable technology, Internet of Things (IoT), non-wearable technology, machine learning, activities of daily living (ADL), Alzheimer's disease (AD), elderly.

I. INTRODUCTION

According to the Alzheimer's Disease International report by Gauthier et al. [1], 55 million people live with dementia worldwide, and this number is expected to rise to 78 million and 139 million by 2030 and 2050 respectively. In the United States alone, it is estimated that approximately 6.7 million people are currently affected by Alzheimer's disease [2]. It is also estimated that 5.2% of people aged > 60 years have dementia on a global scale [3]. This trend poses a great economic burden on governments, families, and other caregivers, as an aging population continues to increase. In a 2022 report by [1], dementia would have been the 14th largest economy in the world if it were a country. Currently it costs US $1.3 trillion to manage this disorder, although soon estimated to reach US $2.8 trillion.

A disorder that impairs cognitive function in mostly, but not exclusively, elderly people, dementia itself is caused by many factors, the most notable being Alzheimer's disease. Stroke, Lewy Body dementia, and alcohol use disorder also contribute. Risk factors include physical inactivity, aging, a low level of education, alcohol use, smoking, sex, and gender [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14]. Although dementia is largely irreversible, it is believed that early detection and treatment can possibly slow the continuous decline. Once dementia is detected at its onset, caregivers can take proactive measures to ensure that its social and economic impact can be mitigated, and elderly people

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who prefer to live alone may be able to manage their daily living activities without being overly dependent on family members.

Owing to the increasing number of people at risk of dementia as well as those already living with the disorder, several diagnostic tools have been used in clinical settings to evaluate cognitive functioning, which sets out the criteria for evaluating and rating the severity of the disease. The tools available are the Diagnostic and Statistical Manual for Mental Disorders (DSM-IV and DSM-5-TR) by the American Psychiatric Association, the Mini-Mental State Examination (MMSE), the Montreal Cognitive Assessment (MoCA) tool, the Clinical Dementia Rating (CDR) scale, and the Global Deterioration Scale (GDS). While the DSM-IV states that memory impairment must be included together with other cognitive domains [43], the DSM-5-TR explicitly highlights the need for evidence of significant cognitive diminution from a former performance level in one or more cognitive domains, namely learning and memory, language, executive function, complex function, perceptual-motor, social cognition, and cognitive deficits that interpose independent daily activities [44]. The MoCA is a 30-point questionnaire that measures visual-spatial ability, naming, memory, attention, language, abstraction, delayed recall, and orientation functions, with a total score of 26 or higher deemed normal, and has an approximately 94% accuracy in identifying Alzheimer's disease [45]. According to [46], the MMSE is a 30-point questionnaire that tests cognitive functioning in orientation, registration, attention, calculation, recall, and language, with a score of 23 or less indicating a cognitive impairment. In [15] and [28], it was observed that the Korean version of the MMSE (K-MMSE) tests for time orientation, place orientation, memory registration, attention and calculation, memory recall, language, and spatio-temporal composition, with a score of 24 or less, as indicative of dementia. While the CDR is used to identify the severity stage of Alzheimer's disease [47], the GDS is used to evaluate and identify the different stages of progressive cognitive decline [48]. With the above cognitive diagnostic tools and recent developments in Internet of Thing (IoT) and wearable technology, researchers have shown interest in developing smart and innovative solutions for the detection, prediction, monitoring, and management of dementia.

Although both IoT and wearable technologies have been leveraged to predict the risk of dementia in the elderly, these studies are still not mature, and therefore, further research is required. The solutions utilize either wearable devices equipped with sensors fitted to the research participants' physical bodies for data collection, or an IoT-based system in the home environment to monitor their Activities of Daily Living (ADL).

In this study, we surveyed recent dementia-related solutions that have been proposed, designed, implemented.

The contributions of this paper are as follows;

- Highlight the current smart solutions for detecting, predicting, monitoring, and managing dementia.
- Present the fundamental tools, technologies and/or devices used for the development of smart solutions tailored for dementia issues.
- Underscore the issues and limitations of current smart solutions for dementia-related problems.
- Summarize publicly available datasets for MCI and dementia-related studies.
- Posit that integrated smart solutions comprising wearable and non-wearable technologies should be the focus of future studies.

The remainder of this paper is organized into eleven sections.

Section II describes the risk factors for dementia. Section III presents current smart solutions and technologies for the detection, prediction, monitoring, and management of dementia. Section IV summarizes publicly available datasets for dementia studies. Section V highlights the data collection and analysis strategies of recent smart solutions. Section VI describes the list of longitudinal studies in the literature while section VII presents the methodology used in this study. The discussion is presented in Section VIII, and Section IX enumerates some of the challenges associated with the integration of smart solutions into existing healthcare systems and how to deal with them. Section X details critical analysis of the state of the art. We then conclude with a summary in section XI.

II. RISK FACTORS OF DEMENTIA

Dementia can be attributed to several risk factors which, if properly managed, can slow its continuous development.

Borelli et al. [5] lists 10 of these risk factors: level of education, physical inactivity, alcohol consumption, active smoking, depression, social isolation, hearing loss, hypertension, obesity, and diabetes. Norton et al. [4] highlighted the following seven modifiable risk factors for dementia: diabetes, midlife hypertension, midlife obesity, physical inactivity, depression, smoking, and low educational attainment. The researchers also asserted that if intervention can be provided to reduce these modifiable risk factors at a rate of 10% every decade, there could be an 8.3% relative reduction in the prevalence of Alzheimer's disease by 2050. This means that every small effort to reduce these risk factors would be critical to improving the cognitive function of those affected, especially as an aging population continues to increase throughout the world. Age, sex and gender, comorbidity, and physical inactivity have also been highlighted as risk factors for dementia [6], [7], [8], [9]. The association between sex differences and dementia risk has also been studied [10], [11], [12]. For [10], in particular, the study could not differentiate between sex differences in either genetic or shared environmental influences on the risk, while Anstay et al. [11] established that women had fewer modifiable risk factors than men. Peeters et al. [12] could not draw a firm conclusion regarding the impact of sex differences on the incidence and prevalence of Alzheimer's disease. To determine the causal relationships between the established causes of dementia, Kuzma et al. [13] reviewed Mendelian randomization studies that investigated the relationship between risk factors and dementia. The study found genetic evidence that supports the relationship between telomere length and Alzheimer's disease with weaker and inconclusive evidence for other risk factors such as smoking. Livingston et al. [14] highlights in the Lancet Commissions 2020 report on Dementia Prevention, Intervention, and Care, 12 established risk factors, namely low education, hypertension, hearing impairment, smoking, obesity, depression, physical inactivity, diabetes, low social contact, alcohol consumption, traumatic brain injury (TBI), and air pollution, all supported by the above-mentioned literature in one way or another.

Recent studies by [84], [85], and [86] showed evidence of an association between long term exposure to air pollution and dementia in the elderly. In particular, Grande et al. [84] and Wilker et al. [85] established in their systematic review and meta-analysis studies that there is an association between ambient air pollution especially, particulate matter 2.5 ($PM_{2.5}$) and Nitrogen dioxide (NO_2) and clinical dementia. Zhang et al. [86] examined the effect of long term exposure to $PM_{2.5}$ on older adults by comparing particulate air pollution from different sources. Evidence from that study indicated that $PM_{2.5}$ may increase the risk of dementia if interventions are not put in place. This could explain why the recent smart dementia solutions discussed in the next section were designed and implemented based on one or more of these risk factors.

A summary of the dementia risk factors is presented in Table 1 below.

III. SMART SOLUTIONS AND TECHNOLOGIES FOR DEMENTIA

As shown in Figure 1, the literature on smart solutions can be classified into wearable, non-wearable, assistive/smart homes, and machine-learning solutions using public datasets.

A. WEARABLE TECHNOLOGY SOLUTIONS

In this section, we discuss proposed wearable technology solutions.

Lim et al. [15] developed a classification model for the early detection of dementia using deep learning. In this study, a smart wearable device comprising an Electrodermal Activity (EDA) sensor for measuring the electrical conductivity of the skin, an accelerometer, and also a temperature sensor was developed to collect data on research participants for a deep learning-based classification model. Godkin et al. [16] assessed the feasibility of using multi sensor wearable devices for people with cognitive limitations as well as neurodegenerative diseases. The study utilized *GENEActiv Original* wearable devices. These devices consisted of a triaxial accelerometer, as well as temperature, light, and cardiography sensors worn on the limbs, bilateral wrists, and chest of the participants. To detect significant moments in people living with dementia, Kwan et al. [17] employed a wearable device consisting of an EDA sensor, a temperature sensor, and a heart rate monitor sensor. The device was worn on the fingertip and supported by an elastic strap to measure the EDA, skin temperature, and heart rate with a connection to an Android phone via Bluetooth. Iaboni et al. [18] used a device worn on the wrist to detect behavioral and psychological symptoms of dementia. The multi modal sensor device consisted of accelerometers and physiological indicators for collecting motion data, blood volume, pulse, EDA, and skin temperature. Lee et al. [22] integrated wearable Electroencephalography (EEG) and Virtual Reality (VR) to screen for mild cognitive impairment (MCI) and dementia. In that study, the behavioral reactions and EEG data collected from the participants were compared between the control and cognitively impaired groups to make determinations. Cherachapridi et al. [23] proposed a time-up-and-go task feature analysis and classification of MCI and dementia using a wearable device. The device, worn on both legs of the participants, contained tri-axis accelerometers and a tri-axis gyroscope to collect data for the classification task. Perugia et al. [24] used EDA to explore diverse arousal states caused by engagement with social robots to improve the quality of care for people with dementia. In [25], [26], and [27], wearable devices were explored to identify and detect agitation in individuals living with dementia. Alam et al. [25] employed a wrist-worn pebble smart watch that featured a tri-axis accelerometer. The inertial motion data of individuals they studied were captured and analyzed to distinguish between the periods of onset, preset, and offset of agitation. To monitor and detect nocturnal agitation, Marcen et al. [26] proposed a wearable device also from *GENEActiv Originals* that has a tri-axis accelerometer to monitor movements of participants with the accelerometry data collected, analyzed, and classified as either a period of agitation or normal. Although [25] and [26] used accelerometers to detect agitation, Melendar et al. [27] used a Discrete Tension Indicator (DTI-2), an EDA sensor developed by Philips Research. The DTI-2 is a single wristband sensor that measures the EDA between two electrodes attached to the skin of the individual. To measure the daily energy intake and total energy expended (TEE) by people living with dementia, Murphy et al. [63] leveraged on the Sensewear Armband, worn on the left upper triceps to monitor physical activity undertaken by the participants. The armband consists of a 2-axis accelerometer, heat flux sensor, galvanic skin response sensor, skin temperature sensor, and a near-body ambient temperature sensor. To detect symptoms of dementia, Bayahya et al. [68] proposed and tested a virtual reality system in their study. The results of the tests were compared with a traditional diagnostic test, the Mini-Cog test. The tests showed that individuals with dementia performed worse in visual-spatial and memory recall tasks compared to those with MCI. Likewise, persons with MCI performed worse compared with the control group for the same tasks. Al-Naami et al. [69] proposed a wireless-sensing smart wearable medical device to monitor and offer real time alerts

TABLE 1. Summary of dementia risk factors.

