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Sensors for Falls and Fall Detection Techniques: From the past to the future

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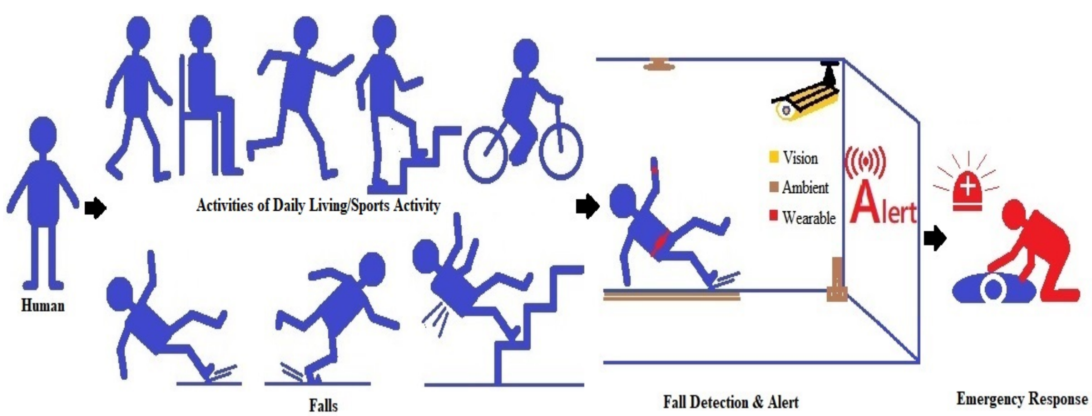
ABSTRACT



Falls are the major problem of today's world and are a serious public health hazard. As per WHO reports, a large number of deaths and injuries occur every year due to falls. The cost of falls and their consequences presents a great issue for the government as well as for society in public health care. Detection of true falls is a great challenge in the public health care area more specifically for Elderly people. A reliable fall monitoring system is necessary for the detection of falls and for reducing their effects. Hence, an automatic fall detection system is a favorite topic among researchers for more than the last two decades. The advancement of technologies and IoTs in the last few years has enabled the area of automatic fall detection and immediate assistance to mitigate the fall consequences among researchers and healthcare industries. The objective of this paper is to provide a detailed review and discussion on falls and various sensors, technologies, and algorithms introduced by different researchers. The literature search has collected and surveyed 100 related studies from referred journals and conferences based on the keywords. Among these studies, the 54 most relevant and influential articles were chosen for detailed analysis from various perspectives like type, sensors, hardware/software, methodology, and performance. The detailed analysis and findings of this review would help the researchers for understanding various trends, technologies, and challenges available in this area and guiding them in their future directions.

Keywords: Fall detection, Fall alert system, Fall prediction, Elderly fall, Elderly health, Falls

INTRODUCTION

Falling is one of the serious and major public health problems in today's world. Falls are the prominent reason for external causes of unintentional injury and death. The second leading cause for accidental or unintentional injury deaths across the world are falls and an estimated 6,84,000 individuals each year die from falls worldwide of which more than 80% are from middle and low-income countries.[1] WHO projects 80% of elders will be living in middle and low-income countries in 2050.[2] Falls account for 40% of all injury deaths and the majority of fall-related hospitalizations are due to bone fractures, upper-limb injuries, hip fractures, Spinal cord injuries, Traumatic brain injuries among which 20% of hip fracture patients die within a year after fall.[3] Globally, approximately 37.3 million falls are severe enough that will require medical attention each year which results in over 38 million DALYs (disability-adjusted life years) lost with 40% DALYs lost

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occurs only in children.[1] Falls result in 20-30% of mild to severe injuries and are an underlying reason for 10-15% of all emergency department visits that requires a hospital stay of the patient varies from 4 to 20 days.[3] According to the WHO report, in 2004, globally 424000 deaths occur due to falling, out of which 95000 (20%) occurs only in India and this number rises to 160000 in India for 2005.[4] Falls and successive injuries are a major public health issue that frequently requires medical assistance.

Due to medical technology and drug advancement, the life expectancy of people increases, as a result, the number of older adults rises throughout the world. According to the World Health Organization(WHO) people having the age of 60 years and above are defined as older adults. The number of people over the age of 60 years is growing at the highest rate of 3.26%/year than any other age group.[3,5,6] People aged 60 years or above were 901 million in 2015, 1 billion in 2020 which represents 12% of the global population, and this count is projected to be 1.4 billion by 2030 and 2.1 billion by 2050 which will represent 22% of the global population. [2,5,7] In China, Canada, Western Europe, and Chile older adults will represent at least 30% of the population in 2050 and in Japan, older adults already represent 30% of the population.[7] As the age increases, the cognitive, sensory, and physical ability of a person reduces which will increase the risk of falls. The frequency of falls increases with age and frailty level and adults over 65 years of age suffer the highest fatal falls.[1] Approximately 28-35% of people aged 65 years and above fell each year and the falling rate increased to 32-42% for those over 70 years of age.[3] Falls lead to 50% & more of hospitalizations due to injury among people above 65 years and around 30-50% of people fell each year who lived in long-term care institutions, and recurrent falls has been observed by 40% of them.[3] As per the study, India 14-53%, China 6-31%, Japan 20%, Barbados 21.6%, Chile 34% of older adults fell each year.[3,8]

Falls and subsequent injuries will result in a financial burden due to medical assistance and hospitalization. It also results in the burden on the caregiver, loss of productivity of family caregiver, and loss of earnings of an individual. The economic impact of falls is critical to family, community, society, and government.[3] Fall prevention and treatment is a challenge to the government as well as to society as the number of old age people increases worldwide and are most prone to falls. Fall injuries like fractures, traumatic brain injury, spinal cord injury have remarkably increased by 131% during the last three decades and if preventive actions are not taken soon then the number of injuries caused by falls is projected to be 100% higher in the year 2030.[3] So the detection of falls is very important in the study of falls as well as in the prevention and treatment of fall-related injuries. The time for which the elderly remains lying on the floor after falling is one of the key parameters that determine the severity of a fall.[9] Timely detection of falls helps in immediate assistance by the caregiver or medical team and reduces the negative effects of falls.[10] Recent research in the area of early detection of falls may enable prevention or minimizes the effects of falls and fall-related injuries. An automatic fall detection system may minimize the burden on the healthcare system, reduces 24x7 need for a caretaker, and increase the independent living of elderly people. Table 1-4 summarizes the age related fall data.

Table 1. Number of deaths in India due to Fall[4]

Year	2004	2005
Deaths in India due to Fall	95000	160000

Table 2. Elderly Population Projection[2,5,7]

Year	2006	2015	2020	2030	2050
Elderly Population >60 years	688 million	901 million	1 billion	1.4 billion	2.1 billion

Table 3. % of Fall in Elderly people per year in different age[3]

Age	≥ 65 years	> 70 years
% of Fall in Elderly people per year	28 – 35 %	32 – 42 %

Table 4. % of Fall in Elderly people per year in different countries[3,8]

Country	India	China	Japan	Barbados	Chile
% of Fall in Elderly people per year	14-53%	6-31%	20%	21.6%	34%

Human motion activities and Falls

The classification of human motion activities is shown in Figure 1. Various motion activities performed by a human are mainly divided into two categories: Voluntary/intentional motion activities and Involuntary/unintentional motion activities. Voluntary/intentional activities include Activities of Daily Living(ADLs) and Sports activities. Activities that are performed by a person on daily basis are called ADLs like standing, walking, running, sit in to/out of a chair/sofa, getting in or out of bed, lying, climbing/descending stairs, bathing, brushing, dressing, etc. Sports activities include cricket, football, swimming, racing, basketball, gymnastics, etc.

Involuntary/unintentional motion activity is Body imbalance which is further classified into Fall and Near-fall situations. Fall is defined as “inadvertently coming to rest on the ground, floor or other lower level, excluding intentional change in position to rest”.[3] Different types of falls are front fall, back fall, right side fall, left side fall, falls from walking or standing, falls from sitting on/ standing from a chair, slip on a wet floor, falling on stairs, stumbling on an obstacle during walking, forward fall on the knee, etc.[11,12] The near-fall situation is one in which a person’s body imbalances and starts falling but recovered him/her self before complete fall and is also known as recoverable fall.[13] In the near-fall situation, a person will gain his/her balance either by self-controlling or by getting the support of hand, leg, railing, or any surrounding things.

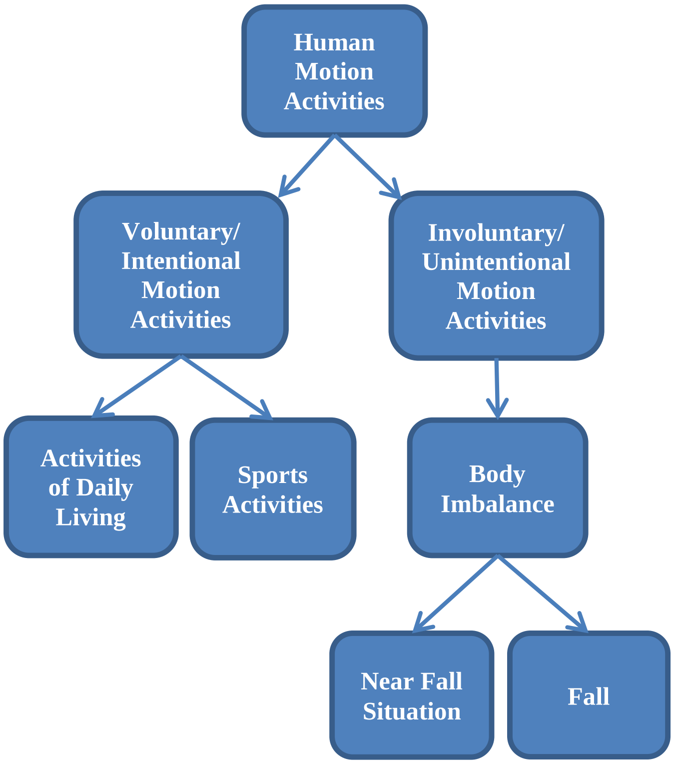

Figure 1. Human Motion Activities.

