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Device Name	Z-Wave / ZigBee	Voice Assistant Compatibility	Upfront Costs	Professional Installation Required	Power Outage Backup	Monthly Fees	Monitoring Contract Required	IFTTT Support	Cellular Backup
ADT Pulse	Yes	Amazon Alexa	Start at $49	Yes	Yes	Start at $28.99	Yes	No	Yes
Vivint Smart Home	Yes	Amazon Alexa, Google Assistant	Start at $99	Yes	Yes	Start at $39.99	No	No	Yes
SimpliSafe Home Security System	No	Amazon Alexa	Start at $229	No	Yes	Start at $14.99	No	No	Yes
Ring Alarm Security Kit	Yes	Amazon Alexa	Start at $199	No	Yes	Start at $10	No	No	Yes
Blue by ADT Home Security System	Yes	Amazon Alexa, Google Assistant	Start at $149.99	No	Yes	Start at $19.99	No	Yes	Yes
FrontPoint Safe Home	Yes	Amazon Alexa, Google Assistant	Start at $99	No	Yes	Start at $44.99	No	No	Yes
Honeywell Smart Home Security Starter Kit	Yes	Amazon Alexa, Google Assistant	Start at $449	No	Yes	Start at $4.99	No	Yes	No
Wyze Sense Starter Kit	No	Amazon Alexa	Start at $19.99	No	No	None	No	Yes	No
Abode iota All-In-One Security Kit	Yes	Amazon Alexa, Google Assistant	Start at $299	No	Yes	Start at $8	No	Yes	Yes
Nest Secure	No	Google Assistant	$399 as tested	No	Yes	Start at $19	No	No	Yes

Table 1: A comprehensive table of commercial smart home devices and their feature

Reference	Sensors	Activities	Purpose
Yamazaki (2007)	Video cameras, microphones, floor pressure,motion, RFIDs	Watching TV, cooking, tracking personal items	Behaviour monitoring, tracking personal items
Patel et al. (2008)	Air pressure	Not mentioned	Residents' location
Rantz et al. (2008)	Video cameras, bed pressure, stove door CSS, motion	Cooking, sleeping, walking in the house	Resting hours, behaviour monitoring
Viani et al. (2013)	Signal strength of wireless devices	Not mentioned	Resident's location
Wilson and Atkeson (2005)	Motion detectors, Pressure mats, CSSs, RFIDs	Eating, bathing, dressing, toileting, cooking,watching TV	Resident's location, behaviour monitoring and prediction
Baker et al. (2007)	Accelerometer, Blood pressure readings, microphones, heart rate, temperature	Movement, blood pressure changes, speech, sound	Healthcare monitoring
Intille et al. (2005)	Infra-red cameras, microphones, pressure mats, motion, water and gas flow, light switches	Cooking, socializing, sleeping, cleaning, relaxing, working	Behaviour monitoring
Noury and Hadidi (2012)	Motion	Not applicable	Producing elderly's life scenario
Riedel et al. (2005)	Video cameras	Getting home and watching TV, eating while watching TV, Reading	Behaviour monitoring
Le et al. (2008)	Motion, CSSs	Bathing, dressing, toileting, eating	Behaviour monitoring
Wood et al. (2008)	Heart rate, movements, ECG, pulse oximeter, weight, pulse monitoring	Toileting, sleeping, showering, eating and drinking, walking,	Healthcare monitoring, behaviour monitoring
Cook et al. (2013a)	Motion, CSSs	Bathing, walking, cooking, eating, relaxing, personal hygiene, sleeping, taking medicine	Behaviour monitoring
van Kasteren et al. (2008)	Motion, CSSs	Toileting, showering, eating and drinking, walking,	Behaviour monitoring

Table 2: Sensors used by various studies [1]

References	Algorithm	Target	Results
Mozer (1998)[9]	ANN (MLP)	ADL (general)	–
Cook et al. (2013b) [4]	ANN (MLP)	ADL (general)	Activity recognition: 64 %
Rivera-Illingworth et al. (2005)	ANN (EcoS)	ADL(healthcare)	Anomaly detection: 74.57 % Activity recognition: 89.14 %
Li et al. (2008)[8]	ANN (OPNN)	ADL (healthcare)	Activity recognition: 92 %
Lotfi et al. (2012)	ANN (ESN)	ADL (healthcare)	Abnormally detection: 93–99 %
Isoda et al. (2004)[6]	DT (C4.5)	ADL (general)	Activity recognition: 90–100 %
Ravi et al. (2005)[10]	DT (C4.5)	ADL (general)	Activity recognition: 57–97.29 %
Manley and Deogun (2007)	DT (ID3)	Resident's location	Mean error in location: 4.9m and 2.5m on 2 datasets
Hagras et al. (2004)[5]	ISL (fuzzy)	ADL (general)	280 rules generated in 72 h
Hagras et al. (2007) [11]	Fuzzy type-2	ADL (general)	RMSE of 0.229
Bouchachia (2011) [2]	GFMMNN (fuzzy?ANN)	ADL (general)	Current error rate reached 0.01
Andreu and Angelov (2013)	Evolving fuzzy classifiers	ADL (general)	F-measure in 60–70%
Bouchachia and Vanaret (2014) [3]	GT2FC (fuzzy)	ADL (general)	81.65% Accuracy for 70% labelled data
Chua et al. (2009)	HMM	ADL (healthcare)	90.75 % behaviour-level recognition accuracy 98.45 % observation-level recognition accuracy
van Kasteren et al. (2010)[12]	HSMM	ADL (general)	F-measure of 65.5 %
Gu et al. (2009)	EPs	ADL (general)	85.84% Average accuracy by time-sliceing
Riboni et al. (2011)	Ontological approach	ADL (general)	80.3 % Accuracy

Table 3: Algorithms used by various studies [1]

Scenario :	Possible Threads	Security Goals Compromised	Degree of Impact
SH1	Eavesdropping (N) Traffic Analysis (N) Message Modification (N) Replay Attack (N) EMS Impersonation (SH)	Confidentiality Integrity Authenticity	L-M
SH2	Repudiation (N) Message Modification(N) Replay Attack (N)	Non repudiation Integrity Authentication	M
SH3	Tampering/Reversal/ Removal of Meter (SH) Illegal Software Modification/Update(SH)	Authentication Integrity	L
SH4	Customer Impersonation (N) Device Impersonation (SH) Message Modification(N) Replay attack(N) Repudiation(N)	Integrity Non repudiation Authentication	L – H
SH5	Customer Impersonation(N) Eavesdropping/Message(N) Interception (N) Message Modification(N)	Confidentiality Integrity Authenticity	L-M

Table 4: Smart Home Security Issues [7]

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