Ref #	Year	Risk Factor(s)	Geographic Area	Study Objective	Methodology	Findings
[4]	2014	Diabetes, midlife hypertension, midlife obesity, physical inactivity, depression, smoking, and low education	Worldwide, USA, Europe, and UK	To estimate preventive potential by explaining risk factor associations.	Meta-analysis, statistical analysis, and paper reviews	Low education level (19.1% worldwide), physical inactivity (highest in USA at 21.0%, Europe at 20.3%, and UK at 21.8%) are highest PAR.
[5]	2022	Education level, hearing loss, hypertension, alcohol consumption, obesity, active smoking, depression, social isolation, physical inactivity, and diabetes.	Brazil	To estimate the population attributable fraction of modifiable risk factors of dementia in the elderly	ELSI Brazil database used for Population Attributable Fraction (PAF) calculation.	Preventable risk factors contribute to 50.5% of dementia cases in Brazil. Hearing loss (14.2%), physical inactivity (11.2%), and hypertension (10.4%) are significant factors.
[6]	2020	Age, female gender, low education, history of stroke, and unemployment	Indonesia	To investigate dementia prevalence, risk, and early symptoms.	MMSE and Structured questionnaire.	Dementia is prevalent in elderly; caregivers lack early symptom knowledge.
[7]	2019	Unemployment/Wealth	UK	To determine association between socioeconomic status and dementia risk	Cohort study	Wealth is associated with lower dementia risk.
[8]	2021	Physical Inactivity, Low Education level, Smoking, Alcohol consumption, Comorbidity, Ageing	-	To explore new brain health services for primary and secondary dementia prevention	Review of modifiable and genetic risk factors, fluid, and imaging biomarkers for risk profiling	Brain health risk profiling includes multidomain models, APOE E4 status, and Magnetic Resonance Imaging (MRI) if available.
[9]	2022	Physical activity, comorbidity	Abbiategrasso, Milan, Italy	To assess dementia incidence in elderly Italians and examine the influence of walking speed, comorbidity, ApoE-E4, and sociodemographic factors on early onset.	Cohort study	Comorbidity is not linked to dementia onset.
[10]	2022	Age, sex, and gender	Sweden	To explore sex differences in genetic and environmental influences on disease risk and age at onset for various dementia types.	Sampling from Swedish Twin Registry and longitudinal studies of older adults	Genetic influences are equal for all dementia types across sexes. Female co-twins indicate higher dementia risk.
[11]	2021	Aging, physical inactivity, economic hardship, sex, and gender	Australia	To study sex differences in memory decline between men and women.	Cohort study	Higher late-life dementia rates in women due to fewer modifiable risk factors over life and greater susceptibleness to hypertension.
[12]	2021	Sex and gender	-	To assess if women have a higher prevalence and incidence of young-onset Alzheimer's disease than men.	Meta-analysis of dementia risk factors in Pubmed and Embase.	Inconclusive findings on sex and gender differences in dementia prevalence
[13]	2018	Education level, smoking, alcohol consumption, body mass index, telomere length, and diabetes	-	To systematically review Mendelian randomization studies by exploring causal links between risk factors and cognitive function or dementia.	Literature review	Strong genetic evidence links telomere length to Alzheimer's disease, while other risk factors like smoking have weaker and inconclusive evidence.
[14]	2020	Less education, hypertension, hearing impairment, smoking, obesity, depression, physical inactivity, diabetes, low social contact, alcohol consumption, traumatic brain injury (TBI), and air pollution.	Worldwide	To identify and report modifiable dementia.	Literature review & Population attributable fraction (PAF)	12 modifiable risk factors identified.
[84]	2023	Air Pollution $PM_{2.5}$ and NO_2	Sweden	To determine the association of air pollution and dementia risk	Systematic review & meta-analysis	Air pollution is a risk factor of dementia development

TABLE 1. ***(Continued.)*** **Summary of dementia risk factors.**

[85]	2023	Air Pollution $PM_{2.5}$ and NO_2	-	To investigate the role of air pollutants in risk of dementia	Systematic review & meta-analysis	$PM_{2.5}$, nitrogen dioxide and nitrogen oxide may be a risk factors for dementia.
[86]	2023	Air Pollution $PM_{2.5}$	USA	To examine $PM_{2.5}$ and dementia association	Cohort study	Higher concentrations of $PM_{2.5}$ were associated with greater rates of incident dementia.

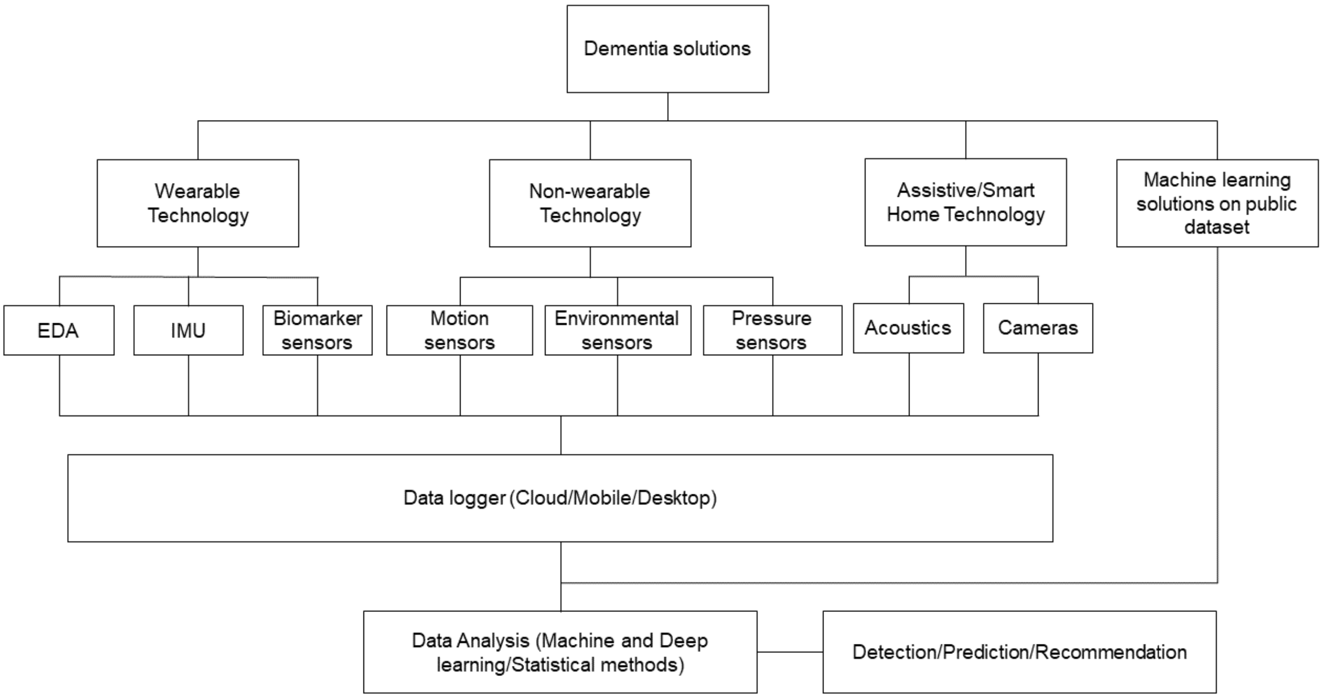

FIGURE 1. **Structure of smart dementia solutions.**

on the daily activities of AD patients. The study employed an accelerometer, gyroscope, oximeter, heart rate sensor, temperature, and GPS as the sensors for the developed system. To find an alternative tool for screening cognitive impairment, Xie et al. [80] employed a wearable sensor-based device for gait measurement in people with amnestic cognitive impairment. In their study, the wearable device consisted of inertial Micro-Electro-Mechanical System (MEMS) sensors fitted under a shoe heel bottom for collecting motion data and transmitting them to a computer for analysis.

Table 2 summarizes wearable technology solutions identified in the literature.

B. NON-WEARABLE TECHNOLOGY SOLUTIONS

In this section, we examine the non-wearable technology solutions employed.

Kim et al. [28] proposed an IoT-based physical activity monitoring system to predict dementia. In that study, the proposed system utilized Passive Infrared Sensors (PIR) installed in defined spaces of the participants' home environments to check for their presence in the defined spaces. Ahamed et al. [29] used a dataset from Cook et al. [49] to identify the early signs of dementia. In [49], motion, light, temperature, pressure, door contact sensors, and actuators were installed in smart homes to monitor the activities of daily living, and from the collected data [29], several features related to dementia were selected to predict the early signs. Ishii et al. [30] developed a machine-to-machine system that employed passive infrared, temperature, humidity, and light sensors. To build an autonomous IoT-based dementia-monitoring system, Li et al. [31] also relied on the dataset from [49] to build an autonomous model for monitoring patients with dementia. Data was collected using motion, light, temperature, pressure, door-contact sensors, and actuators installed in the residences of two people living together. Chong et al. [32] used ambient motion and door contact sensors to collect data to predict the medical conditions of Alzheimer's disease in

TABLE 2. Summary of wearable solutions on dementia detection, prediction, monitoring, and management.

Ref #	Year	Domain Studied	Participants	Results	Description	Data Source	Ground Truth	Data Processing/Analysis	Sensors Used	Pros	Cons	Location Worn
[15]	2022	Dementia	18	Acc. - 99%	A smart healthcare-based system for classification of dementia using deep learning.	Generated from experiment.	K-MMSE	Deep Neural Network with principal component analysis.	EDA sensor, accelerometer, and temperature sensor.	Non-invasive, detection, and classification functions	Small sample size, and limited clinical dementia-related information	Wrist
[16]	2021	Dementia	39	Median adherence to multi-sensor wear - 98%	Feasibility of a continuous, multi-sensor remote health monitoring approach in persons living with neurodegenerative disease.	Generated from experiment.	Pittsburgh Sleep Quality Index (PSQI), General Anxiety Disorder-7 (GAD-7), Quick Inventory of Depressive Symptomology-Self-Report (QIDS-SR), MoCA and modified Ranking Scale (mRS)	Statistical analysis.	light sensor, temperature sensor, electrocardiography, and accelerometer.	Monitors ADL of users.	Discomfort from wearing multiple sensors.	Chest, wrist, and ankle
[17]	2019	Dementia	6	Acc. - 70%	Wearable Technology for Detecting Significant Moments in Individuals with Dementia.	Generated from experiment.	Participants' feedback, video, and interview reviews	Statistical analysis using MATLAB	Triple point sensor (EDA, temperature, and heart rate).	Detects salient moments, open source, and customizable.	Potential overfitting, performance not a true reflection due to missed sessions.	Fingertip
[18]	2022	Dementia	6	Median AUC - 0.87	Wearable multimodal sensors for the detection of behavioral and psychological symptoms of dementia using personalized machine learning models.	Generated from experiment.	Clinically significant agitation events flagged by staff.	Generic and personalized machine learning models	Empatica E4 (EDA, Accelerometer, Blood Volume Pulse, and Skin temperature sensor.)	Indicates importance of multiple sensors for digital biomarkers for detecting behavioral symptoms.	Short battery life for night activities, limited to daytime monitoring.	Wrist

the elderly. Sensors were installed at defined locations in the flats of the participants to detect behavioral patterns. Ianculescu et al. [35] developed a system for monitoring, assessing, and predicting MCI in elderly individuals. This system used a PIR sensor, both temperature and humidity sensors, an altimeter, a pressure sensor, an air quality sensor, an accelerometer, and a gyroscope. The sensors were then used to collect motion, physical activity, and medical and lifestyle data. Lussier et al. [38] developed an IoT-based system to monitor the activities of daily living of an elderly person with Alzheimer's disease. In that study, the researchers employed PIR sensors, magnetic contact sensors, and smart electric switches to collect data from participants in order to understand the clinical relevance of ambient-assisted living in real life, and to help complement the delivery of home care services. Sumali et al. [40] used machine learning based on acoustic features for automatic pseudo-dementia screening to classify patients with both dementia and depression. In this study, participants were engaged in a free-talk session interview using a vertical array microphone, and the sessions were recorded. Features were then selected from the recorded sessions, and machine learning was applied to those features to classify the participant as having depression or dementia based on the quality of the speech recorded during the

TABLE 2. *(Continued.)* **Summary of wearable solutions on dementia detection, prediction, monitoring, and management.**