Falls: Causes and Consequences

There are many causes of falls as shown in Figure 2. Few of them are personal and few of them are environmental. Falls occur as a result of complex interactions of personal and environmental factors that will directly or indirectly affect the health of an individual. The causes of falls are mainly divided into four categories: Biological, Behavioural, Environmental, and Socioeconomic.[3] Biological factors are the inert characteristics of an individual that are related to the human body. Age and gender are unchangeable biological factors. As age increases the ability to control body movements and actions decline as a result, the risk of falls is highest in older adults. Along with unconsciousness, Chronic illnesses like Parkinson's, seizures, arthritis, paralysis, and osteoporosis can also increase the risk of falls. With the aging effect, the physical, affective, and cognitive capability of a person also declines which also increases the fall risk. Behavioral factors include those regarding human actions, reactions, emotions, habits and daily choices. Behavioral risk factors like multiple medication use, excess alcohol intake, carelessness in routine work, lack of exercise, inappropriate footwear, etc. will also increase the risk of falls. The behavioral risk factors are potentially modifiable by an individual to reduce the risk of falls. Environmental factors include the interaction of an individual's physical condition and surrounding environments like home hazards and hazardous features in the public environment.[3] Environmental factors themselves alone can not cause falls, but the interaction of human action with these factors can cause falls. Environmental factors like narrow steps, wet and slippery floors and stairs, obstacles in path, looser rugs, insufficient lightning, cracked or uneven sidewalks, poor building design, etc. are home and public hazardous features that will cause falls.[3] Socioeconomic factors are those which influence the social conditions and economic status of individuals as well as the ability of the community to challenge them.[3] Socioeconomic factors like low education level, low-income level, inadequate housing facilities, lack of social interactions, lack of community & safety resources, and limited access to health & social services especially in remote areas will increase the risk of falls.[3]

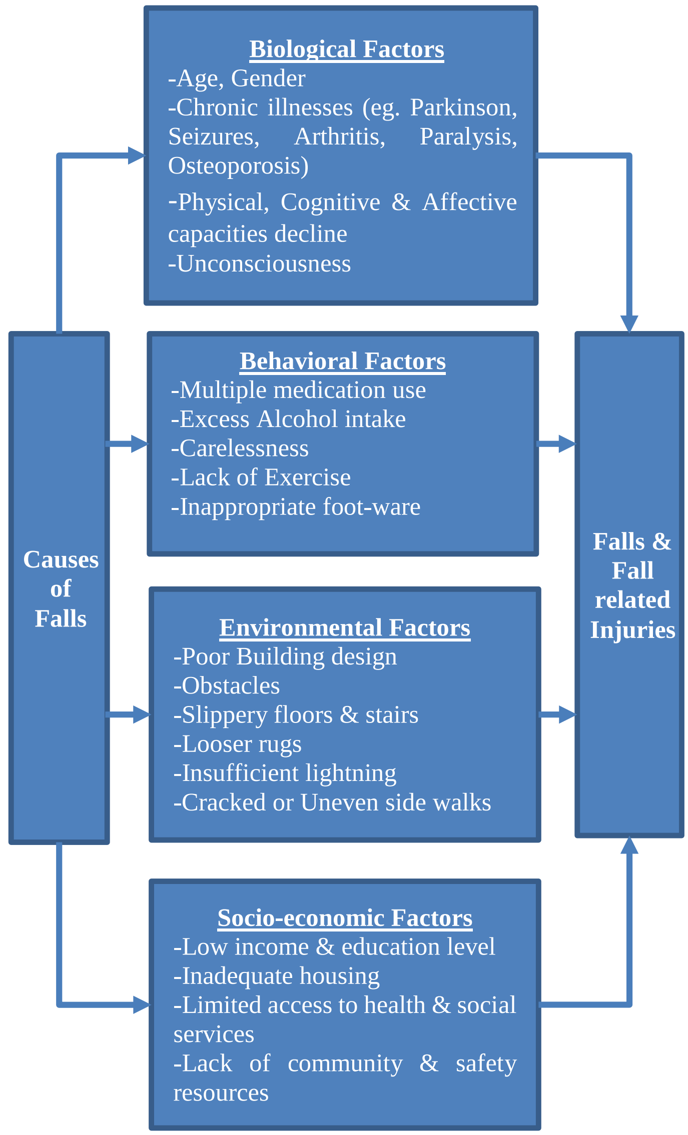

Figure 2. Causes of Falls.[3]

The consequences of falls are shown in Figure 3. The consequences of falls are mainly divided into five categories: Physical, Financial and Medical, Psychological, Social, Governmental, and Community.[14] Physical consequences of falls include possible injuries like bone fracture, hip fracture, soft tissue injury, spinal cord injuries, traumatic brain injuries, etc., pain, bedrest and discomfort of the patient, reduced mobility and possible long-term disability of the patient, loss of independence and ability

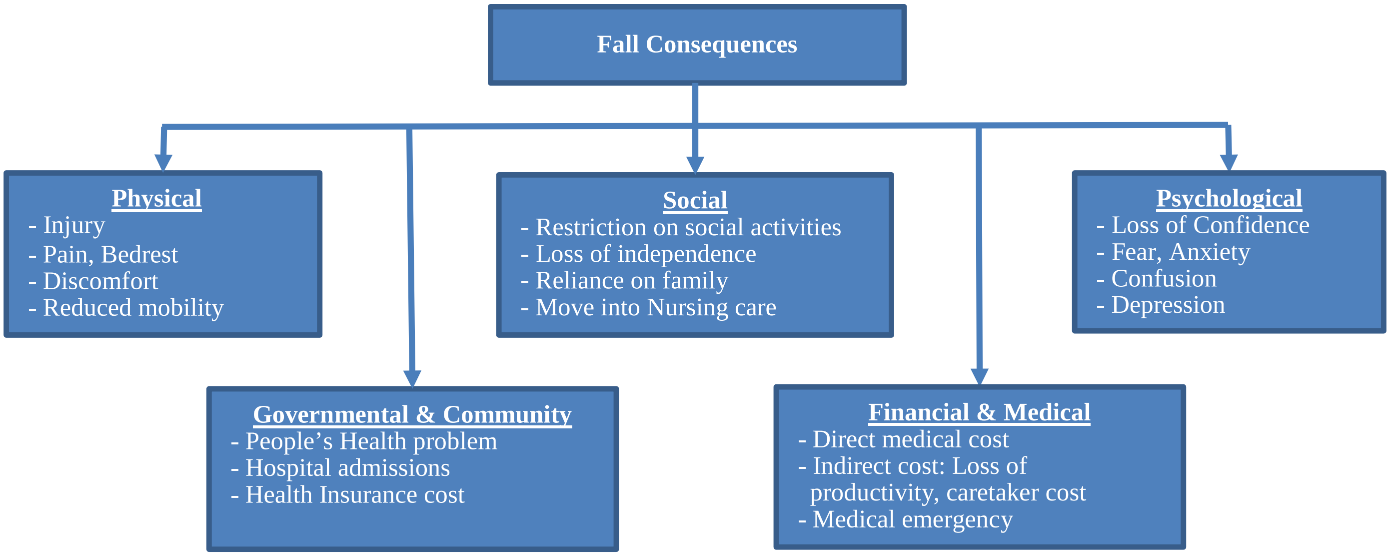

Figure 3. Consequences of Falls.[14]

to look after him/her self.[14] Psychological consequences result in a lack of confidence while walking and moving due to increased fear of repeated falling, confusion, fear and anxiety, distress, depression, and embarrassment.[3,14] Social consequences of falls lead to restriction of possible routine social and daily activities, loss of autonomy and reliance on family, friends, or caretakers, and possibly move into nursing care centers or aging homes.[3,14] Financial and medical consequences include medical emergencies, direct health care costs of hospitalization and medications along with required services like consultation charges, physiotherapy, rehabilitation, hospital and social care, outpatient services after discharge.[3,14] The indirect cost of falls signifies the loss of productivity of an individual as well as a family caregiver which results in terms loss of income and financial burden.[3] The average cost of fall-related injury hospitalization for people of the age of 65 years and above varies from US$ 6646(Ireland) to US$ 17,483(USA) and this cost is estimated to rise to US$ 240 billion by the year 2040 only in the US.[3] In India, the average cost of hospitalization is US$ 835.[8] The falls will result in average lost earnings of approximately US$ 40,000 per year in the UK.[3] Governmental and community consequences represent that falls can have highly destructive effects on public health and greatly increases the hospitalization of patients along with increases the health insurance costs.[3] As the old age population increases worldwide, it is very difficult for the government, society, health care organizations to prevent elderly falls and to provide effective treatment for falls.

Fall Detection Techniques

Over the last two decades, many researchers have contributed significantly to various fall detection techniques. For accurately detecting different types of falls several different techniques are required. Fall detection techniques should be able to differentiate Activities of Daily Living(ADLs) from falls and accurately detect the fall. The major challenge is that few ADLs look like falls that are correctly omitted in fall detection. Various types of fall detection techniques are shown in figure 4. Based on the type of sensor and device used, the fall detection techniques are divided mainly into four categories: a) Vision sensor-based b) Ambient sensor-based c) Wearable sensor-based d) Multimodel sensing.[15]

Vision sensor-based

Cameras are generally employed in vision-based fall detection systems which will provide a naturalistic approach to detect human falls without any intrusion on the human body. Vision-based systems make use of RGB camera, RGB-Depth camera, infrared vision sensor, or marker-based system.[15] RGB cameras provide a rich source and good accuracy in detecting human falls and are widely used in surveillance applications. The RGB-Depth camera can capture depth images in addition to routine RGB images for creating a 3-D image. Infrared vision sensors with low resolution are employed to reduce privacy issues. In visual marker-based techniques, cameras are employed only to track the visual markers placed on the human body instead of capturing RGB images and are mostly used in gait analysis and body motion analysis.