Ref #	Year	Domain Studied	Participants	Results	Description	Data Source	Ground Truth	Data Processing/Analysis	Sensors Used	Pros	Cons	Location Worn
[22]	2022	Cognitive Impairment	59	Acc. 58.6% - 80.0% for various attention tasks.	Synergy Through Integration of Wearable EEG and Virtual Reality for Mild Cognitive Impairment and Mild Dementia Screening.	Generated from experiment.	Petersen criteria, McKhann criteria, K-MMSE, and GDS.	Machine Learning and Statistical Analysis.	EEG and VR.	Non-invasive, and EEG analysis is self-sufficient, without the need for specialist post-processing.	Requires larger population testing, further study needed for effectiveness.	Face
[23]	2022	MCI & Dementia	54	Acc. - 86.94%, Sensitivity - 97.4%	Prescreening MCI and Dementia Using Shank-Mounted IMU During TUG Task	Generated from experiment.	Thai Mini Mental-Status examination (TMSE) and Diagnostic and Statistical Manual (DSM-V)	Machine Learning, Statistical Analysis, and Pearson correlation	IMU (Gyroscope and Accelerometer)	Successful classification of dementia for preclinical screening	Limited by small training dataset, slightly worse performance for various dementia sub-types	Leg
[24]	2017	Dementia	14	Engagement measure in dementia can be enriched by psycho physiological measures	Explorations in the Psychophysiology of Engagement with Social Robots in Dementia	Generated from experiment.	GDS, Observational Measurement of Engagement (OME), Observed Emotion Rating Scale (OERS) by the experiment's facilitator.	Statistical analysis using SPSS and Observational rating scale	EDA.	Highlights the importance of psychophysiological measures in dementia engagement.	Small sample size, limited diversity.	Wrist
[25]	2017	Dementia	3	Sp. - 58%	Motion Biomarkers for Early Detection of Dementia-Related Agitation	Generated from experiment.	Caregiver observations using a tablet-based app.	Machine Learning (K-mean clustering with PCA).	IMU (Accelerometer)	System differentiates agitation states.	Does not consider Temporal relationships, small sample size.	Wrist

free-talk session. To detect MCI in older people, Teh et al. [58] proposed a fuzzy Adaptive Resonance Associate Map (fuzzy ARAM) neural network for data generated from a smart home sensing environment for 49 participants. The data included physical activity, sleep pattern, and heart rate. Their proposed model achieved an initial F1-score of 58.3% when data from all the participants with missing values were used for training and validation. To further test the effectiveness of the neural network, all missing values were removed and 25 participants' data was used which yielded an improved F1-score of 76.2%. To determine night-time wandering in people living with dementia, Ault et al. [65] employed off-the-shelf motion, window, and pressure sensor solutions in their homes for monitoring activities of dementia patients. The purpose of the study was to detect unattended exits from home, identify risk of falls in dementia patients, and also assess the degree of stress caregivers endure due to wandering of patients at nights. In [66], Tiersen et al. proposed a user-centered approach to designing smart sensing home environments for people with dementia. Their investigation was geared towards the functional, behavioral, and environmental needs of people living with dementia in smart homes. Amiribesheli et al. [67] proposed a tailored prototype for dementia care in smart homes. To improve

TABLE 2. *(Continued.)* **Summary of wearable solutions on dementia detection, prediction, monitoring, and management.**

Ref #	Year	Domain Studied	Participants	Results	Description	Data Source	Ground Truth	Data Processing/Analysis	Sensors Used	Pros	Cons	Location Worn
[26]	2016	Dementia	11	Acc. - 78.86%	Wearable Monitoring for the Detection of Nocturnal Agitation in Dementia.	Generated from experiment.	Reference dataset with controlled movements imitating nocturnal agitation supervised by a medical officer.	Machine learning (SVM).	IMU (Accelerometer)	Scalable protocol for clinical settings.	Difficulty detecting certain movements, possible confusion with normal movements.	Wrist
[27]	2017	Dementia	9	Acc. - 73.5%	Measuring Electrodermal Activity to Improve the Identification of Agitation in Individuals with Dementia.	Generated from experiment.	Structured nursing assistant observations.	Binary logistic regression.	EDA	Simple and easy to use by caregivers and nurses.	Limited in differentiating negative and positive emotions.	Wrist
[63]	2017	Dementia	20	TEE was positively correlated (r=0.52) with BMI & strongly correlated with body weight (r=0.81)	Measurements of daily energy intake and total energy expenditure in people with dementia in care homes:The use of wearable technology	Generated from experiment.	MMSE	Statistical method	heat flux sensor,IMU, galvanic skin response sensor, and skin temperature sensor.	Simultaneously monitors and provides alerts	Small sample size	Left hand

on the acceptability rate, their study considered the specific requirements and needs of dementia patients in terms of their care cycle for the development of the prototype departing from the general approaches. In [70], Tan et al. studied the detection of MCI in elderly people living independently through the monitoring of daily living activities using multi-modal ambient sensors. Using objective sleep quality as a predictor, Chen et al. [71] identified seniors living with MCI. The authors majorly leveraged on bed, PIR, door contact, sensorized medication box, water sensors, as well as Android Phone, and Raspberry pi. To identify changes in daily activity patterns in people living with dementia, Fletcher-Lloyd et al. [76] utilized a PIR motion sensor, a fridge door sensor, a smart plug for the kettle, and at least one smart plug for a toaster, microwave oven appliances to collect activity data. In that study, a Markov chain model was developed for the identification of changes in the daily activities of people living with dementia. Okada et al. [77]

TABLE 2. *(Continued.)* **Summary of wearable solutions on dementia detection, prediction, monitoring, and management.**

Ref #	Year	Domain Studied	Participants	Results	Description	Data Source	Ground Truth	Data Processing/Analysis	Sensors Used	Pros	Cons	Location Worn
[68]	2021	Dementia	115	Demented people performed worse in visuo-spatial and memory recall than MCI people	Smart Health System to Detect Dementia disorders using virtual reality	Generated from experiment.	Mini-Cog test	Statistical method	Virtual reality glass	More engaging and interactive	Requires high powerful computing hardware, users may experience motion sickness, discomfort when using VR	Face
[69]	2021	AD	13	Sp - 95%, 93%	A new prototype of smart wearable monitoring system solution for Alzheimer's patients	Generated from experiment.	The Bland Altman statistical test	Statistical method	IMU, oximeter, heart rate sensor, temperature, GPS	Provisioning of alerts for quick intervention	Data privacy concerns due t o the use of cloud	Wrist
[80]	2019	MCI	68	Walking velocity m/s - 0.96± 0.12	Wearable sensor-based daily Life walking assessment of gait for distinguishing individuals with amnestic mild cognitive impairment	Generated from experiment.	MMSE, MoCA	inertial Micro-Electro-Mechanical System (MEMS) sensors	Easy to use	Lack of non-amnestic participants does not characterize the patterns for the different subtypes of MCI	Feet	

proposed two approaches for predicting dementia scale in patients. In their study, a humanoid robot was provided to the participants for interaction while their indoor activity data was collected using the received signal strength indicators of an access point in the house. Data from the robot interaction and indoor activity were fused as input to 4 different classifiers. Out of the 4 classifiers, Random Forest produced the best result with an accuracy of 87.5%. In [82], Minamisawa et al. developed a machine learning model to classify dementia scale using daily activity data collected from door, motion, location, and sleep sensors installed in the houses of 56 older adults. They then extracted the activity pattern as features and fed it into a Support Vector machine (SVM) model which gave an accuracy of 87.1%. Bertini et al. [83] proposed an autoencoder model for the classification of mild cognitive impairment and early dementia using recorded audio files. In their study, 96 participants were asked to record 3 audio files each with the duration ranging from

10s to 9 minutes resulting in a total 228 audio files. Data augmentation technique was applied to the dataset before feeding it to the autoencoder model. Khosroazad et al. [100] employed the SleepMove device for recording respiratory and movement parameters during sleep without contact with the individual. The researchers recruited 40 participants in their study and the neural network that was applied to the collected data achieved 88% accuracy.

Table 3 summarizes the non-wearable technology solutions identified in the literature.

C. ASSISTIVE/SMART HOME SOLUTIONS

In the literature, assistive/smart home solutions can be wearable, non-wearable, or both. In [19], Roopaei et al. developed an assistive *DeepReminder* wearable glass embedded with artificial perception using deep learning to identify known faces in near real time to help patients diagnosed with Alzheimer's disease with short-term memory issues. Mohammed et al. [20] developed a wearable device that can detect objects, and store their information in a database, thus guiding users to where they might have misplaced valuable items, and is capable of learning new items because it takes pictures of household items that the user could potentially lose. This is an effective memory-assistive device. Kulkarni et al. [21] implemented a backtracking algorithm in a wearable device to assist people with their daily activities. The device can monitor the location of individuals living with dementia, and assist them in returning to their homes in case they are lost, send emergency notifications to their caregivers or family members, and remind them of their daily tasks. Sokullu et al. [33] employed six ambient IoT sensors, including a fluid detection sensor, temperature and humidity sensors, light sensors, gas sensors, and pressure-sensitive mats, to develop a system to ensure the safety of people living with MCI and dementia. An additional wearable sensor was added to the developed system to provide early warnings to assist them in overcoming problems in their daily living activities in emergency situations. Bai et al. [34] explored the sleeping patterns of people living with dementia for precision care, using a motion-sensing mattress. The mattress was built with 30 ON or OFF pressure-sensing areas to detect and prevent bed falls. Boumpa et al. [36] proposed an acoustic-based system to assist in person recognition. The system utilizes smartphones, wristbands, and smart speakers to stimulate the memories of patients when family and caregivers are in their homes. The system is designed in such a way that smartphones or wristbands are given acoustic identification tags connected to a smart speaker via Ethernet, Wi-Fi, or Bluetooth, and a connection to a cloud server that stores information about the family members and caregivers. When a familiar person is detected by the system, a sound is produced by the smart speaker to stimulate the memory of the patient to know that a familiar person is present in the house. To aid independent living and social connectedness in the elderly, Forkan et al. [37] proposed and developed an IoT-based system using motion, latch, pressure, and light sensors. The behavioural patterns of the participants were collected using sensors to automatically detect significant changes in their behavioural patterns. Cheung et al. [41] developed a system to monitor the bedside activities of the elderly at night to prevent wandering using an infrared 3D time-of-flight sensor as well as Ultra-Wideband Impulse Radar (UWB-IR) sensors. Yun et al. [42] utilized RGB-D sensors to monitor and detect the outgoing activities of elderly people to support home care services delivery. To track indoor and outdoor location and walking step information of people with mild cognitive impairment, Garcća-Requejo et al. [72] developed a wearable device comprising Microphone, Buzzer, earpiece, Raspberry pi3, GPS for determining anomalous changes in MCI patients. This was done to locate users when they are disoriented over a long-range Lorawan. Chokri et al. [74] developed a collar wearable device to provide psychological support for people with MCI. The device is capable of performing facial recognition to identify family and non-family families as well as tracking location of patients. To remotely monitor physiological measurements on elderly people living with dementia, David et al. [75] employed a custom application, blood pressure machine, pulse oximeter, body weight scale, and thermometer, and data analytics to aid remote healthcare. The participants recorded physiological measurements once daily and transmitted the readings through the application for analysis. Lim et al. [78] employed a combination of wearable and non-wearable sensors in a clinical setting to validate the performance of ADL tasks. In all, 13 different ADL tasks were performed by the participants and their success rates were measured. The purpose of their study was to clinically corroborate the role of ADL measurements as a digital biomarker for cognitive impairment. Their results showed that people living with dementia had a lower task performance success rate compared to people with MCI and normal people.

Table 4 summarizes assistive solutions identified in the literature.

D. MACHINE-LEARNING SOLUTIONS ON PUBLIC DATASETS

Ahamed et al. [29] and Li et al. [31] relied on the Centers for Adaptive Studies on Advanced Systems *(CASAS)* public dataset to build a model for the detection and prediction of dementia based on the activities of daily living of participants captured in that dataset. While [29] preferred the fine decision tree, K-Nearest Neighbor (KNN), Ensemble boosted, and RUSBoosted based on their F1-score values, [31] preferred the Random Forest because of its interpretability for user trust purposes and high accuracy. Revathi et al. [39] leveraged a publicly available dataset *(Data World Repository)*, and selected the hypertension and diabetes features to build a model for the early detection of cognitive decline. In [50], a deep neural network with scaled Principal Component

TABLE 3. Summary of non-wearable solutions on dementia detection, prediction, monitoring, and management.