Ambient sensor-based

The ambient sensor-based fall detection techniques make use of proximity sensors, light sensors, audio-visual sensors, floor vibration sensors, ultrasonic sensors, radio frequency sensors, and pressure sensors to collect the data on physical activities of a person from the surrounding environment. The interaction between Human motion activities and the output of ambient sensors can be used for the detection of a person's physical activities and falls.

Wearable sensor-based

Advancements in technologies like telecommunication, microelectronics, sensor manufacturing, BioMEMS, embedded systems with miniature circuits, wireless data transmission, and powerful batteries are encouraging to design such systems small enough for people to carry and use in the digital health monitoring system. Nowadays, wearable sensors are small enough so they can be integrated into various personal accessories and gadgets such as garments, wrist watches, necklaces, shoes, hats, wristbands, socks, eyeglasses, gloves, headphones, smartphones, etc. Different wearable sensors used for human fall detection are an accelerometer, gyroscope, electronic compass, magnetometer, ultrasonic sensor, pulse rate sensor, force sensor, wearable camera, etc.

Multi-model sensing

Multi-model sensing uses two or more types of sensors at the same time to achieve more comprehensive and reliable information about human activities. The sensing mechanism can use two or more types of methods discussed earlier like a combination of two or more from vision, ambient or wearable sensors.

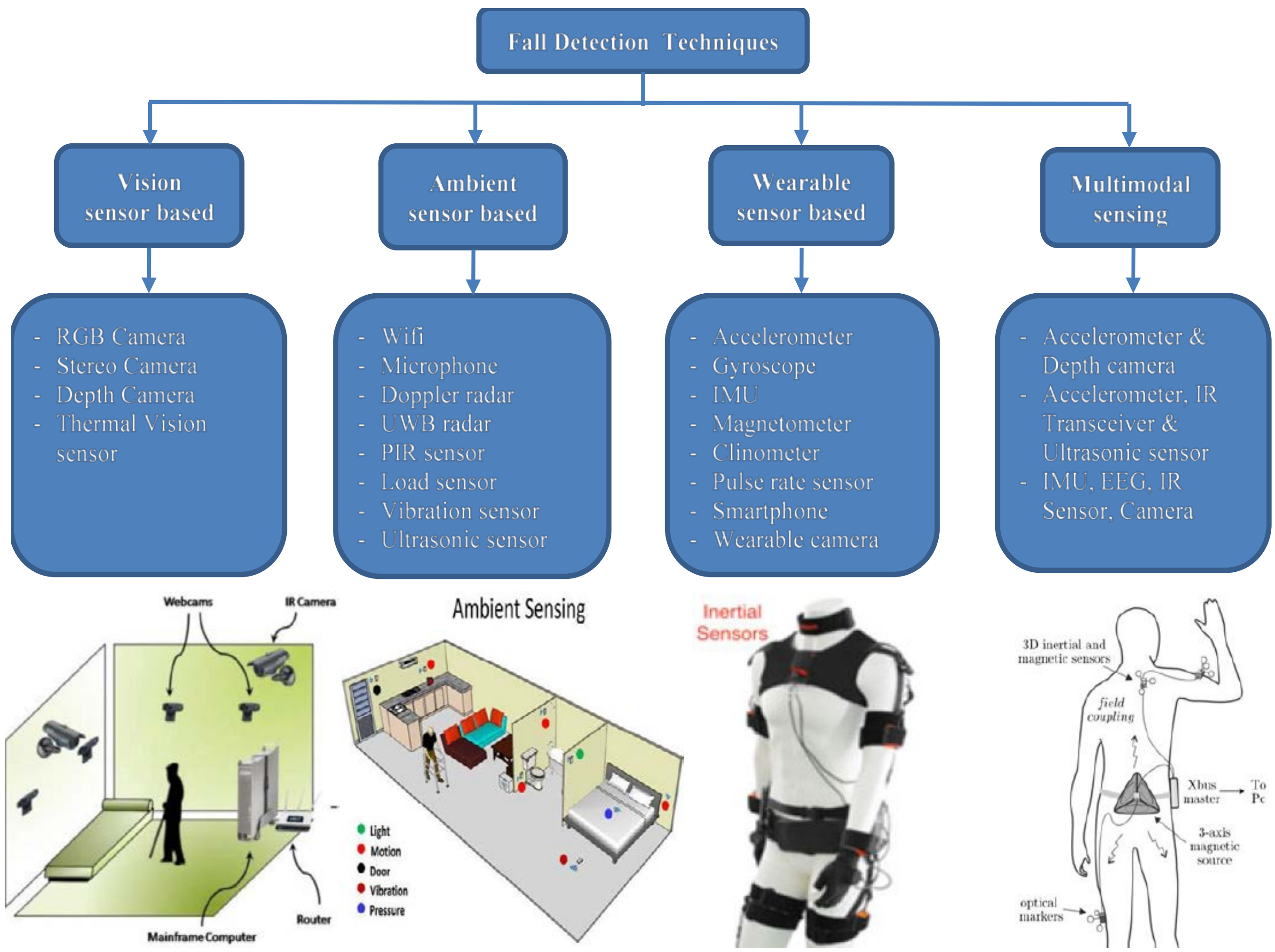

Figure 4. Fall Detection Techniques.[15,16]

METHODOLOGY RELATED TO LITERATURE

VISION SENSOR-BASED

Vision-based detection of falls is preferred by researchers as they are free from obstruction on the body. Previously the camera-based approach had privacy issues, but after introducing Kinect, depth sensor, and thermal vision sensor, these issues are solved to some extent. M.A. Ali et al.[17] presented fall recognition using RGB camera and Human skeleton's coordinates key points using OpenPose algorithm. OpenPose's Human skeleton algorithm gives 13 keypoints and coordinates of human skeleton in real time. From these keypoints & coordinates, author proposed method that uses x-coordinates of head center and shoulder center, shoulder points' y-coordinates, ratio of height of head center to ground and angle between shoulders' centerand ground. These key features are compared with threshold to recognize the human fall. After fall detection, the proposed method also checks for self recovery after fall to reduce false alarm/emergency alarm for person who able to recover without significant injury. G. Anitha et al.[18] proposed Deep learning based elderly fall detection using RGB camera. Initial preprocessing of video frame includes resizing, augmentation and Min-max normalization. Spatial features are extracted using MobileNet model. Temporal features are extracted using GRU model. The classification stage used Group Teaching Optimization Algorithm (GTOA) with Stacked AutoEncoder(SAE) to classify fall and non-fall activities. The performance of proposed model is evaluated using Multiple Camera Fall (MCF) dataset and UR Fall Detection (URFD) dataset. C. Zhong et al.[19] came up with a low-cost and low-resolution non-invasive thermal vision-based approach for multi-occupancy fall detection in a living environment. Multi-occupancy thermal images are decomposed into one or more thermal single-occupancy sub-images using image binarization and contour detection. Convolution Neural Network(CNN) and Robust Radial Basis Function Neural Network trained via minimization of the Localized Generalization Error(LG-RBFNN) are used for feature extraction and classification. High-resolution RGB cameras are the oldest type of sensor used in vision-based fall detection for few decades. Few fall detection datasets are currently also available online. RGB camera-based video data from UR fall detection dataset was used by J.J. Gracewell and S. Pavalarajan[20] to present a vision-based approach for the detection of falls based on a machine learning algorithm by using the spatial and temporal information of video data. By subtracting the current frame from the background model, the moving person is detected as a foreground object. The spatial model is generated by the posture of fall and normal activities, and the temporal model is generated with the use of optical flow features. The keyframes are extracted based on the maximum horizontal and vertical displacement of the centroid of foreground. The selected keyframes are subjected to spatial and temporal classification. Recognition of accidental falls by extracting skeleton information of the human body using the open-source library OpenPose (real-time human skeleton recognition system) developed by Carnegie Mellon University (CMU) was proposed by W. Chen et al.[21] Three main parameters used in this approach to detect falls are: speed of descent at the center of the hip joint (0.09 m/s), the human body centerline angle with the ground (< 45°), and the width-to-height ratio of the human body external rectangular (≥1). Embedded systems having advantages of standalone, portability, cheapness, and less computational power requirement. An Embedded system containing a System on Chip(SoC) “Hisilicon-Hi3516CV300” with bundled RGB camera “M12-4IR(3MP)-C” was proposed by K.L. Chung et al.[22] Gradient difference-based foreground detection approach along with dilation and multi-frame-based approach is used to construct a more complete foreground model. The variation of the centroid in a multi-frame is used to detect the fall. Fall detection determination is based on whether the centroid on the floor area for more than threshold time or not. If yes then an alarm signal is sent for first-aid help. Recent advancements in vision sensors include depth cameras like Kinnect and others which incorporates RGB camera and depth sensor. L. Chen et al.[23] developed multiple states fall detection system for senior citizens using a depth camera that can identify the fall and non-fall state of a person. RealSense D435 depth camera by intel is used to capture the visual information. They have presented machine learning and deep learning-based method, and compare their performance. The machine learning method used the Histograms of Oriented Gradient(HOG) for extracting image features and the Support Vector Machine(SVM) for classification. The deep learning method used AlexNet and GoogLeNet convolution neural network architecture. The action view clips of falls and non-falls are sampled, done pretreatment, body maps are binarized and recovery of incomplete body map is done using the depth map. Nowadays open-source hardware and software are famous amongst researchers to design standalone systems. S. Choi and S. Youm[24] had set up a system to detect elderly falls by collecting and analyzing video information through open-source hardware and send a text message when a fall is detected. Raspberry Pi camera V2 model with Raspberry Pi-2B+ development board is used as hardware, open-source Computer Vision for real-time video processing, and Python as a programming language. Image binarization is used to distinguish the background and the moving object. The rectangular object frame is found out and the slope of the rectangular frame is calculated to track the object. The change in slope and the time difference between slope changes are the parameters used for fall detection. During the falling, the slope of the object frame suddenly changes which means the change in slope is above the threshold and the time difference between consecutive frames is below the threshold value. When a fall is detected, an SMS alert is sent to the guardian’s mobile. M. Macas et al.[25] used pattern classification for camera-based real-time elderly fall detection and alarm system. The system is designed and implemented using Vivitek IP camera “IP8131W”, PC, open-source computer vision, HighGUI module, and video module. A moving person is detected using Gaussian mixture-based foreground/background segmentation. The barycenter of the person is calculated and the ellipse is fitted to the moving pixels. The slope of the velocity vector for two consecutive positions of the barycenter is calculated. Three features defined by authors for real-time fall detection are Average velocity slope of barycenter, Maximal vertical acceleration of barycenter, Ellipse angle. Using these three features, authors have checked the performance of four different classifiers: Linear Bayes classifier(LB), Quadratic Bayes classifier(QB), Parzen Classifier(PC), 3-Nearest Neighbours classifier(3NN). Single camera-based 3D tracking for outdoor fall detection for smart healthcare was presented by M. Ko et al.[26] Samsung Galaxy S7 edge is used to capture outdoor video information. A moving person is detected using background subtraction, binarization, noise filtering, and morphological operations. The bounding ellipse that contains the detected person is superimposed on the original input image. The supervised learning technique is used to generate depths from an input image. The computed depth map and corresponding human ellipse are used for 3D tracking with the Extended Kalman filter. For the detection of fall, the data measured from the image are center position of ellipse, semi-major and semi-minor axis, rotation angle w.r.t X-axis, associated velocity. E.E. Stone et al.[27] proposed a method for detecting elderly falls in the homes of older adults using Microsoft Kinect as a depth camera, PC, and a two-stage fall detection system. 3D foreground objects are segmented from each depth image frame using a dynamic background subtraction algorithm. The vertical state of a 3D object for an individual frame is characterized using a maximum height of the object, the height of the object’s centroid, points from an object with a height below 38cm. On-ground events are identified through temporal segmentation of vertical state in time series and five features are extracted namely Minimum vertical velocity, Maximum vertical velocity, Mean average velocity, Occlusion adjusted change, and Minimum frame to frame vertical velocity. Fall confidence is computed for each on-ground event using five extracted features and an ensemble of decision trees. Table 5 summarizes Vision sensor-based literature review.