Ref #	Year	Domain Studied	Participants	Results	Description	Data Source	Ground Truth	Data Processing/Analysis	Sensors Used	Pros	Cons
[28]	2022	Dementia	18	AUC - 0.99	IoT-based unobtrusive physical activity monitoring system for predicting Dementia.	Generated from experiment.	K-MMSE	Deep neural network with PCA and quantile scaler.	PIR / Door Contact	Energy-efficient, easy to install, non-invasive, detects and predicts dementia risk	Small sample size
[29]	2020	Dementia	-	Acc. - 90.47%	Internet of Things and Machine learning for identifying the early signs of dementia	CASAS	DSM-IV	Machine learning classifiers with K-fold cross validation	Motion sensors, light sensors, temperature, pressure, and door contact sensors	Model can identify early onset of dementia.	Limited dataset, some complementary signs not captured.
[30]	2016	Dementia	1	Acc. - between 80-100%	An early detection system for dementia using M2M/IoT platform	Generated from experiment.	Participants interviewing	Statistical analysis	Motion, sound, Light, kitchen item, and pressure sensors.	System can detect dementia at early stages	Small sample size
[31]	2022	Dementia	2	Acc. - 99.13%	An AIoT-enabled autonomous dementia monitoring system	CASAS.	DSM-IV	Machine learning classifier (Random Forest)	Motion, sound, Light, kitchen item, and pressure sensors	Real-time monitoring to determine normal activity	Small sample size
[32]	2014	Alzheimer diseases	20	-	Predicting Potential Alzheimer Medical Condition in Elderly using IoT Sensors	Generated from experiment	-	Statistical analysis (using Tableau)	Motion sensors.	Monitors behavior pattern, potential early diagnosis system	Poor sensor quality, lack of qualitative data for ground truth verification
[35]	2022	MCI	50	Acc. - 77.5%	Addressing mild cognitive impairment and boosting wellness for the elderly through personalized remote monitoring	Generated from experiment	MMSE and Alzheimer's Disease Assessment Scale-Cognitive (ADAS-Cog)	Machine learning	PIR sensor, Temperature and humidity sensor, Altimeter, Pressure sensor, Air quality sensor, Accelerometer, and gyroscope.	Potential for early MCI detection, supports independent living.	Clinical validation not obtained yet.
[38]	2020	Alzheimer diseases	1	-	Using Ambient Assisted Living to Monitor Older Adults with Alzheimer Disease	Generated from experiment	Caregiver's assessed observations	Statistical analysis	PIR sensor, Magnetic contact sensor, smart electric switches.	Detection of significant behavioral change.	Difficulty determining multiple occupants in the home simultaneously.
[40]	2020	Dementia & Depression	120	Acc. - 89.7%	Speech Quality Feature Analysis for Classification	Generated from experiment	MMSE, GDS, and Hamil-	Machine learning & Statistical analysis	Vertical Array microphone.	Differentiates dementia and depression, good for	Experiment in Japanese, needs

TABLE 3. *(Continued.)* **Summary of non-wearable solutions on dementia detection, prediction, monitoring, and management.**

					of Depression and Dementia Patients		ton depression rating scale			automated screening.	testing with non-Japanese datasets.
[58]	2023	MCI	49	F1-Score - 76.2%	Predictive self-organizing neural networks for in-home detection of Mild Cognitive Impairment	Generated from experiment	MMSE, MoCA, CDR	Deep learning (fuzzy ARAM)	PIR, contact, pressure, a smart-plug, Bluetooth beacon sensors, and heart rate device	Identifies variability of sleep measure as a predictor of MCI	Small sample size
[65]	2020	Dementia	5	Effective for redirection, safety, and allows the caregiver to feel relaxed at nights	Smart home technology solution for night-time wandering in persons with dementia	Generated from experiment	Caregiver feedback	Statistical analysis	Motion sensor, Window Sensor, pressure sensor	Good for monitoring purposes	Small sample size
[66]	2021	Dementia	70	Preventing illness and injury is highly important for patients and caregivers	Smart Home Sensing and Monitoring in Households With Dementia: User-Centered Design Approach	Semi-structured interviews, workshops, and focus groups	Participants feedback	Qualitative analysis	-	Good for new research and development paradigm of IoT smart homes	Privacy in smart home design was not considered
[67]	2018	Dementia	5	System reduces difficulties of dementia care for common care scenarios	A tailored smart home for dementia care	Generated from experiment	MMSE	Statistical analysis	Contact switch, PIR motion, and pressure sensors	Emphasizes unique needs of dementia patients	System usability was ignored
[70]	2018	MCI	17	High forgetfulness, sign of MCI, was detected by the system	Early Detection of Mild Cognitive Impairment in Elderly through IoT: Preliminary Findings	Generated from experiment	Caregiver feedback	Statistical analysis	PIR motion sensor, door contact, bed sensor	Non-invasive and safe	Only 3 features used for analysis
[71]	2019	MCI	49	Recall - 70%	Objective Sleep Quality as a Predictor of Mild Cognitive Impairment in Seniors Living Alone	Generated from experiment	PSQI, GDS, & Clinical Investigator	Statistical analysis	Bed sensor, PIR, door contact, commercially available wearable, sensorized medication box, water sensor	Unobtrusive	Subjective assessment
[76]	2023	Dementia	73	Increase in daytime	A Markov Chain Model for Identifying	Generated from experi-	MMSE	Markov chain modeling	PIR, window, Smart Plug	Anomaly detection is patient or	Model is tailored

TABLE 3. ***(Continued.)*** **Summary of non-wearable solutions on dementia detection, prediction, monitoring, and management.**

				kitchen activity & significant decrease in night-time kitchen activity (t(147) = -2.90, p <0.001).	Changes in Daily Activity Patterns of People Living with Dementia	ment			sensors	household specific	to patient affecting generalization
[77]	2019	Dementia	32	Acc.- 87.5%	Dementia scale classification based on ubiquitous daily activity and interaction sensing	Generated from experiment	Revised Hasegawa's dementia scale (HDS-R)	Machine learning (Random Forest)	Humanoid robot, Access point (bluetooth)	Simple and non-invasive	Cognitive test as ground truth was not performed by professional staff
[82]	2022	Dementia	56	Acc. - 87.1%	Dementia scale score classification based on daily activities using multiple sensors	Generated from experiment	MMSE	Machine learning (SVM)	Door, motion, location , and sleep sensors	Effective for supporting dementia detection	Participants included bed-ridden people with low MMSE
[83]	2021	Dementia	96	Acc. - 90.57%	Automatic speech classifier for mild cognitive impairment and early dementia	Generated from experiment	MMSE, MoCA	Autoencoder, multi-layer perceptron	Olympus-Linear PCM Recorder LS-5	Exploits the potential of automating speech for dementia prediction	Small dataset
[100]	2023	Dementia	40	Acc. - 88%	Sleep signal analysis for early detection of Alzheimer's disease and related dementia	Generated from experiment	MoCA	Neural Networks and Kernel algorithms	SleepMove^{TM}	Safe and non-invasive	Small sample size

Analysis (PCA) was applied to the Korea National Health and Nutrition Examination Survey *(KNHANES)* dataset to predict potential dementia patients. Dhakal et al. [51] applied 9 machine learning classification algorithms to the full feature set from the Open Access Series of Imaging Studies *(OASIS)* dataset to build a model for the prediction of dementia. Out of the 9 algorithms, SVM gave the highest accuracy. Stamate et al. [52] proposed an approach grounded on survival Random Forest and survival Elastic Net to predict the time to dementia onset using the English Longitudinal Study of Ageing *(ELSA)* dataset. In that study, it was found that survival Random Forest outperformed survival Elastic Net with a concordance index (c-index) of 0.851. Kumar et al. [53] proposed a model for the detection of dementia in speech using Machine Learning (ML) and Deep Learning (DL) algorithms. For ML, the algorithms used include SVM, Random Forest, Reduced Error Pruning Tree, and a Random Tree. With respect to the DL methods, an Artificial Neural Network, a Convolutional Neural Network, a Recurrent Neural Network, and a Parallel Recurrent Convolutional Neural Network were all utilized. In [54], Nguyen et al. proposed an ensemble learning model that combines ML and DL using MRI brain images in the Alzheimer's Disease Neuroimaging Initiative *(ADNI)* dataset for training and validation. Reference [55] utilized the National Alzheimer's Coordinating Center Uniform *(NACC-UDS)* dataset to develop a model that identifies the progression of MCI to dementia in individuals.

TABLE 4. Summary of assistive/smart home solutions on dementia detection, prediction, monitoring, and management.

Ref #	Year	Domain Studied	Participants	Results	Description	Data Source	Ground Truth	Data Processing/Analysis	Sensors Used	Pros	Cons	Category	Location Worn
[19]	2018	Alzheimer-diseases		Acc. - 90.68%	A Wearable IoT with Complex Artificial Perception Embedding for Alzheimer Patients	Public dataset (Labeled faces in the Wild)	A personalized patient database for facial features	Deep learning model	Wearable glass	Non-invasive, scalable, and real-time use	Risk of unauthorized access to the system for image uploads.	Wearable	Face
[20]	2019	Dementia	-	Acc. - 92%	An artificially intelligent wearable device for dementia patients	Generated from experiment.	OpenCV saliency detector and K-means clustering on images.	Machine learning	Raspberry pi	High accuracy, locates missing items, learns new and familiar items.	Bulky	Wearable	Face
[21]	2020	Dementia	1	-	An implementation of backtracking algorithm for navigation in LoRa-enabled wearable device for dementia patients	Generated from experiment.	System tested with geofence radius of 1500m	An observational analysis	Lora and GPS	Cost-effective, easy to use, long battery life	Irritating haptic feedback	Wearable	Hand
[33]	2020	Dementia & MCI	2	Acc. - 96.4%	IoT supported smart home for the elderly.	Generated from experiment	Two volunteers acting as MCI patients for a 10-day evaluation. Data recorded and checked against actual actions and activities.	Statistical analysis	Magnetic Reed switches, temperature and humidity sensors, gas sensor, and fluid detection sensors, pressure sensitive mats, and LDR photo-resistance sensors.	Non-invasive, low cost, and energy-efficient.	Small sample size.	Non-wearable	-

El-Geneedy et al. [56] developed a deep-learning based pipeline based on *(OASIS)* Version 3 for the classification and diagnosis of Alzheimer's disease stages. Katsimpras et al. [57] assessed the risk of normal individuals progressing to dementia in the short term and long term given early-stage observations using machine learning. In that study, the short term is within a year and the long term is within 1 to 5 years. Out of 6 models, the under-bagging decision tree produced the best results in both short and long term prediction models with precision of 0.75 and 0.63 respectively. The dataset used for their model was collected from the Oxford Project to Investigate Memory and Aging (OPTIMA). Leveraging on the daily life activities dataset from CASAS (Kyoto) project, Alsubai et al. [59] proposed an automated cognitive health assessment model for the detection of dementia in older adults. Out of the 4 machine learning models and the deep neural network validated, multi-layer perceptron produced the best result with an accuracy of 96%. In [60], Arifoglu et al. applied recursive autoencoders to the Aruba testbed dataset from CASAS to detect dementia-related abnormal behavior. The analysis involved supervised and semi-supervised tests of sub-activities and activity-related anomalies to ascertain the performance of the recursive autoencoders. In the end, the semi-supervised

TABLE 4. *(Continued.)* **Summary of assistive/smart home solutions on dementia detection, prediction, monitoring, and management.**

Ref #	Year	Domain Studied	Participants	Results	Description	Data Source	Ground Truth	Data Processing/Analysis	Sensors Used	Pros	Cons	Category	Location Worn
[34]	2023	Dementia	31	Acc. - 97.4%, AUC - 0.997	Deriving multiple-layer information from a motion-sensing mattress for Precision Care	Generated from experiment.	Daily sleep data compared with established baseline sleep pattern and PSQI.	Machine learning (Multi-layer perceptron).	Pressure sensor	Identifies abnormal situations, helps caregivers communicate with family	Limited generalization to other health conditions, only sleep-related data captured	Non-wearable	-
[36]	2019	Dementia	3	Correct functionality - 100%.	An Acoustic-based smart home system for people suffering from dementia	Generated from experiment.	Tested with one dementia patient and two familiar people in a large room.	Statistical analysis.	Smart speakers, smart phone, smart watch.	Simple and non-invasive	Small sample size	Non-wearable	-
[37]	2019	Elderly ADL	6	Acc. - 94%	IoT solution to assist independent living and social connectedness in the elderly	Generated from experiment.	Participants provided feedback about the efficacy of the system.	Machine learning (LTSM)	Motion sensor, latch sensor, bed sensor, light sensor, and speaker	Captures elderly's behavioral changes, improves social support.	Small sample size	Non-wearable	-

yielded an appreciable accuracy of 78.78% for activity anomaly test and 78.49% accuracy for sub-activity anomaly test. Khalil et al. [64] adopted multi-layer perceptron for a federated learning-based model for the diagnosis of AD. This study leveraged blood bio-sample dataset from Alzheimer's Disease Neuroimaging Initiative (ADNI) website. Both centralized and distributed federated learning were tested in their study for performance evaluation in terms of accuracy and resource utilization. Although the distributed model gave a higher accuracy of 89% compared to 86% accuracy of the centralized learning, memory resource utilization is higher (26%) making the centralized approach the better choice with resource utilization of 10%. To predict and classify categories of dementia, Bansal et al. [73] proposed a superpixel autoencoder technique in their study. The authors used 416 samples of MRI data from the OASIS-1 (OASIS) dataset. Comparing their model with the state of the art works showed that the proposed model is superior with accuracy of 90.2%.

TABLE 4. *(Continued.)* **Summary of assistive/smart home solutions on dementia detection, prediction, monitoring, and management.**

Ref #	Year	Domain Studied	Participants	Results	Description	Data Source	Ground Truth	Data Processing/Analysis	Sensors Used	Pros	Cons	Category	Location Worn
[41]	2022	Dementia	26	Acc. - 99.8%	A Night-time monitoring system to prevent elderly wandering in hostels.	Generated from experiment	A 3D ToF sensor captures a solid silhouette image of an individual with contour shading, with caregiver comments for additional context.	Machine learning	Infrared 3D time-of-flight (ToF) sensor and Ultra-Wideband Impulse Radar (UWB-IR) sensor.	Extendable to fall detection and sleep quality assessment.	Sensor sensitivity minimum distance to bed is low; intrusive	Non-wearable	-
[42]	2019	Dementia	4	Acc. - 91%	A monitoring system to support home health care for the elderly with dementia by detecting going out activities based on RGB-D sensors.	Generated from experiment	Image-searching database for evaluation.	Feature descriptors, chi-squared distance matching and manual (Observational analysis)	RGB-D sensors.	Can notify caregivers of patients' locations.	Limited sensitivity of sensor, manual data analysis, small sample size	Non-wearable	-
[72]	2023	MCI	1	Acc. - 92.8%	Activity Monitoring and Location Sensory System for People With Mild Cognitive Impairments	Generated from experiment	-	Staistical	IR receiver, global navigation satellite system (GNSS), accelerometer, and LoRa	Useful for appreciably long range distance	Requires high capacity battery	wearable	Arm

Abbassian et al. [79] employed the ADNI version 3 MRI-based dataset for building a hybrid convolutional neural network model to classify early mild cognitive impairment and normal cognition. Their model yielded an average area under the curve (AUC) of 86.9%. In [81], Haque et al. applied a convolutional neural network to the MIT GazeCapture and Emory's ADRC dataset for eye-tracking application in efforts to estimating the presence of MCI in users of the mobile version of Visuospatial Memory Eye-Tracking Test (VisMET) with an accuracy of 70%. In that study, the VisMET application was deployed on an iPad and utilized a transfer learning technique to train a deep neural network to track eye gaze through which memory features were extracted to determine the cognitive status of 250 participants for the experiment. To detect transition to MCI at a future time, Narasimhan et al. [99] applied a deep learning algorithm to the Oregon Center for Aging and Technology (ORCATECH) time series-based dataset to learn patterns in daily activities of

TABLE 4. *(Continued.)* Summary of assistive/smart home solutions on dementia detection, prediction, monitoring, and management.

Ref #	Year	Domain Studied	Participants	Results	Description	Data Source	Ground Truth	Data Processing/Analysis	Sensors Used	Pros	Cons	Category	Location Worn
[74]	2022	MCI	162	Acc. - 99.38%	Secure IoT Assistant-Based System for Alzheimer's Disease	-	Deep learning (CNN)	Microphone, Buzzer, ear-piece, Raspberry pi3, GPS, google assistant	Safe and secure	Putting device around all the time makes it uncomfortable	wearable	Neck	
[75]	2023	Dementia	82	median rate of alerts - 0.066 or 0.233 per day per participant	Remote Monitoring of Physiology in People Living With Dementia:An Observational Cohort Study	MMSE	Statistical method	Blood pressure machine, pulse oximeter, body weight scale, and thermometer	Safe and simple to use	No-wearable	-		
[78]	2021	Dementia & MCI	38	Dementia group success rate - 49.3% MCI group success rate - 78%	Clinical application of the experimental ADL test for patients with cognitive impairment: pilot study	K-MMSE, CDR, GDS, Barthel Index Activity of Daily Living (B-ADL), Instrumental Activity of Daily Living (I-ADL)	Statistical analysis	IMU, PIR sensors, frame sensor, stationary resource device, mobile identification device	Potential to help clinicians understand the cognitive level of patients.	Non-wearable & wearable	Hand		

individuals. The dataset consists of activities such as gait and mobility, sleep and activity patterns, medication adherence, and computer use captured by ambient sensors installed in the homes of the participants. The Long-Short Term (LSTM) model developed in the study achieved appreciable accuracy of 83.84%.

Table 5 is a summary of the machine-learning solutions on public dataset identified throughout the literature.

IV. PUBLICLY AVAILABLE DATASET FOR DEMENTIA STUDIES

Throughout the literature, 13 different datasets which are publicly available either through direct download or upon request and approval were used by 19 different studies. These range from facial images, neuroimages, speech, household survey data on health and nutrition status, economic, quality of life of the elderly, activities of daily living in smart homes, as well as chronic disease data. The data world repository contains data about chronic diseases like diabetes, hypertension, etc. This dataset is easily downloadable from the data.world website after signing up. The labeled faces in the Wild (LFW) dataset, which was used by [19] is a list of public benchmarking images used for face verification and can easily be downloaded from the LFW website. The dataset contains over 13000 face images. References [29], [31], [59], and [60] utilized the CASAS dataset for the detection and prediction of dementia and MCI. The CASAS dataset is real data generated from activities of daily living of people in their homes and available for download on the CASAS website. The Open Access Series of Imaging Studies (OASIS), which is a neuroimaging data, was employed by [51], [56], and [73] for predicting dementia and classifying different stages of AD respectively in the literature. While OASIS version 1 is easily downloadable from the OASIS-BRAINS official website, version 3, used by [56], can be downloaded after signing the OASIS data use agreement and access request has been approved. Another public neuro-imaging dataset found in the literature is the Alzheimer's Disease Neuroimaging Initiative (ADNI). This contains MRI brain images collected from study volunteers and used by [54], [64], and [79] in the literature. Access is contingent on completion of data use agreement, request submission, and approval. The Pitt Corpus DementiaBank leveraged by [53] is a speech-based dataset collected from a total of 401 participants with 108 being the control group, 208 living with dementia, and 85 with unknown diagnosis. The data is password protected and requires registration before it can be downloaded. The Korea National Health and Nutrition Examination Survey (KNHANES) is a surveillance system that determines the health and nutritional status of Koreans and also serves as the research infrastructure for studies on risk factors and diseases. This was utilized by [50] to predict dementia in the literature. The data is publicly made available on the official website of KNHANES through registration. The English Longitudinal Study on Aging (ELSA) dataset consists of data on the health, social, well-being, as well as economic situations in the English population for people over 50 years. The data is accessible through the UK Data Service after registration and approval has been given. In [39], the dataset contains chronic disease related data which can be accessed upon request. However, staff of the data holding institution can easily access it by login into the database. The National Alzheimer's Coordinating Center Uniform (NACC-UDS) employed by [55] is a longitudinal data on the cognitive status of participants. The data can be downloaded on a secure website after a requester has received a user name, password, and link (with expiration period) to download the data files. Haque et al. [81] employed the GazeCapture and Emory's ADRC datasets to develop a convolutional neural network model for measuring cognitive impairment in their study. GazeCapture is a dataset for eye-tracking and contains data from over 1450 people with 2.5mil frames while Emory's dataset contains approximately 90000 frames from 250 people. GazeCapture can be accessed after registration and account has been activated whereas a data request has to be submitted for Emory's. In addition, the Oregon Center for Aging and Technology (ORCATECH) dataset was leveraged by [99]. Access to the ORCATECH dataset is by submission of a request via an online form. Table 6 shows the summary of public dataset and their mode of access.

V. DATA COLLECTION AND ANALYSIS

Many approaches have been adopted in the literature for the collection, storage, and analysis of data for systems proposed to detect, predict, and monitor dementia in the elderly population. These approaches use either a smartphone, customized desktop, or cloud database infrastructure for data storage and machine learning, deep learning, and statistical analysis.

In wearable solutions, [16], [17], [24], [63], [68], [69], and [80] used statistical analysis methods in their data analysis. Lim et al. [15] collected and stored sensor-based experimental data using a customized data logger. Features were extracted from the dataset and deep learning classifiers using principal component analysis, and different scalars were used to predict dementia risk in the participants. To mitigate potential overfitting of the model due to small and imbalanced dataset, the authors employed leave-one-subject-out (LOSO) cross validation method in building their model. In [18], [22], [23], [25], [26], and [27], machine learning algorithms, including Logistic Regression, SVM, and K-means clustering, were employed for data processing.

With respect to non-wearable solutions, Kim et al. [28] collected and stored sensor-based data from the experiments using a customized data logger. Here as well, features were extracted from the dataset and deep learning classifiers using PCA, and different scalars were used for the analysis to predict dementia risk. The researchers also employed the LOSO cross validation method to quell potential overfitting. In [29], [31], [34], [35], [58], [77], [82], [83], and [100], machine and deep learning algorithms including Random Forest, Naive Bayes, SVM, neural network, K-Nearest Neighbor, Logistic Regression, Ensemble RUSBoost, autoencoder, fuzzy ARAM, as well as Multi-layer perceptron were explored for data processing. Sumali et al. [40] leveraged both statistical analysis and machine learning for data processing, whereas [30], [32], [33], [38], [65], [67], [70], and [71] used only statistical analysis. For the assistive/smart home solutions, [33], [36], [72], [75], and [78] adopted the statistical analysis approach, and Kulkarni et al. [21] not only used the statistical methods, observational methods were also utilized for the data analysis. Reference [19] and [74] used a deep learning algorithm for training their models. In [20], [34], [38], and [41], machine learning algorithms were used for data processing and analysis. In the machine-learning solutions on the public dataset category, the analyses were all based on machine learning and deep learning algorithms classifiers as in [29], [31], [39], [57], [59], [60], [64], [73], [79], [81], and [99] all relying on publicly available datasets

TABLE 5. Summary of machine learning solutions on public datasets for detecting, predicting, monitoring, and managing dementia.

Ref #	Year	Domain Studied	Results	Description	Data Source	Ground Truth	Data Processing/Analysis	Pros	Cons
[29]	2020	Dementia	Acc. - 90.47%	IoT and Machine learning for identifying the early signs of dementia	Public dataset (CASAS)	DSM-IV	Machine learning classifiers with K-fold cross validation	Model can identify early onset of dementia	Dataset limited to the sensing environment; some complementary signs of dementia onset not captured.
[31]	2022	Dementia	Acc. - 99.13%	An AIoT-enabled autonomous dementia monitoring system	Public dataset (CASAS)	DSM-IV	Machine learning classifier (Random Forest)	Automatically determines a patient's normal activity in real-time	Small sample size
[39]	2022	Alzheimer's diseases	AUC - 0.90	Early Detection of Cognitive Decline Using Machine Learning Algorithm and Cognitive Ability Test	Public dataset (Data World)	Cognitive Ability Test (CAT)	Machine learning (SVM &RF)	Provides earlier and accurate screening for further clinical testing	Risk factor variables are limited to only hypertension and diabetes.
[50]	2021	Dementia	AUC - 0.855	A Deep Neural Network-Based Method for Prediction of Dementia Using Big Data	Public dataset (KN-HANES)	Electronic health records (EHR)	Deep learning (DNN/scaled PCA)	Useful for early detection of likely dementia patients,	Imbalanced dataset and lack of longitudinal data
[51]	2023	Dementia	Acc - 96.77%	Dementia prediction using machine learning	Public dataset (OASIS)	MMSE	Machine learning with least absolute shrinkage and selection operator (LASSO)	Useful for dementia detection in early stages	Manual substitution of missing values in dataset
[52]	2023	Dementia	cindex - 0.851	Predicting Risk of Dementia with Survival Machine Learning and Statistical Methods: Results on the English Longitudinal Study of Ageing Cohort	Public dataset (ELSA)	Informant Questionnaire on Cognitive Decline in the Elderly (IQCODE) and Interviews	Machine learning	Predicts time to dementia onset	High percentage of missing values in dataset and limited to UK population
[53]	2022	Dementia	ML Acc - 87.6% and DL Acc - 85%	Dementia Detection from Speech Using Machine Learning and Deep Learning Architectures	Public dataset (Pitt Corpus of the Dementia Bank)	-	Machine learning and Deep learning	Robust for detecting dementia	Only speech features were used.
[54]	2022	Alzheimer's diseases	AUC - 0.962	Ensemble learning using traditional machine learning and deep neural network for diagnosis of Alzheimer's disease	Public dataset (ADNI)	MMSE & CDR	Machine learning and Deep learning	Faster and reliable prediction of Alzheimer's disease on MRI images	Does not cover detection of mild cognitive impairment.
[55]	2023	Dementia	Acc - 87.5%	A hybrid machine learning approach for prediction of conversion from mild cognitive impairment to dementia	Public dataset (NACC-UDS)	Modified Petersen criteria &DSM-IV	Machine learning	Cost-effective and non-invasive	Based on small dataset