Table 5. Summary of Vision sensor-based Literature Review

Technique	Source & Year	Sensors	Sensor Location	Algorithm/ Method/ Library	No & Type of Subjects/ Dataset	Type of Activity/ Falls considered	Data Collected / Tested under	Performance
Vision sensor-based	M.A. Ali et al.[17] 2022	RGB Camera	Tripod	OpenPose, Feature Threshold	2 Subjects	Fall: falling, standing up after fall ADLs: walking, standing	Indoor Lab Environment	Sensitivity: 98.7% Specificity: 94.6% Accuracy: 97.7%
	G. Anitha et al.[18] 2022	RGB Camera	Wall near ceiling	Deep Learning	MCF Dataset, URFD Dataset	Fall: forward, backward, sideway, fall during sitting, loss of balance ADLs: walking, sitting, standing up, crouching down, lying down, bending	Lab Environment	Dataset / Pre. / Sens. / Spec. / Accu. MCF: 99.97, 100, 99.86, 99.91 URFD: 100, 99.98, 99.98, 99.98
	C. Zhong et al.[19] 2021	Thermal vision sensor	Ceiling	Convolution Neural Network (CNN) and Radial Basis Function	3 participants (2-M, 1-F), 25 to 35 years	Empty room, standing/walking alone, fallen alone, 2-3 people standing/walking, one person fallen and one standing/walking	Smart Lab Environment	Accuracy=97.31% (single occupancy) Accuracy=95.89% (multi occupancy)
	J.J. Gracewell et al.[20] 2021	Microsoft Kinnect	Ceiling, Wall	Machine Learning	UR fall detection dataset	30 labeled falls & 40 labeled ADLs	Room Environment	Accuracy=97.14% Precision=93.75%
	W. Chen et al.[21] 2020	Surveillance camera	Wall	Convolution Neural Network & Supervised learning, OpenPose	10 Experimental subjects	60 falls & 40 non-falls (fall, stand up after a fall, squat, stoop, walk, sit down)	Lab Environment	Sensitivity=98.3% Specificity=95% Accuracy=97%
	K.L. Chung et al.[22] 2019	RGB Camera	Wall	Threshold, Variation of centroid	3 subjects (2-F, 1-M)	9-Simulated Falls (forward, backward, left, right, fall from bed, chair, standingup) 5-Non-fall activities (walking, lying/sitting on bed/chair, squatting, fake fall)	Real room environment	Accuracy=98% Precision=100% Sensitivity=96.6%
	L. Chen et al.[23] 2019	Depth Camera	Wall	Machine learning, Deep learning	3 Subjects	6000 non-fall action images, 3000 fall action images	Ideal Lab Environment	Method / Sens. / Spec. / Acc. ML (HOG+SVM): 100%, 89.1%, 85.2% DL (AlexNet): 100%, 99.9%, 99.9% DL(GoogLeNet): 100%, 99.7%, 99.8%
	S. Choi et al.[24] 2019	Raspberry pi camera V2	Wall	Threshold (change of object frame slop wrt time)	1 young subject	10 fall Experiments	Living indoor environment	Sensitivity=90% (Fall detection rate)
	M. Macas et al.[25] 2018	IP camera	Wall	Statistical pattern classification	4 subject	532 fall and 6864 non-fall events	Ideal Living environment	Classifier / Sens. / Spec. / ROC LB: 85.85%, 79.31%, 0.76 QB: 84.74%, 67.43%, 0.77 PC: 81.77%, 83.90%, 0.72 3NN: 81.09%, 85.82%, 0.89

Technique	Source & Year	Sensors	Sensor Location	Algorithm/ Method/ Library	No & Type of Subjects/ Dataset	Type of Activity/ Falls considered	Data Collected / Tested under	Performance
Vision sensor-based	M. Ko et al.[26] 2017	Mobile Camera	Wall	Depth based human tracking using Extended Kalman Filter	2 subject	Two test video: normal (no fall) and abnormal (fall)	Outdoor Environment	--
	E.E. Stone et al.[27] 2015	Microsoft Kinnect	Wall corner near ceiling	Machine Learning (Decision Tree)	16 older adults (9-F, 7-M) 67 to 97 year Falls by stunt actor	445 falls by stunt actor, 9 naturally occuring fall	Actual home of older adults	**Sensitivity** (Fall detection rate) standing downfalls = 98% sitting downfalls = 70% lying downfalls = 71%