TABLE 5. ***(Continued.)*** **Summary of machine learning solutions on public dataset for detecting, predicting, monitoring, and managing dementia.**

[56]	2023	Alzheimer's disease	Acc - 99.68%	An MRI-based deep learning approach for accurate detection of Alzheimer's disease	Public dataset (OASIS-3)	Modified Petersen criteria	Deep learning	Resilient and high accuracy	Does not predict early stages of AD.
[57]	2022	Dementia	Short-term prec. - 0.75, Long-term prec. - 0.63	Improving Early Prognosis of Dementia Using Machine Learning Methods	Public dataset (OPTIMA)	MMSE	Machine learning	Useful for detecting potential progression of dementia	OPTIMA dataset is imbalanced
[59]	2023	Dementia	Acc. - 96%	Automated Cognitive Health Assessment Based on Daily Life Functional Activities	Public dataset (CASAS)	MMSE	Machine & Deep learning	Provides appreciable accuracy for detecting dementia	Small dataset size
[60]	2021	Dementia	Acc - 78.78%	An Detection of Dementia-related abnormal behaviour using recursive auto-encoders	Public dataset (CASAS)	-	Deep learning (Recursive auto-encoder)	Can be used as an alternative when there is no training set or a limited training set available	Cannot relate one activity to another and neglects temporal information
[64]	2023	AD	Acc - 86%	A Dementia diagnosis technique based on AI and hardware acceleration	Public dataset (ADNI)	-	Machine learning (MLP)	Fast, resource-efficient, and non-invasive	High latency can affect communica-tion between local devices and central server
[73]	2021	Dementia	Acc - 90.2%	A superpixel powered autoencoder technique for detecting dementia	Public dataset (OASIS)	-	Deep learning (au-toencoder)	Scalable, capable of predicting and classifying 3 categories of dementia	Not robust
[79]	2023	MCI	AUC - 86.9%	A Early Mild Cognitive Impairment Detection using a Hybrid Model	Public dataset (ADNI3)	-	Deep learning (CNN)	Appreciable performance for classifying MCI	Cannot be used as a standalone diagnostic tool
[81]	2021	MCI	Acc - 70%	Deep convolutional neural networks and transfer learning for measuring cognitive impairment using eye-tracking in a distributed tablet-based environment	Public dataset (GazeCap-ture & Emory ADRC dataset)	MoCA	Deep learning (CNN)	Scalable	Generalization of the trained model outside the study cannot be assured

and selecting either the relevant features or the full feature set for the models.

In the following studies, either a mobile application, desktop dedicated as a server, or storage platform in the cloud were used for storing sensor-based data, which were then later processed and analyzed using either one or a combination of the two approaches described in this section. Godkin et al. [16] reported that wearable devices were capable of storing data that were collected and later retrieved manually for analysis. In [17], sensor data collection and storage were initiated using an Android smartphone paired with a wearable device via Bluetooth. The data collected in [19] were saved in a database where the matching of image vectors occurs to assist patients with dementia. Images can be

TABLE 5. *(Continued.)* **Summary of machine learning solutions on public dataset for detecting, predicting, monitoring, and managing dementia.**

Ref #	Year	Domain Studied	Results	Description	Data Source	Ground Truth	Data Processing/Analysis	Pros	Cons
[99]	2023	MCI	Acc - 83.84%	Employing Deep-Learning Approach for the Early Detection of Mild Cognitive Impairment Transitions through the Analysis of Digital Biomarkers	Public dataset (ORCATECH)	CDR, MMSE	Deep learning (LSTM)	Inexpensive and non-invasive	It can only be used for initial MCI screening purposes

TABLE 6. **Publicly available dataset for dementia studies.**

Dataset	Year Published	Participants Age group(Yrs)	Number of Participants	Males	Females	Collected Location	Type of dataset	Availability Mode
Data.world [103]	2016	40-65	-	-	-	US centers for disease control and prevention	Chronic disease indicator data (e.g. diabetes, hypertension, etc.)	Available online
CASAS [104]	2013	54 - 75+ years	400	-	-	Smart home environment	ADL	Available online
LFW [105]	2007	-	1680	-	-	Web	Facial images	Available online
OASIS [106]	2007	18 - 96	416	160	256	Washington University Alzheimer Disease Research Center (ADRC)	Neuroimaging	Available online
OASIS-3 [106]	2019	42 - 95	1098	487	611	Washington University in St. Louis (ADRC)	Neuroimaging	Approval required
ADNI [107]	2004 - 2022	55 - 90	822	478	344	Multi-sites (63 sites in US and Canada)	Neuroimaging	Approval required
Pitt Corpus DementiaBank [108]	1994	46.2 - 88.7	281	103	178	University of Pittsburgh School of Medicine	Speech/Audio	Approval required
KNHANES [109]	1998 - present	≥ 1	152137 (1988 - 2011)	72470 (1998 - 2011)	79667 (1998 - 2011)	Korea Centers for Disease Control and Prevention (KCDC)	Health and nutritional status data	Approval required
ELSA [110]	2002 - present	≥ 50	-	-	-	Face-to-face interview and self-administered questionnaire	Health, social, well-being, and economic circumstances data	Approval required
NACC-UDS [111]	2005 - Present	≥ 65	50259	21545	28714	ADRC Clinics	Cognitive Status data	Approval required
GazeCapture [112]	2016	-	1474	-	-	Amazon Mechanical Turk and in-class recruitment at University of Georgia	Eye tracking	Approval required
Emory's ADRC [113]	2005 - present	55.9 - 81.4	3004	1216	1788	Clinical setting	Images	Approval required
ORCATECH [114]	2010	77.4 ± 8.0	233	63	170	Smart home environment	ADL	Approval required

uploaded via a mobile application or web platform. In [22], Lee et al. used an EEG recording device mounted on VR to collect data on the effect of the synergy of combining VR and EEG recordings in the context of cognitive impairment screening, and then applied machine learning classifiers with leave-one-out cross-validation (LOOCV) together with statistical analysis for the entire data analysis work. Lim et al. [15] and Kim et al. [28] stored sensor-derived data using customized data logging computers for processing and analysis.

VI. LONGITUDINAL STUDIES

In the literature, eighteen studies were identified to have utilized the longitudinal approach. These papers relate to modifiable risk factors of dementia, non-wearable solutions, machine learning solutions based on public dataset, and assistive/smart home solutions. These works varied in terms of the number of participants and duration. Out of the eighteen studies, 12 ranged between 0.7 to 5 years. One study lasted for 8 years, 4 ranged between 10 to 17 years while one lasted for 23 years. Duration for 2 works could not be identified.

Although we identified 18 longitudinal studies, it is either the dataset used were collected longitudinally and made public or the researchers conducted their own longitudinal study. In the risk factor area, [5], [10], [84], and [86] all leveraged on data from ELSI Brazil database, Swedish Twin Registry, Swedish National study on Aging and Care in Kungsholmen (SNAC-K), as well as the US Environmental Predictors of Cognitive Health and Aging for analysis to come out with their findings.

With respect to the non-wearable solutions, [38] and [76] conducted their won experiment longitudinally. Similarly, [75] conducted original longitudinal study.

In the area of machine learning solutions, we observed that [51], [52], [53], [54], [55], [56], [57], [64], [73], [79], and [99] employed datasets that were collected longitudinally with varying duration. The longitudinal datasets used in this papers include OASIS, OASIS-3, ADNI, ADNI3, NACC-UDS, ELSA, as well as the Pitt Corpus DementiaBank. A summary of the longitudinal works in the literature is shown in table 7.

VII. METHOD

A. SEARCH STRATEGY

The following keywords were used to perform a general search for recent smart solutions: Studies that focused on detecting, predicting, monitoring, and assisting patients with dementia from 2016 to 2023 were considered, with the exception of one study in 2014, which was included only because of its relevance in predicting potential Alzheimer's disease. With respect to the risk factors of dementia, studies from 2018 to 2023 were considered, except for another one in 2014, which was also included because of its extensive analysis of population-based data for the potential of preventing Alzheimer's disease. Search terms included keywords such as Dementia, Alzheimer's Disease (AD), wearable, IoT, predicting, detecting, smart home, assistive, healthcare, Activities of Daily Living (ADL), Mild Cognitive Impairment (MCI), Cognitive Impairment (CI), Elderly, Unobtrusive, system, IoT-Based, Sensor-based, classification and dementia risk were used for the search in IEEE Xplore, ACM, MDPI, Google Scholar, ScienceDirect, JMIR, and PubMed.

B. STUDY SELECTION

The steps that were followed for the collection of studies are stated below:

- The study should have been conducted between 2016 and 2023 in the case of dementia solutions, and from 2018 to 2023 for dementia risk factors.
- A total of 217 articles focusing on detecting, predicting, monitoring, and assisting patients with dementia, MCI, and AD were considered based on their titles and abstracts.
- The 217 papers were broadly sorted into wearable and non-wearable solutions based on the title, abstract, design solutions, and data collection procedure.
- After a full reading, two more categories, assistive/smart home solutions and machine-learning solutions on public dataset, were created. The former can either be wearable, non-wearable, or both, with the latter relying only on a public dataset for predictions using machine-learning classifiers.
- A total of 64 studies that focused on predicting, detecting, monitoring, and managing dementia were selected.
- An additional 14 studies that focused on the modifiable risk factors of dementia, in which most of the dementia solutions were modeled, were included.

Figure 2 depicts the process flow for the study selection.

VIII. DISCUSSION

The emergence of IoT is helping the transformation of healthcare delivery, and presents opportunities to find innovative solutions to make a positive impact on a populations health. This study aimed at surveying various smart solutions that have been proposed, developed, and implemented for the early detection, prediction, monitoring, and management of dementia patients to assist caregivers and clinicians manage their health. Solutions developed or proposed in previous studies are either wearable or ambient sensor-based solutions. These homogeneous solutions introduce limitations to the collection of datasets for the analysis and prediction of dementia risk, monitoring, and management of patients. In the case of wearable devices, researchers are able to collect the dataset at the instance of the device being worn by the participant. Likewise, the non-wearable solutions are based on ambient sensors, and the dataset is collected when participants are present in the smart environments setup for the study.

TABLE 7. Longitudinal studies in the literature.

Ref #	Author(s)	Domain studied	Participants	Duration
[5]	Borelli et al.	Risk factor for dementia	9412	2 years
[10]	Beam et al.	Risk factor for dementia	13559	2 to 5 years
[38]	Lussier et al.	Dementia	1	490 days
[51]	Dhakal et al.	Dementia	150	1707 days
[52]	Stamate et al.	Dementia	7556	14 years
[53]	Kumar et al.	Dementia	204	5 years
[54]	Nguyen et al.	AD	204	5 years
[55]	Bucholc et al.	Dementia	37568	13 years
[56]	El-Geneedy et al.	Dementia	1098	15 years
[57]	Katsimpras et al.	Dementia	164	8 years
[64]	Khalil et al.	Dementia	821	5 years
[73]	Bansal et al.	Dementia	150	1707 days
[75]	David et al.	Dementia	82	2 years
[76]	Fletcher-Lloyd et al.	MCI & Dementia	73	427 ± 257 days
[79]	Abbassian et al.	MCI & Dementia	446	5 years
[84]	Grande et al.	Risk factor for dementia	2512	23 years
[86]	Zhang et al.	Risk factor for dementia	27857	10.2 years
[99]	Narasimhan et al.	MCI & Dementia	265	33 months

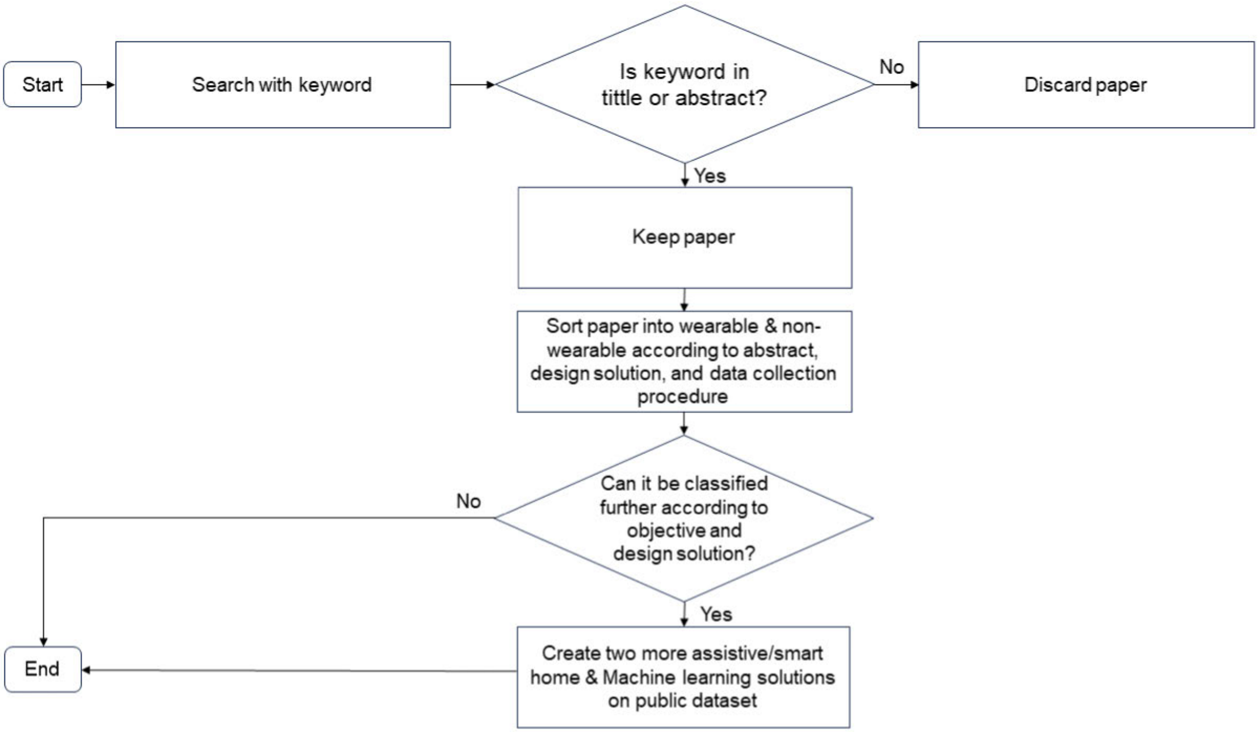

FIGURE 2. Process flow for the studies selection.

In the following sub-sections, we discuss some of the limitations and issues observed in the literature.

A. THE NUMBER OF PARTICIPANTS

One major challenge in conducting research of this nature involving human individuals is the number of participants. The number of participants indicates the amount of a dataset that can be collected. As can be seen in Tables 2 and 3, the average number of participants for the various studies in both wearable and non-wearable solutions were 31 and 37 respectively. Though these numbers are not bad, it is imperative to note that by the end of the study and data pre-processing begins, some participants' data and other missing values might not be useful for analysis purposes due to damaged sensors or participants who stopped wearing their device. Their non-compliance poses a risk of getting only a small amount of data from the study. On the other hand, the absence of participants in the smart environment setup in the case of the non-wearable solution also increases the likelihood of obtaining a sparse amount of data which may occur when participants are often involved in outdoor activities. This suggests that the higher the number of participants, the larger the amount of data that can be collected and thus the better the reliability and generalizability of the results.

B. GENERALIZABILITY

The generalizability of a study is crucial to its adoption and acceptance. The problem that limits the generalizability of the solutions in the literature albeit their effectiveness to detect, predict, monitor, and manage dementia in the elderly is the issue of an imbalanced dataset. This arises due to the classification of the participants from the results of dementia evaluation tools like the MMSE and MoCA. It is either the number of participants classified to be at risk of dementia is in the majority or in the case in Lim et al. [15] and Kim et al. [28] where out of eighteen participants used for the studies, only four were at risk of dementia according to the MMSE results, therefore the minority. Feeding such an imbalance dataset into a machine learning model requires innovative techniques to obtain a balance which comes with its own advantages and disadvantages. This limits the generalizability of the model. Therefore, further studies which involve a greater number of patients will be required to test both the reliability and generalizability.

C. SENSING TECHNOLOGIES (DEVICES)

Be it a wearable or non-wearable solution, the use of commercially available off-the-shelf sensors is the fundamental means of collecting dataset for the studies. The type and quality of sensors used for the studies contributes greatly to the amount and quality of dataset. The energy efficiency of the devices is a major concern, and determines how long a device can run continuously for data collection. In the wearable solutions, devices mostly need to be battery-powered to enable participants move about freely in their daily activities. Any reasonable limitation on the energy capacity of the devices means that data cannot be generated continuously thereby reducing the amount of data. As observed in Iaboni et al. [18], the short battery-life of the multi-modal sensors limited data collection to daytime activities thereby missing significant behavioral and psychological symptoms of dementia at night. Device management becomes tedious and time-consuming. There has to be a conscious effort in periodic replacement and recharging of batteries in environments where there is no source of electrical power.

With respect to the non-wearable solutions, the sensitivity range of the sensors, as well as poor communication signals between sensors and gateways due to physical structures and location of sensing devices in the sensing environment impacts the data collection process. In Kim et al. [28], PIR devices used were limited to 8m range and 120 degrees coverage. Any activity outside this range and angular coverage cannot be captured by the device if the sensor is installed in a wider space.

D. GROUND TRUTH

The correctness and reliability of smart dementia solutions are hinged on the availability of ground truth information. To be able to evaluate the correctness of a solution and make inferences from it, there should be a gold standard to match the performance or output of the solution against it. In as much as ground truth information is crucial to the validity and correctness of the solution, this was disregarded by Chong et al. [32] which then introduces some limitation to their findings. It is imperative that a study of this nature be validated with ground truth information to boost confidence in the solution and enhance the level of acceptance. With the availability of MMSE, DSM-IV and DSM-5-TR, MoCA, GDS, and CDR as established and accepted diagnostic tools for cognitive impairment, we underscore their usage as a fundamental source of ground truth information for dementia solutions as observed in the literature. In the absence of these tools, other qualitative approaches such as participant feedback, observations, and professional opinion can be employed.

E. MACHINE LEARNING OR STATISTICAL ANALYSIS

In the literature, we observed that either machine learning, statistical methods or both were employed in the proposed solutions. However, with the advancements in machine-learning algorithms and innovative features they present for building models, it is important to underscore the limitations that come with the statistical analysis albeit its strength in making inferences about the relationship between two variables. In statistical analysis, there is always the assumption of linear relationships between variables in which non-linear relationships may not be captured. This presents a difficulty in capturing complex interactions between different risk factors of dementia for modeling a smart solution for dementia-related problems. Moreover, the manual selection of features in statistical analysis requires domain or expert knowledge. The lack of domain knowledge poses a risk of omitting important features for the model and thus not performing well on new and unseen datasets. As the datasets grow, it becomes computationally expensive and infeasible to rely on statistical approaches for smart solutions. However, with machine-learning, models are capable of selecting features automatically, then performing better on new and unseen datasets for predictions when training and validation are done appropriately.

Although statistical methods are useful for predictive modeling, it is imperative to highlight the need for complex machine-learning models for smart solutions as the aging population increases and innovative solutions are being proposed and implemented to aid in the activities of the elderly.

F. PRIVACY ISSUE

The collection and analysis of sensitive information regarding the personal health data of patient subjects raises privacy concerns. Conscious efforts have to be made to ensure that the data is collected non-invasively where the privacy and security of the data is maintained to avoid unauthorized access and potential misuse. Obtaining informed consent of participants to use their data for smart solutions is a necessity. However, because individuals living with dementia have cognitive impairments, it is important to involve relatives, caregivers, and legal representatives to aid in the decision process to participate or not. Solutions that track participants' health conditions, behaviors, and habits over time raise concerns issues as to how the profiled information may be used. These concerns raise trust and acceptance of the proposed solutions especially by elderly individuals who are not accustomed to technology. In Cheung et al. [41], we observed that 3 elderly individuals refused to participate because of privacy concerns raised as result of the use of 3D ToF sensor that is capable of taking images of individuals.

With the aforementioned issues, it is important to note that some data protection and privacy measure like encryption is implemented as part of the solution to avoid unauthorized access and misuse of the data thereby boosting confidence, trust, and acceptance of the solution.

G. WEARABLE VS. NON-WEARABLE TECHNOLOGY

Wearable and non-wearable technologies each offer unique advantages and challenges in the context of smart solutions for detecting, predicting, monitoring, and managing dementia in the elderly. Wearables, such as smartwatches and fitness trackers equipped with IMUs, EDA, and biomarker sensors, provide continuous, real-time monitoring of health parameters like physical activity, sleep patterns, and even cognitive functions through dedicated applications. This continuous data stream can offer comprehensive insights into a patient's health and detect early signs of dementia. However, the accuracy of wearables may be influenced by sensor quality and user compliance. Non-compliance becomes prominent in wearable cases as users tend to remove the device due to comfort issues. We observed in the literature only one study achieved accuracy above 90% while five were below 90%. In contrast, non-wearable solutions like smart home systems equipped with sensors can assess daily activities and detect deviations from normal behavior, providing a continuous, less invasive, and more accurate form of monitoring. This correlates with our identification of three studies in literature that achieved accuracy above 90%.

In terms of cost, smartwatches are generally expensive but wearables are generally more affordable and accessible. However, there may be recurring expenses for replacements and updates. Non-wearable technologies often have higher start-up costs due to the need for specialized equipment and installation yet can be cost-effective afterwards. In terms of patient compliance, wearables tend to promote better adherence as they are designed for convenience and can be easily integrated into daily routines. This is crucial for elderly patients, who may find frequent clinical visits burdensome. However, non-wearable technologies may face challenges in patient adherence such as where cameras are installed, privacy may be of concern.

H. EMERGING SOLUTIONS

With ethical and privacy issues becoming prominent in smart health solutions, there has to be a shift from the current approach to smart solutions for elderly care. One of such solutions is Tiny Machine Learning (TinyML) which offers a promising solution for dementia care, and represents a significant advancement in the future of health monitoring management. TinyML involves deploying machine learning algorithms on low-power, resource-constrained devices, enabling real-time, intelligent data processing directly at the edge. This technology is particularly suited for dementia care, where continuous, unobtrusive monitoring of patients is crucial. By integrating TinyML into wearable devices and smart home systems, it is possible to detect early signs of cognitive decline, monitor daily activities, and alert caregivers to potential issues without relying on constant internet connectivity or expensive cloud computing resources. The low power consumption and cost-effectiveness of TinyML make it an accessible and sustainable option for long-term care, potentially improving the quality of life for individuals with dementia and easing the burden on caregivers and healthcare systems.

TABLE 8. Comparison of wearable and non-wearable technologies.

	Wearable Technology	Non-Wearable Technology
Accuracy	Moderate	High
Cost	Moderate	Initial cost high
Patient Compliance	Low	Moderate

Moreover, the integration of cognitive training applications, social robots, and voice-activated assistants like Amazon Alexa and Google Home can provide support for dementia patients by enhancing cognitive function, offering companionship, and assisting with daily tasks and reminders, ultimately contributing to a comprehensive and effective care solution.

IX. INTEGRATION OF SMART SOLUTIONS AND EXISTING HEALTHCARE SYSTEMS

Integrating wearable and non-wearable smart solutions into existing healthcare systems is a multidimensional challenge that necessitates careful consideration of many factors. To guarantee smooth connection and data transmission, interoperability problems between various devices and electronic health record (EHR) systems must be resolved first. This means removing obstacles to compatibility and creating standardized integration methods. Furthermore, in order to comply with strict legal standards such as Health Insurance Portability and Accountability Act (HIPAA) and General Data Protection Regulation (GDPR), strong security measures are required to protect patient information from breaches and unauthorized access.

Furthermore, healthcare companies must manage the challenges of workflow integration, merging new data streams and insights into existing clinical processes while maintaining efficiency and quality of treatment. Scalability is another major challenge. healthcare systems must support the growing volume of data generated by wearable and non-wearable devices, demanding infrastructure, storage capacity, and analytics updates. Along with these technological prob-

TABLE 9. Comparison of state-of-the-art on smart solutions for dementia surveys & reviews.