AMBIENT SENSOR-BASED

Ambient-based fall detection techniques are used by people because users need not wear anything on the body as well as there are no privacy-related issues as in the case of vision-based techniques. K. Nishio et al.[28] constructed fall detection model using single Microwave Doppler sensor and Hidden Markov Model used in continuous wave Doppler mode. Three different states of motion are used in sequential transition from stand to fall condition and associated velocity during each state is used for fall detection. The Hidden Markov Model on ergodic basis is used to handle non-fall events those looks like fall event. Microwave Doppler sensor is attached on the ceiling such that microwaves radiated downward. Any activity occur in the range of microwave, the output signal carries the information about activity with frequency propotional to activity velocity. Wavelet transform is applied to output signal to findout highest frequency component in frequency distribution corresponding to activity velocity. These frequency components are quantized based on threshold selected by top 5% intensity to find out observable value for Hidden Markov Model. Fall and nonfall detection models are generated using aggregating the activities that produce high likelihood. Unknown activity is classified by comparing likelihood with the detection model. P. Wang et al.[29] presented UWB radar based fall detection system using Convolution Neural Network (CNN) and Adaptive chammel selection algorithm. The Radar system collect the data due to human activity and give two dimensional data of slow time sampling and fast time sampling which corresponds to actual time and object distance from radar respectively. The low frequency noises in collected data are filteredout using FFT filtering and frequency domain feature image is extracted. The high frequency noise is removed using SVD algorithm and time domain feature image is extracted. The author proposed algorithm based on adaptive channel selection to differentiate background from subject activity using mean energy of channels. The frequency and time doamain feature images are fed to Convolution Neural Network using L2 regularization and dropout layer for robust fall detection. K. Hanifi et al.[30] used CW Doppler radar for elderly fall detection along with monitoring vital signs. Window based technique is used to preprocess radar signal and Major Physical Activities(MPAs) are identified using threshold of sliding RMS. Once MPA is detected, important time & frequency domain features of corresponding signal window is extracted. These labelled features are used to train and test machine learning models like DT, SVM, kNN, NB & LDA. Once the system detects a fall and absence of MPA after fall, it confirms the fall and vital signs are monitored while emergency contact has been notified. J. Clemente et al.[31] presented a real-time smart system based on floor vibration signal for person identification, fall detection, localization, and notification. The system is designed using smart 3-channel seismic sensors to collect floor vibration signals, Raspberry Pi 3, and battery. The collected signal is enhanced by eliminating background noise using the wavelet denoising method. After that, event detection and separation take place using signal isolation. Once the event is detected and separated, feature extraction is done in both the time and frequency domain. Finally, event and footstep are classified using the supervised machine learning algorithm SVM. By using the propagation speed of floor vibration waves and the location of seismic sensors, the event location is identified. Pressure-sensitive and large-scale carpet with self-powered fall detection based on textile-triboelectric nanogenerators (t-TENGs) arrays inset in normal textile was proposed by A. Yu et al.[32] Smart t-TENGs constructed by conductive fibers in the core and normal clothing fibers in the shell using the weaving method. TENGs work on the principle of Maxwell's displacement current generation due to two friction surfaces under external force. A smart carpet (1.5m x 2.0m) is designed using these self-powered t-TENGs having pressure sensitivity of 0.07 kPa^{-1} in the range of 0.8 to 11.8 kPa and a quick response time of less than 28ms. During the walk, cells under the area of the foot only are activated and during fall, multiple cells under the area of the body are activated that can be used to detect the fall. A true unobstructed and device-free fall detection technique using radio signals based on wireless networks in-home set up for independent living of an elderly was presented by Y. Wang et al.[33] The technique analyzes the correlation between radio signal variations and human activities by analyzing the radio propagation model. It uses wifi signal variations for analyzing human activities within the environment. Wireless routers are used as Access Points(APs) and desktop PC with NIC is used as Monitoring Points(MPs). Channel State Information(CSI) estimates the channel properties of the communication link. CSI describes how a signal propagates in the channel by summing the effects of time delay, amplitude attenuation, and phase shift. The physical activity within the environment varies the CSI. The features of CSI used for the classification of activities are Normalized standard deviation, Offset of signal strength, Period of motion, Median absolute deviation, Interquartile range, Signal entropy, and Velocity of signal change. The performance of the technique was verified using two algorithms: One-class Support Vector Machine and Random Forest classifier with SVD matrix factorization. A. Irtaza et al.[34] proposed a method of elderly fall detection by capturing environmental sounds with a microphone and analyzed them using Acoustic Local Ternary Patterns. Reflection of pain directly occurs through the screaming or falling sound of a person. Low-frequency environmental sounds are suppressed by Hidden Markov Model-based Component Analysis(HMM-CA). The features are extracted for acoustic signals through acoustic Local Ternary Patterns(acoustic-LTP). Classification of the feature vector is performed through the SVM classifier. Recorded 100 fall event sounds that include falls on hands, side, back, and knees through human subject along with object falling. These fall sounds are then merged with a standard dataset to replicate a real-world environment. B.Y. Su et al.[35] employed a principle of the Doppler effect to detect human falls using ceiling-mounted Doppler range control radar. Pulse-Doppler range control radar mounted at ceiling center pointing downward is used. The doppler frequency shift is observed due to motions from human falls and non-falls are sensed by Doppler radar and there is significant variation in Doppler shift for fall and non-fall activities. Discrete Stationary Wavelet Transform(SWT) is performed on radar data to generate wavelet coefficients which are used to identify the possible time location at which fall activity occurs. SWT coefficients of scale-4 form a feature vector, which is used by the Nearest Neighbour classifier to perform fall versus non-fall classification. S.J. Redmond et al.[36] developed an unobstructed system to detect falls at nighttime using wireless passive infrared sensors and load sensors. Passive infrared sensors are installed in the corner of each room to the walls at a height of 2.5m. FlexForce load sensors are placed under the chair, sofa, and bed legs. Sensor event data are processed by two sub-algorithms: Fall with unconsciousness(Type-1 fall) and Fall with repeated attempted recovery (Type-2 fall). Type-1 falls are characterized by a long inactive period on all sensors which lasts longer than the threshold time. Type-2 falls are characterized by the pattern of continuous PIR longer than defined time while load sensors are inactive. Y. Li et al.[37] used a microphone array to develop an acoustic fall detection system that automatically detects a human fall and reports it to the caregiver. A circular array of eight omnidirectional microphones with a radius of 25cm was built. After the sound data collection from the microphone array, sound localization is first applied to determine the position of the sound source. If the source is located above ground then it will be considered as non-fall and no further processing is required, else BeamForming(BF) technique is used to enhance the sound signal using estimated source position. Mel-Frequency Cepstral Coefficients(MFCCs) features are extracted and the Nearest Neighbour classifier determines whether the sound is from fall or not. M. Alwan et al.[38] set up a passive and unobstructed floor vibration-based system for elderly fall detection. Piezoelectric vibration sensor coupled to a floor surface, battery-powered preprocessing electronics, and wireless communication is used for fall alarm. Human activities like walking, running, falling, and object falling on the floor can cause different and measurable vibrational patterns on the floor. The vibration signature of the floor generated by human falls is significantly different from other activities, so it is possible to detect human falls by monitoring the vibration pattern on the floor. A special piezoelectric sensor coupled to the floor surface and processing electronics detects a fall only when the vibration pattern like frequency, amplitude, duration, succession, etc. obtained from the floor matches with the pattern induced when a person falls on the floor. Table 6 summarizes Ambient sensor-based literature review.

Table 6. Summary of Ambient sensor-based Literature Review

Technique	Source & Year	Sensors	Sensor Location	Algorithm/ Method/ Library	No & Type of Subjects/ Dataset	Type of Activity/ Falls considered	Data Collected / Tested under	Performance
Ambient sensor-based	K. Nishio et al.[28] 2022	Microwave Doppler Sensor	Ceiling	Threshold (Wavelet Transform & Hidden Markov Model)	20 Male (21 to 24 year)	3 Fall (Tripping, Slipping, Fainting) 4 nonfall (Walking, Pickingup, Sitting down, Sitting up)	Indoor Lab Environment	Accuracy = 95% Sensitivity = 92% Specificity = 98%
	P. Wang et al.[29] 2022	UWB Radar	Desk	Deep Convolution Neural Network & Adaptive channel threshold	9 Male Volunteers (24 to 40 Years)	3 Fall (stand to fall, bow to fall, squant to fall) 400 set containing 3 type of fall	Indoor Environment	Accuracy = 94.92% Sensitivity = 95.12% Precision = 89.46%

<table>
<tr><th>Technique</th><th>Source & Year</th><th>Sensors</th><th>Sensor Location</th><th>Algorithm/ Method/ Library</th><th>No & Type of Subjects/ Dataset</th><th>Type of Activity/ Falls considered</th><th>Data Collected / Tested under</th><th>Performance</th></tr>
<tr><td rowspan="7">Ambient sensor-based</td><td>K. Hanifi et al.[30]
2021</td><td>CW Doppler Radar</td><td>Ceiling, Chest level</td><td>Threshold, Machine learning (DT, SVM, kNN, NB, LDA)</td><td>10 Volunteers (6-M, 4-F)</td><td>4 fall (falls while walking/sitting, falls from bed while sleeping, falls from bed while getup, falls while get to the bed) Total 121 fall events
6 ADLs: sitting, standing, lying down, changing position in bed, kneeling, picking from floor) Total 117 nonfall events</td><td>Bedroom Environment</td><td><table><tr><th>Radar Position</th><th>Subject state</th><th>Respi. rate Accu.</th><th>Pulse rate Accu.</th></tr><tr><td>Ceiling</td><td>Lying</td><td>90.7%</td><td>94.8%</td></tr><tr><td>Chest level</td><td>sitting</td><td>97.7%</td><td>95.3%</td></tr></table><table><tr><th>ML Model</th><th>Sensitivity</th><th>F1-score</th><th>Accuracy</th></tr><tr><td>DT</td><td>0.77</td><td>0.76</td><td>0.77</td></tr><tr><td>SVM</td><td>0.87</td><td>0.88</td><td>0.89</td></tr><tr><td>5-NN</td><td>0.80</td><td>0.79</td><td>0.79</td></tr><tr><td>NB</td><td>0.81</td><td>0.84</td><td>0.81</td></tr><tr><td>LDA</td><td>0.90</td><td>0.85</td><td>0.88</td></tr></table></td></tr>
<tr><td>J. Clemente et al.[31]
2020</td><td>3-channel Seismometer</td><td>Floor corners</td><td>Machine Learning (SVM)</td><td>6 subjects</td><td>Walk, fall, jump, object drop, door close, drawer close, hitting table</td><td>Indoor Environment</td><td><table><tr><th>Detection</th><th>Accuracy</th><th>Precision</th></tr><tr><td>footsteps</td><td>92.35%</td><td>89.3%</td></tr><tr><td>falls</td><td>73%</td><td>24.6%</td></tr><tr><td>Person Identification</td><td>91.23%</td><td>74.16%</td></tr></table></td></tr>
<tr><td>A. Yu et al.[32]
2020</td><td>t-TENGs Pressure sensitive carpet</td><td>Floor</td><td>Threshold</td><td>-</td><td>Walk, fall</td><td>Indoor Environment</td><td>Pressure sensitivity of 0.07 kPa^{-1} in the range of 0.8 to 11.8 kPa, 28ms quick response time</td></tr>
<tr><td>Y. Wang et al.[33]
2017</td><td>Wifi router</td><td>Indoor on table</td><td>Machine Learning (One-class SVM, Random Forest)</td><td>10 subjects (8-M, 2-F)</td><td>Walking, standing up, sitting down, falling (200 times at 8 locations)</td><td>Chamber, Lab, Dormitory</td><td><table><tr><th>Method</th><th>Precision</th><th>False Detection</th></tr><tr><td>One class SVM</td><td>83 to 96%</td><td>11 to 18%</td></tr><tr><td>Random Forest</td><td>89 to 98%</td><td>10 to 15%</td></tr></table></td></tr>
<tr><td>A. Irtaza et al.[34]
2017</td><td>Microphone</td><td>Indoor</td><td>Acoustic-LTP, Machine learning (SVM)</td><td>RWCP sound scene data set, Daily sound dataset, 100 fall sounds with associated events</td><td>Falls on hands, side, back, knees, object falling</td><td>Indoor</td><td>Accuracy = 97.41%</td></tr>
<tr><td>B.Y. Su et al.[35]
2015</td><td>Pulse doppler RADAR</td><td>Ceiling</td><td>SWT, Machine learning (k-NN Classifier)</td><td>3 subject (2-F, 1-M)</td><td>21 fall types, 8 ADLs Total= 105 falls, 704 ADLs</td><td>Lab environment, bathroom & living room of senior residence</td><td>Sensitivity = 92.3% to 97.1%
Specificity = 81.4% to 92.2%
Accuracy = 83.5% to 93%</td></tr>
<tr><td>S.J. Redmond et al.[36]
2014</td><td>Passive Infrared sensors, Load sensors</td><td>Room corner on wall, under bed, chair, sofa legs</td><td>Time Threshold based sensor status</td><td>3 older subjects</td><td>Fall with unconsciousness, Fall with attempted recovery</td><td>Real home environment</td><td>0.53 false detection alarm/day</td></tr>
</table>