Ref #	Author(s)	Year	Wearable	Non-Wearable	Assistive/Smart Home	Artificial Intelligence	Modifiable Risk Factors
[61]	Quek et al.	2023	No	No	No	Yes	No
[62]	Lawson et al.	2023	Yes	Yes	Yes	No	No
[87]	Harper et al.	2020	Yes	No	No	No	No
[88]	Subetha et al.	2020	Yes	No	No	No	No
[89]	Li et al.	2022	No	No	No	Yes	No
[90]	Cote et al.	2021	Yes	No	No	No	No
[91]	Yehuda et al.	2021	Yes	No	No	No	No
[92]	Waleed et al.	2022	Yes	No	No	No	No
[93]	Petra et al.	2018	Yes	Yes	No	No	No
[94]	Dhakal et al.	2019	Yes	No	No	No	No
[95]	Chimamiwa et al.	2022	No	Yes	No	No	No
[96]	Moyle et al.	2021	No	Yes	No	No	No
[97]	Puterman-Salzman et al.	2023	No	No	No	Yes	No
[98]	Asiri et al.	2023	Yes	Yes	Yes	No	No
[101]	Lyall et al.	2023	No	No	No	Yes	No
[102]	Parsapoor et al.	2023	No	No	No	Yes	No
[This work]			**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

lems, financial considerations are important, as the adoption and maintenance expenses of these technologies may strain resources for healthcare institutions with restricted budgets.

In addition, assuring user adoption and acceptance by healthcare professionals and patients is critical, often requiring training and educational activities. Overcoming these difficulties requires coordination among healthcare stakeholders, technology vendors, regulatory authorities, and other interested parties. By successfully negotiating these challenges, healthcare organizations may capitalize on the transformative potential of wearable and non-wearable technologies to improve patient care, increase operational efficiency, and drive healthcare delivery innovation.

To address these challenges, particularly security, blockchain technology can be adopted at the edge to protect data generated by wearable and non-wearable devices. As highlighted by Nguyen et al. [115], blockchain technology provides privacy and security by creating an immutable ledger for managing patient medical records as data is generated. In that study, the researchers successfully integrated a lightweight mobile-edge computing (MEC) framework with blockchain in IoT applications, showing improved performance, privacy, and security compared to existing solutions. Given that privacy is a major concern, we believe that utilizing blockchain and TinyML to address security and privacy issues in dementia care can significantly enhance the general acceptance of smart solutions and their integration into existing systems.

X. STATE OF THE ART

Reviews and surveys related to smart solutions for older adults living with dementia and MCI have gained interest due to the applications of wearable, IoT, assistive, and AI technologies in recent times.

In [87], [88], [90], [91], [92], and [94], the authors focused their reviews, comparative analysis, meta-analysis, explorations, and evaluations on wearable solutions for dementia studies. Harper et al. [87] performed a systematic review of wearable devices used for predicting dementia-related agitation. In that study, the strengths and weaknesses of the sensors were assessed. The authors suggested the development of an inexpensive device which measures EDA, heart rate, and limb movements using accelerometer to improve on accessibility for use in broader studies and real-world applications. However, they ignored the detection and prediction of the onset of dementia. Subetha et al. [88] conducted comparative analysis of assistive technologies for the early detection and prediction of dementia with the objective of projecting wearable technologies for dementia solutions. While their study considers the early detection and prediction of dementia, it does not consider remote monitoring and managing of dementia patients. To evaluate studies that employ wearable technology in dementia patient care, Cote et al. [90] carried out a systematic review and meta-analysis of identified literature. They concluded that the studies were limited by their heterogeneity, incapable of classifying dementia sub-type and stage, and lack of corroboratory clinical trials. Whereas we consider the modifiable risk factors of dementia to inform the choice of technology to be implemented, the researchers did not consider these factors and also ignored the early detection, prediction, monitoring, and managing of dementia. In [91], Yehuda et al. explored the opportunities in the current studies on wearable sensors for gait analysis in older adults living with dementia. They underscored the effectiveness of wearable devices in the measurement of gait activity levels, and posited that further research works that employ standardized protocols should be undertaken to examine the impact and usefulness of wearable devices in gait-related features like fall prediction and early diagnosis in people living with dementia. Their study gave no attention to non-wearable and other assistive smart home solutions that non-invasively help in the early detection, monitoring, and managing of dementia patients. Waleed et al. [92] undertook a review of wearable devices for people living with AD. The purpose of the study was to explore the state-of-art wearable technologies for Alzheimer diseases. However, this study failed to acknowledge the availability and application of AI and non-wearable technologies in the care of people living with AD whereas our study encompasses wearable, non-wearable, as well as artificial intelligence technologies. Dhakal et al. [94] reviewed and proposed a framework for indoor and outdoor monitoring of patients living with dementia. They analyzed wearable devices and their mode of data collection and transfer, data accessibility during storage, and throughout analysis. While our study focused on wearable, non-wearable, AI solutions, their study concentrated on only wearable devices.

To assess the effectiveness and capabilities of non-wearable-based smart home solutions, Chimamiwa et al. [95] and Moyle et al. [96] surveyed and reviewed existing literature. Specifically, Chimamiwa et al. surveyed state-of-the-art on activity recognition and anomaly detection in smart homes for elderly individuals living with dementia. They argued that activity recognition and anomaly detection lack the capability to recognise occupants' habits, changes in habits, and the loss of habits, which can potentially indicate a transition in the dementia stage. In [96], Moyle et al. reviewed existing studies to ascertain the effectiveness of smart home technologies to aid the health outcomes of community-dwelling older people living with dementia. They asserted that success of smart home technologies to support people living with dementia is unclear and proffered recommendations for future works in smart home technologies for community-based dementia care.

In [61], [89], [97], [101], and [102], the researchers underlined AI techniques and solutions for dementia-related studies in their works. Quek et al. [61] performed a scoping review on the use of AI techniques for detecting mild cognitive impairment. While we looked at all forms of smart solutions including wearable, non-wearable, assistive, AI, as well as the risk factors of dementia and MCI, the focus of their study was to explore the AI techniques available for the detection of MCI. They identified 4 categories of AI for MCI studies. The authors concluded by highlighting the significance of AI in MCI detection, and emphasized the need for public interests in making large datasets available for the development of effective AI models for healthcare delivery. Li et al. [89] reviewed the capabilities applying artificial intelligence (AI) for the development of digital biomarkers for early detection of dementia. They were of the view that future directions for developing new digital biomarkers to assist early detection of dementia may include smart environments, non-invasive tests, and overcoming the challenge of integrating different digital biomarkers to multi-modal tools more accurately. In their study, data generation, which is a critical input to AI models, monitoring and managing of dementia patients were ignored. On the contrary, in our study, we cover the generation of data by proposing the integration of wearable and non-wearable solutions. Puterman-Salzman et al. [97] conducted a scoping review to consider and evaluate AI technologies for the early detection of dementia using motion data. This study identified the use of either machine learning, deep learning or hybrid algorithms with AUC, accuracy, sensitivity, specificity, and f1-score being the widely used performance metrics. Although they looked at other studies that used motion data, the focus was on the application of AI in making predictions, whereas our work focused on multiple technologies including wearable, non-wearable, AI, assistive smart homes, as well as modifiable risk factors of dementia. Lyall et al. [101] performed a narrative review of applied models and digital health for predicting dementia risk, diagnosis, prognosis, and advancement. The authors concluded by advocating for melioration in applied modeling is beneficial to the exploitation of digital health. In this article, we considered the risk factors and technologies including wearables and non-wearables which influence the type of smart solution employed in AD studies. Parsapoor et al. [102] reviewed AI and non-AI assessments for dementia to provide AI developers information and insight into non-AI assessments, techniques, and available datasets for the development of AI solutions.

To identify digital approaches for assessing activity of daily living-related behaviors in people living with MCI, Lawson et al. [62] performed a systematic review on the studies that have employed digital methods. In that study, ambient motion and contact sensors were found to be the most commonly used methods. The risk factors of MCI which inform the choice of solution and AI technologies were not considered in their study whereas our work encompasses all these domains. In [93], Petra et al. performed a review of technological solutions for elderly people living with AD. The objective of their study was to summarize the use of technological solutions for ameliorating the health and safety for people with AD. They recommended that policy makers and care providers should collaborate with technology developers and researchers on strategies for the implementation of assistive technologies in different care environments. In [98], Asiri et al. reviewed different monitoring technology devices for the care of older people living with cognitive impairment. In their study, the risk factors and application of AI technologies were not the focus, whereas we considered a holistic approach to smart solutions for detecting,predicting, monitoring, and managing dementia.

Table 9 shows a comparison of the state-of-the-art studies with our work.

XI. CONCLUSION

This study aimed to highlight smart solutions that have been proposed, developed, and implemented recently to detect, predict, monitor, and manage dementia in the elderly. This was necessary because of both the increasing number of elderly people and the number of risk factors present for dementia in this population. This paper helps shed more light on the direction of the current studies and solutions. It also presents opportunities for new solution paradigms to improve existing solutions. We further argue that an integrated solution comprising wearable and non-wearable technologies with multiple risk factor variables is necessary and should be the focus of future studies.

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SAMPSON ADDAE received the B.S. degree in computer science from the University of Cape Coast, Cape Coast, Ghana, in 2011, and the M.Sc. degree in project management from the Kwame Nkrumah University of Science and Technology, Kumasi, Ghana. He is currently pursuing the Ph.D. degree in computer science with Kent State University, Kent, OH, USA. From 2012 to 2019 and from 2019 to 2022, he was a Project Coordinator and the Project Manager at Huawei Technologies (Ghana) SA Ltd. responsible for optical transport network deployment and managed services respectively. He is also a Graduate Teaching Assistant and a Student Researcher with the Smart Communities and IoT Laboratory. His research interests include the Internet of Health Things, smart communities, embedded systems, machine learning, and TinyML.

JUNGYOON KIM received the B.S. degree in electronics and the M.S. degree in electrical and computer engineering from the University of Ulsan, South Korea, in 2004 and 2006, respectively, and the Ph.D. degree in information sciences and technology from Pennsylvania State University, University Park, PA, USA, in 2014. He is currently an Assistant Professor of computer science with Kent State University, where he is also the founding Director of the Smart Communities and IoT Laboratory. His research interests include smart health and well-being, especially in real-time cardiovascular disease and stress monitoring, physiological sensor designs, and intelligent analytics for decision supports; environmental monitoring and assessment movement monitoring; and ubiquitous computing, especially in embedded system designs, energy-efficient processing, and programming model for networking performance.

ARTHUR SMITH received the B.S. degree in biochemistry from Youngstown State University, Youngstown, OH, USA, in 1998, the M.D. degree from the College of Medicine, Northeast Ohio Medical University, in 2002, and the M.S. degree in computer science and information systems from Youngstown State University, in 2021. He is currently pursuing the Ph.D. degree in computer science with Kent State University. From 2002 to 2005, he was a Family Medicine Resident at the Mercy Hospital, Youngstown. From 2006 to 2008, he was an Emergency Resident at Metropolitan Hospitals, New York, NY, USA. Afterward, he was an attending Emergency Physician Faculty Member at Mercy Hospitals, from 2008 to 2019. He is also an Assistant Professor of emergency medicine with Northeastern Ohio Medical University. He also enjoys understanding the mathematical mechanisms behind deep learning. His research interests include deep learning optimization of the electrocardiogram, cuffless blood pressure modalities, and the use of natural language processing for medical home use.

PRIYANKA RAJANA received the bachelor's degree in electronics and communication engineering from the Avanthi Institute of Engineering and Technology, India, in 2017. She is currently pursuing the master's degree with the Department of Software Convergence, Soonchunhyang University, South Korea. Her research interests include image processing and video anomaly detection.

MISUN KANG received the B.S., M.S., and Ph.D. degrees in computer science and engineering from Ewha Womans University, Seoul, South Korea, in 2007, 2012, and 2017, respectively. She was a Research Fellow with the Department of Computer Science and Engineering, Ewha Womans University. She was also a Staff Engineer at Samsung Display. She is currently an Assistant Professor with the Department of Computer Software Engineering, Soonchunhyang University. Her research interests include computer graphics, virtual reality, and bio-medical image processing.