Technique	Source & Year	Sensors	Sensor Location	Algorithm/ Method/ Library	No & Type of Subjects/ Dataset	Type of Activity/ Falls considered	Data Collected / Tested under	Performance
Ambient sensor-based	Y. Li et al.[37] 2012	Microphone array	On wall with 2.46m height	Mel-Frequency Cepstral Coefficients, Machine learning (Nearest Neighbour Classifier)	3 stunt actors (2-F, 1-M)	20 types of falls, 20 types of non-falls (Total 120 fall & 120 non-fall data)	Lab, room and realistic living environment	Sensitivity=100% Specificity=97% Accuracy=98% (under no background noise)
	M. Alwan et al.[38] 2006	Piezoelectric floor vibration sensor	Floor	Pattern matching	2 Dummies	70 dummy falls, 53 object drops	Lab Environment	Sensitivity=94.87 to 100% Specificity=93.28 to 100% (with 95% confidence interval)

WEARABLE SENSOR-BASED

Wearable sensor-based fall detection techniques are employed due to their low cost, are free from area restriction, and can be embedded in various personal accessories. F. Augusto Sodre Ferreira de Sousa et al.[39] proposed pre-impact fall detection system using Tri-axial accelerometer and height of the subject. The algorithm uses physiological characteristics like height from sensor position to user's feet(ground), distance between head and sensor (considered as subject's height) are used along with kinematic features extracted from accelerometer data like SVM of acceleration, tilt angle of body with respect to gravity, distance of sensor normal to the ground and angular displacement of body to identify fall and nonfall activities. The algorithm uses threshold of 1.2 factor of subject's height and 0.4g of SVM to confirm the falling. To classify whether the person is in the balanced boundary circle or not, the difference of ground distance and total angular displacement is calculated. The goal of the system is to detect preimpact fall and determine ongoing fall instant to predict loss of balance. The performance of proposed algorithm is validated using SisFall database with considering 10 ADLs. S. Wang et al.[40] proposed method to identify slip outcome as loss of balance (LOB) and no Loss of balance (NLOB) using triaxial accelerometer data and machine/deep learning model. It is helpful to identify the risk of slip-related falls before the actual fall. Slip trials are conducted using movable platform with low friction embedded in walk path that slides freely in forward-backward. Collected data from triaxial accelerometer worn on lower back are classified into LOB and NLOB using machine learning (Time series forest classifier-TSF, Multiple symbolic representations and symbolic sequence classifier-Mr-SEQL) and deep learning (Time Le-Net, Inception Time) approach. The performance for both modalities are compared for near-fall (LOB) detection. M.H. Habaebi et al.[41] presented a method that uses AndroSensor app to collect smartphone accelerometer, gyroscope and gravity sensor data and classify as ADLs or fall using machine learning algorithm. Collected data from smartphone sensors for all activities is preprocessed and six features namely maximum, minimum, mean, variance, kurtosis, skewness are extracted using MATLAB. Using these features four machine learning algorithms namely Support vector machine, Complex tree classifier, k-nearest neighbour and Logistic regression are used for performance evaluation out of which SVM gives best performance. O.Z. Salah et al.[13] developed edge AI based elderly fall detection system having three layer architecture: edge, fog and cloud. The edge layer is consist of wearable device having inertial measurement unit, LoRa transceiver and Arduino Nano 33 BLE microcontroller deployed with light weight deep learning model. Raspberry Pi4 is used in fog layer which is LoRa gateway connected directly to internet. For web/mobile app servers, cloud services and global storage cloud layer is used. Instead of cloud, the deep learning model is implemented on microcontroller in wearable device for lower computational power and real-time response. The proposed FDS is trained, tested and validated using SisFall dataset. M. Waheed et al.[42] proposed wearable device based fall detection mechanism which handles missing values in sensor data to become noise tolerant with high accuracy and precision. Wearable sensor data from SiSFall and UPFall dataset were preprocessed to balance Fall & ADL data using equal length and number to avoid biased learning along with MCAR missing data treatment. Preprocessed data was splitted into train & test dataset. Two BiLSTM architecture stacked on eachother with additional dropout was used for deep learning to train & test the data in two classes of Fall & ADL. Robust activity and slow fall detection system is proposed by X. Chen et al.[43] A system is designed with a waist-worn wearable sensor with an embedded inertial measurement unit, a barometer and a reference ambient barometer. 3-acceleration, 3-angular velocity, and 2-barometric pressure signals are fed to the deep neural network (DNN) to select the features and classify fall events. The first two stages of DNN contain two convolution neural networks for feature detection and downsampling by a pooling layer. The third stage is the bidirectional long short-term memory (bi-LSTM) layer that gains the information from past and future. The Softmax layer is used in the last stage to identify the probability of an event belonging to a fall or ADL. F. Othmen et al.[44] proposed a Supervised Dictionary learning algorithm namely SRC, FDDL, and LRSDL for wrist-based wearable fall detection. Data was collected by tri-axial accelerometer(4g), gyroscope(500 °/sec) and magnetometer (0.88 Gs) embedded in IMU GY-80 and Arduino Uno with a sampling rate of 100 Hz using 22 volunteers with different ages performed various fall events and ADLs. The collected data is pre-processed and the feature is extracted with the movement decomposition method. Only the vertical component of movement (Vertical Acceleration, Vertical Velocity, Vertical Displacement) and orientation (yaw, pitch, roll) decomposition are used. Three SDL algorithms SRC, FDDL, and LRSDL are trained and tested using raw data and extracted features for different combinations of sensors. SRC algorithm with only one accelerometer sensor gave the best result compared to other methods. A tri-axial accelerometer-based intelligent fall detection algorithm with wearable IoT using a deep learning network was proposed by F. Ahamed et al.[45] The fall detection algorithm is built and tested with Feed Forward Neural Network(FFNN) and Long-Short Term Memory(LSTM) based deep learning networks. UR Fall Detection(URFD) dataset having video recording and accelerometer signals of 30-labeled fall events and 40-labeled ADL events were used for the development and testing of the fall detection algorithm. Acceleration signal data is prepared for training by removing random error time stamps and reducing data points in equal length. Applied FFNN with input size of 8715 data points, 100 neurons in the hidden layer, two output classes: ADL & Fall, and scaled conjugate backpropagation function is used. Applied bidirectional LSTM layer with an output layer size of 100 with input layer size of two features: instantaneous frequency & spectral entropy, two classes in the final classification layer. Training and evaluation of two deep learning algorithms were done using the URFD dataset. Using a tri-axial accelerometer and clinometer based on a smartphone, a real-time fall detection system was developed by Y.S. Su et al.[46] Asus ZenFone2 Laser(ZE50K1) with android OS is used for the development of a real-time fall detection system. Smartphone built-in accelerometer sensor for measurement of body acceleration and electronic compass for phone's angle detection is used for the detection of falls and ADLs with the location of smartphone in the waist pocket. The weighted moving average of the motion signal is used to remove noisy peaks. Three parameters: the weightlessness that is free fall, the impact that is body impact on the ground, the stillness that is no motion activity after falling on the ground are employed to detect and confirm fall. The acceleration threshold is checked for weightlessness and impact during fall, while the phone's angle and acceleration standard deviation are checked for stillness after falling on the ground. Validation of these three events confirms the fall and sends an alert. Six activities including fall, sit down, jump, lying down, walk and run were analyzed. The system differentiated ADLs from falls and clearly detected falls in different directions. Q.T. Huynh et al.[47] presented a cloud-based system for in-home fall detection and activity assessment using a wearable device. Human motion activity data is collected by MPU-9250 based wearable device or smartphone. Cloud server computing part uses Amazon Dynamo DB for flexible SQL database service, Amazon S3 for simple cloud storage service, Elastic compute cloud for data processing and alert management, LoRa for connecting the wearable device to cloud server. Accelerometer and gyroscope sensor data from the wearable device are collected for fall and activity classification. Three features used for the fall detection algorithm in the wearable device are lower fall threshold of acceleration, upper fall threshold of acceleration, and upper fall threshold of angular velocity. The wearable device can detect fall and sends alert to the cloud server for alert management. Information features of daily activities from sensor data are extracted and uploaded on the cloud server for later analysis and daily activity classification. S.K. Gharghan et al.[48] used the technique of power reduction and wireless power transfer to build an energy-efficient elderly fall detection system using the Human Vital Signs Monitoring System(HVSMS). Triaxial accelerometer ADXL345, pulse rate sensor, ArduinoPro mini, GSM module SIM800L, GPS module NEO-M8N, wireless power transfer XKT-412, and rechargeable Li-Ion battery based wearable device placed on the upper arm. Data Event(DE) algorithm is proposed in which normally accelerometer and pulse rate sensors are in wake state and GPS and GSM modules are in a sleep state. Acceleration magnitude threshold for more than fall event time and abnormal pulse rate are used as measures to detect falls. When the fall is detected, the patient's information along with his/her geolocation is sent in the form of SMS to emergency contacts. 17 experiments were conducted and validated for 17 different locations in three cities of Iraq. The current consumption of HVSMS is reduced from 85.85mA to 9.35mA by using the DE algorithm. A wearable camera and accelerometer-based method proposed by K. Ozcan et al.[49] on portable devices for fall detection. Inbuilt camera and accelerometer sensor of Samsung Galaxy S4 smartphone tied with the belt placed on the waist with a camera and screen in front is used. Histogram of Edge Orientation(EO) and Gradient Local Binary Patterns(GLBP) is derived from each frame of the smartphone camera. Dissimilarity distances D_{EO} and D_{GLBP} are computed between current and previous frames. Whenever the sum value of D_{EO} X D_{GLBP} and accelerometer data is greater than the threshold then a fall is detected and an alarm is triggered. 10 subjects performed 30 non-fall activities for testing the algorithm. J. Santiago et al.[50] designed cell phone and pendant type wearable device based fall detection system for elderly people which has the capability of communicating with cellphone within a 100ft radius thus removes the need for carrying a cell phone all the time. The system uses a wearable pendant that houses MPU6050(Accelerometer & Gyroscope), Bluetooth module, Teensy3.1 microprocessor, battery, panic button, and mobile application through which wearable pendant can communicate with a cell phone. If acceleration exceeds the defined threshold then the device checks for gyroscope variations. If position variation in any direction exceeds the defined threshold then fall has been detected and a 30-sec timer has started. At this moment if the person is conscious and well then he/she might cancel emergency protocol. If not, then the pendant will send an alert message to the mobile application. 12 tests each containing five different types of falls were tested using a designed system. J. K. Lee et al.[51] developed pre-impact fall detection including near-fall conditions using a wearable inertial sensor-based approach. Waist mounted triaxial accelerometer and gyroscope signal was recorded at 128Hz using eleven healthy young male adults for various fall, near-fall and ADL activities. Verical velocity based approach used for pre-impact detection of fall which was compared with common acceleration threshold based method for fall versus ADL and non-fall scenario. Vertical velocity is obtained from vertical acceleration from inertial sensor signal. Downward vertical velocity is related to descending phase of fall before impact and acceleration magnitude is associated with peak acceleration occurs at fall impact. Negative vertical velocity exeeds the threshold confirms the starting of fall and peak negative vertical velocity confirms fall impact. Verical velocity and acceleration magnitude based approach is compared for falls vs. ADLs and falls vs. non-fall scenario using recorded data. Table 7 summarizes Wearable sensor-based literature review.

Table 7. Summary of Wearable sensor-based Literature Review

<table>
<tr><th>Technique</th><th>Source & Year</th><th>Sensors</th><th>Sensor Location</th><th>Algorithm/ Method/ Library</th><th>No & Type of Subjects/ Dataset</th><th>Type of Activity/ Falls considered</th><th>Data Collected / Tested under</th><th>Performance</th></tr>
<tr><td rowspan="6">Wearable sensor-based</td><td>F. Augusto Sodre Ferreira de Sousa et al.[39]
2022</td><td>Tri-axial accelerometer</td><td>Waist (Front)</td><td>Threshold (Subject Height & acceleration)</td><td>9 young Volunteers (2-F, 7-M) SisFall database for Validation</td><td>4 Fall (Backward, Forward, Rightward, Leftward)
5 ADL (Sitting, Standing, Picking object, Walk, Run)
Total 135 Falls & 86 ADLs</td><td>Lab Environment</td><td>Sensitivity = 94.04%
Specificity = 97.67%
Accuracy = 95.86%
Average Lead Time = 259ms</td></tr>
<tr><td>S. Wang et al.[40]
2022</td><td>Tri-axial accelerometer</td><td>Lower back</td><td>Machine Learning (TSF, Mr-SEQL)
Deep Learning (TLeNet, Inception Time)</td><td>34 old adults (≥60 years)</td><td>Total 798 slip trials conducted</td><td>Lab Environment</td><td><table><tr><th>Method</th><th>Accuracy</th></tr><tr><td>TSF</td><td>77.6%</td></tr><tr><td>Mr-SEQL</td><td>64.1%</td></tr><tr><td>TLeNet</td><td>83.8%</td></tr><tr><td>Inception</td><td>86.7%</td></tr></table></td></tr>
<tr><td>M.H. Habaebi et al.[41]
2022</td><td>Smartphone (Accelerometer, Gyroscope, Gravity)</td><td>waistline</td><td>Machine Learning (SVM, CT, knn, LR)</td><td>1 middle aged female</td><td>4 Fall (Backward, Forward, Right, Left)
5 ADL (Sleeping, Walking, Sitting, Kneeling, Jogging)</td><td>Lab Environment</td><td>Sensitivity = 100%
Specificity = 100%
Accuracy = 100%</td></tr>
<tr><td>O.Z. Salah et al.[13]
2022</td><td>Tri-axial accelerometer</td><td>waist</td><td>Machine Learning (KNN, SVM), Deep Learning (CNN, LSTM)</td><td>SisFall dataset(23 young adults, 15 older adults)</td><td>19 types of ADLs by all subjects and 15 types of fall by young subjects & 1 elder subject</td><td>Classroom Open spaces</td><td><table><tr><th>Classifier</th><th>Sens. (%)</th><th>Spec. (%)</th><th>Accu. (%)</th></tr><tr><td>KNN(5)</td><td>80.06</td><td>78.21</td><td>79.11</td></tr><tr><td>SVM</td><td>87.21</td><td>78.48</td><td>82.27</td></tr><tr><td>CNN</td><td>95.1</td><td>94.86</td><td>95.55</td></tr><tr><td>LSTM</td><td>97.87</td><td>95.21</td><td>96.78</td></tr></table></td></tr>
<tr><td>M. Waheed et al.[42]
2021</td><td>Triaxial accelerometer & Gyroscope</td><td>Waist (SisFall), Waist, wrist, neck, thigh, ankle (UPFall)</td><td>Deep Learning (Bi-LSTM)</td><td>SisFall dataset (23 young adults, 11-M, 12-F)
UPFall dataset (17 young adults, 9-M, 8-F)</td><td>SiSFall: 19-ADLs, 15-Falls
UpFall: 6-ADLs, 5-Falls</td><td>SiSFall: Classroom, Open spaces
UPFall: Lab Environment</td><td><table><tr><th>Dataset</th><th>Accu. (%)</th><th>Sens. (%)</th><th>Spec. (%)</th><th>Prec. (%)</th></tr><tr><td>SiSFall</td><td>97.41</td><td>100</td><td>95.45</td><td>94.28</td></tr><tr><td>UPFall</td><td>97.21</td><td>99.54</td><td>94.56</td><td>95.41</td></tr></table></td></tr>
<tr><td>X. Chen et al.[43]
2020</td><td>IMU, Barometer</td><td>Waist</td><td>Deep Learning (CNN, Bi-LSTM)</td><td>11-Subject (7-M, 4-F)</td><td>Sitting on the floor, sudden fall, squatting down, slow fall, low impact fall with fast recovery, and noised ADLs</td><td>Indoor Environment</td><td>Accuracy = 90.33%.</td></tr>
</table>

Technique	Source & Year	Sensors	Sensor Location	Algorithm/ Method/ Library	No & Type of Subjects/ Dataset	Type of Activity/ Falls considered	Data Collected / Tested under	Performance
Wearable sensor-based	F. Othmen et al.[44] 2020	IMU GY-80	Wrist	Supervised Dictionary Learning Algorithm (SRC, FDDL, LRSDL)	22 Volunteers	Falls (Forward, Backward, Left side, Right side, fall after rotating waist) ADLs(Walking, sitting on chair, Clapping hands, moving an object, tying shoes)	-	**For SRC Algorithm** Accuracy= 99.8% Sensitivity = 100 % Specificity = 99.6%
	F. Ahamed et al.[45] 2020	Tri-axial accelerometer	Pelvis region/ Lower back	Deep Learning Algorithm (FFNN, LSTM)	UR fall detection dataset	30 labeled falls [forward fall from standing, seating & walking] & 40 labeled ADLs [walking, walking followed by lying down in bed, walking & seating in room, picking up objects from floor]	Room Environment	**Algorithm** / **Accuracy** / **Precision** footsteps / 92.35% / 89.3% falls / 73% / 24.6%
	Y.S. Su et al.[46] 2020	Tri-axial accelerometer & clinometer based on smartphone	waist pocket	Acceleration & angle threshold	-	fall, sit down, jump, lying down, walk and run	-	-
	Q.T. Huynh et al.[47] 2019	MPU-9250 or Smartphone	Waist belt	Acceleration & Angular velocity Threshold	10 adult subjects	Standing, walking, sitting down, standing up, lying down, sitting up, stepping, running, falling	Lab Environment	Sensitivity: 96.3% Specificity: 96.2%
	S.K. Gharghan et al.[48] 2019	Tri-axial accelerometer & Pulse rate sensor	Upper arm	Acceleration & Pulse rate threshold	-	-	17 experimental location	Current consumption is reduced from 85.85mA to 9.35mA by using the DE algorithm
	K. Ozcan et al.[49] 2016	Wearable camera & Accelerometer (Smart phone)	waist	Dissimilarity distance & Acceleration threshold	10 Subjects (1-F, 9-M)	30 non-fall activities (sitting down, standing up, walking, lying down)	Lab Environment	Sensitivity: 91% False Detection: 2.6%
	J. Santiago et al.[50] 2017	Accelerometer & Gyroscope	Pendant in neck	Acceleration & Angular rotation Threshold	-	12- experimental test with five types of falls (backwards, right side, left side, diagonal towards left, diagonal towards right)	Lab Environment	**Accuracy** Backward & Left side fall: 92% Diagonal & Right side fall: 83%
	J. K. Lee et al.[51] 2015	Tri-axial accelerometer & gyroscope	Anterior side of waist	Vertical Velocity & Acceleration Threshold	11 adult male subjects	231 falls(slip, trip, faint, hit/bump, misstep, stand to sit, sit to stand), 165 near-falls(slip, trip, misstep, hit/bump, sit to stand), 165 ADLs(walking, stand to sit,stand to lie, sit to stand,picking up)	Lab Environment	**Performance** / **Method** / **Sensitivity** / **Specificity** Fall vs. ADLs / Vertical velocity / 97.4% / 99.4% Fall vs. ADLs / Acc. magnitude / 98.7% / 99.4% Fall vs. non-fall / Vertical velocity / 95.2% / 97.6% Fall vs. non-fall / Acc. magnitude / 84% / 85.5%

MULTI-MODEL SENSING

To take the advantage of different types of sensing techniques, multi-model fall detection technique come into the picture which uses two or more types of techniques for more reliable detection of fall. L. Martínez-Villasenor et. al[52] presented a multi-model technique that uses five IMU(3-axis accelerometer, 3-axis gyroscope & luminocity), one EEG sensor, six infrared sensors and two camera systems to create fall detection dataset and detect fall. The collected data from all sensors are preprocessed and windowing technique is used for feature extraction. Twelve time-domain features and six frequency-domain features are extracted for three window sizes. Most appropriate features are selected using two feature selection methods. Using selected features, four ML models are trained and tested for seven different sensor modalities. Among all the modalities and window sizes, IMU+EEG+CAM based approach gives the best results using Multi-Layer Perceptron and 1 sec window size. Using an accelerometer and depth sensor, an improved fall detection system was proposed by B. Kwolek and M. Kepski[53]. It is a combination of wearable and vision-based sensing techniques. A tri-axial accelerometer is wirelessly connected to PandaBoard through Bluetooth. Microsoft Kinnect is used as a depth camera and connected via USB to PandaBoard. OpenNI is used to acquire depth images and the PandaBoard ES development platform is used for mobile applications. A body-worn accelerometer at the pelvis wirelessly transmits motion data and depth maps are acquired by the Kinnect sensor to an embedded system. If acceleration magnitude is above the defined threshold then the system starts extraction of a person using a depth map by Kinnect sensor. Then extraction of features like acceleration threshold, the ratio of width to height of person's bounding box, the ratio of the height of a person in the current frame's bounding box to physical height of a person, the distance of person's centroid to the floor, standard deviation from the centroid for the abscissa and the applicate are performed. K-NN classifier is utilized for fall classification. URFD dataset and simulated fall experiments from five young volunteers were used for training and testing purposes. S. Moulik and S. Majumdar[54] have presented an automatic fall detection and alert system using ambient and wearable-based multi-model sensing FallSense. IR transceiver(940nm), ultrasonic sensor(HC-SR04), tri-axial accelerometer(ADXL345), Arduino board, Fuzzy inference system, and MATLAB are employed in the implementation of the system. Nine IR transceiver pairs are installed in opposite walls near the floor to detect LED cutoff during human activity. Two ultrasonic sensors are installed on the inner roof to find the distance of the moving person from the roof. An accelerometer is worn on the wrist of a person to detect human motion. Three features number of cutoff LEDs, distance from ultrasonic sensors, and resultant acceleration are inputted to the Fuzzy Inference System(FIS) which gives output in terms of chances of falls. The system uses the Mamdani model as a fuzzy inference technique, the centroid as a defuzzification method, and the trapezoidal membership function. Crisp value(chances of fall) generated by FIS is thresholded to 60% to generate fall alert. The system was evaluated using activities that imitate falls and ADLs in a small-scale implementation model with 1000 test cases. Table 8 summarizes Multi-model sensing based literature review.

Table 8. Summary of Multi-model sensing based Literature Review

Technique	Source & Year	Sensors	Sensor Location	Algorithm/ Method/ Library	No & Type of Subjects/ Dataset	Type of Activity/ Falls considered	Data Collected/ Tested under	Performance
Multi-model sensing	L. Martínez-Villasenor et al.[52] 2019	IMU EEG IR sensor Camera	Left wrist, under the neck,right pocket, waist center, left ankle Forehead 0.4m above floor 1.82m above floor in frontal & lateral view	Machine Learning (Random Forest, Support Vector Machine, Multi-Layer Perceptron, K-Nearest neighbour)	17 healthy young adults (9-M, 8-F) 18-24 years	5 falls (falling forward using hands, falling forward using knees, falling backward, falling sideward, falling sitting in empty chair) 6 ADLs (walking, sitting, standing, picking up an object, laying, jumping)	Lab Environment	Modality / Performance: IMU+EEG+CAM MLP (1sec) Accu.(%): 94.32±0.31 Preci.(%): 76.79±1.59 Sensi.(%): 67.30±1.42 Speci.(%): 99.43±0.03 F1-score(%): 70.44±1.25
	B. Kwolek et al.[53] 2015	Accelerometer & Depth sensor	Accelerometer near Pelvis & Depth sensor on ceiling, wall	Acceleration Threshold & Machine Learning (K-NN Classifier)	UR fall detection dataset & simulated fall by 5 subjects	URFD Dataset (30 fall & 40 ADLs), Simulated falls & ADLs(walking, sitting, crouching down, leaning down/picking up objects from the floor,lying on settee)	Room Environment	Performance: URFD Dataset / Independent Test Accuracy: 95.71% / 95.83% Precision: 90.9% / 90.91% Sensitivity: 100% / 100% Specificity: 92.5% / 92.86%

Technique	Source & Year	Sensors	Sensor Location	Algorithm/ Method/ Library	No & Type of Subjects/ Dataset	Type of Activity/ Falls considered	Data Collected/ Tested under	Performance
Multi-model sensing	S. Moulik et al.[54] 2019	IR transceiver Ultrasonic sensor, Tri-axial accelerometer	Wall Ceiling Wrist	Thresholding & Fuzzy logic	1000 Simulated test case in small scale model	1000 Simulated test case in small scale model	Small scale model	16% less False detection compared to existing single sensor based thresholding methods

COMPARATIVE ANALYSIS

In this section, we gave comparative analysis of our literature review in Table 9.

Table 9. Comparative Analysis of Fall Detection Techniques

Technique	Sensors	Sensor Location	Advantages	Drawbacks	Sources
Vision-sensor based	- Single RGB camera - Multiple RGB cameras - Stereo camera - Depth camera - Thermal vision sensor	- Wall - Ceiling - Corner of the room	- No physical restriction on the Human body - Detection of Human motion activities in 2D & 3D - Able to detect multiple events simultaneously	- Multiple/Depth camera-based approach is complex & expensive - Used only in an indoor structured environment - User's privacy can be compromised - Suffered from "Line of sight" problem - Suffered from varying lightening condition	M.A. Ali et al.[17] G. Anitha et al.[18] C. Zhong et al.[19] J.J. Gracewell et al.[20] W. Chen et al.[21] K.L. Chung et al.[22] L. Chen et al.[23] S. Choi et al.[24] M. Macas et al.[25] M. Ko et al.[26] E.E. Stone et al.[27]
Ambient -sensor based	- Wifi router - Microphone - CW/Pulse Doppler Radar - PIR sensor - Load sensor - Floor vibration sensor - Ultrasonic sensor - Microwave Doppler Sensor - UWB Radar	- Anywhere in Room - Ceiling - Chest level - on the wall near the floor - floor - Bed/Chair/sofa - Desk	- Users do not have to wear anything on the body - No physical restriction on the Human body - User's privacy can not be compromised	- Detection area is limited - Expensive to build up a large monitoring area with Ambient sensors - High rate of false detection & limited accuracy - Used only for Indoor environment - Sensor location affects the fall detection performance - Pet movement results in false alarm	K. Nishio et al.[28] P. Wang et al.[29] K. Hanifi et al.[30] J. Clemente et al.[31] A. Yu et al.[32] Y. Wang et al.[33] A. Irtaza et al.[34] B.Y. Su et al.[35] S.J. Redmond et al.[36] Y. Li et al.[37] M. Alwan et al.[38]

Technique	Sensors	Sensor Location	Advantages	Drawbacks	Sources
Wearable-sensor based	- Accelerometer - Gyroscope - Magnetometer - Clinometer - Pulse rate sensor - Smartphone - Wearable camera - IMU	- Chest - Waist - Forehead - Ear - Neck - Shoulder - Back - Wrist - Ankle - Foot	- Does not suffer from "Line of sight" problem - Used for both indoor & outdoor environment - Small size & could be integrated into personal accessories - User's privacy could not be compromised	- User has to remember to wear a sensor/device - Causes discomfort and intrusive if not of small size & properly designed - Sensor location affects the performance	F. Augusto Sodre Ferreira de Sousa et al.[39] S. Wang et al.[40] M.H. Habaebi et al.[41] O.Z. Salah et al.[13] M. Waheed et al.[42] X. Chen et al.[43] F. Othmen et al.[44] F. Ahamed et al.[45] Y.S. Su et al.[46] Q.T. Huynh et al.[47] S.K. Gharghan et al.[48] K. Ozcan et al.[49] J. Santiago et al.[50] J. K. Lee et al.[51]
Multi-model sensing	- IMU, EEG, IR Sensor, Camera - Accelerometer & Depth camera - Accelerometer, IR Transceiver & Ultrasonic sensor	- Wrist, waist, ankle, pocket, neck, forehead, on the wall near the floor - Pelvis, ceiling, wall - Wrist, wall, ceiling	- Achieve more comprehensive & reliable information - Low rate of false detection & good accuracy	- Complex & expensive due to the use of two or more types of sensors - Area restriction - Slow processing time	L. Martínez-Villasenor et al.[52] B. Kwolek et al.[53] S. Moulik et al.[54]

Conclusion

This study provides a detailed review of falls and their detection techniques available today that include vision-based, ambient-based, wearable-based, and multi-model sensing. We have included a variety of sensors and methods used in various fall detection techniques by selecting the 54 most appropriate articles on falls and fall detection techniques. Each technique has its own merits and demerits which are also discussed.

Most of the systems were tested in a laboratory environment or specifically structured environment and we can not expect the same performance in a real-life environment. The majority of the systems were evaluated using healthy young individuals or stunt actors and their performance may be subject-specific. The Vision/camera-based approach presents the ethical issue of an individual's confidentiality and privacy, area restriction, affordability, and false detection in case of voluntary action like lying, picking up from floor or moving towards the floor. The ambient-based approach requires a setup in the entire monitoring area which is quite expensive and restrictive. Performance is affected by sensor location and false detection due to falling objects or the movement of pets in the monitoring area. The wearable-based approach is cheap, has no ethical issue, no area restriction, and can be integrated into various personal accessories, but the user should remember to wear a device, intrusive if not of small size, performance depends on sensor location and false detection in case of few ADLs. The multi-model approach is more accurate and reliable but is expensive, complex, area restrictive, and also slow processing time as multiple sensor signals have to be processed.

Further research should focus on removing area restrictions of the monitoring device, affordability, reducing false detection rate, evaluating its performance in a real-life environment, preserving user's privacy, designing small and unintrusive wearable device and universality so every needy person will use it. The research should also focus on pre-impact fall detection which detects the fall in its initial phase before a person's impact on the ground, so the user will be warned and fall may be prevented. Technological advancement, BioMEMS, and miniature sensor system design could be used for the integration of wearable devices in personal accessories for the robust and unobstructed fall detection system.

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Conflict of Interest

The authors do not have any conflict of interest for the publication of this work.

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