Development of a Contactless Patient Fall Detection System Using Radar Sensors

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Abstract

Falls are among the most significant causes of injury, functional decline, and loss of independence in older and hospitalized patients. Delayed recognition of an event increases the risk of a prolonged lie, hypothermia, dehydration, rhabdomyolysis, and delayed care for fractures or traumatic brain injury. Wearable sensors, video cameras, and ambient sensors partly address the monitoring challenge but are limited by user adherence, privacy concerns, dependence on lighting, and incomplete room coverage. Radar sensors enable contactless measurement of range, radial velocity, direction, and the spatial distribution of reflections without producing a conventional image. This review examines continuous-wave Doppler, FMCW, UWB, and millimeter-wave MIMO radars, micro-Doppler analysis, range-Doppler maps, point clouds, and machine-learning algorithms. A fall is represented as a sequence comprising loss of balance, reduction in body height, contact with a surface, and the post-fall state. Experimental studies demonstrate high accuracy under controlled conditions; however, clinical generalizability is limited by small samples, the predominance of simulated falls, hardware heterogeneity, and the absence of standardized operational metrics. Implementation requires prospective multicenter studies, participant- and room-level data separation, assessment of false alarms per patient-day, local processing, cybersecurity, and integration with a clinical response workflow. A radar system should be regarded as a component of comprehensive patient safety rather than a substitute for fall prevention and clinical observation.

Keywords: falls; contactless monitoring; radar sensors; FMCW radar; millimeter-wave radar; micro-Doppler; machine learning; patient safety.

1. Introduction

Falls are among the leading causes of unintentional injury and death, particularly in older adults. Risk increases in the presence of frailty, osteoporosis, sarcopenia, cognitive impairment, orthostatic hypotension, polypharmacy, neurological disorders, and a history of falls. Consequences include fractures, traumatic brain injury, reduced mobility, fear of falling again, and increasing dependence on assistance [1-4].

A particularly dangerous situation arises when a patient is unable to stand up or call for help. Prolonged time on the floor is associated with hypothermia, dehydration, pressure injuries, rhabdomyolysis, and delayed diagnosis of acute conditions. In hospitals, falls often occur while patients are getting out of bed, going to the bathroom, or moving without assistance; in homes and long-term care facilities, the system must account for furniture, walking aids, the presence of other people, and months of continuous operation [2, 3].

Wearable accelerometers and gyroscopes provide individual kinematic data but depend on correct placement, battery charge, and adherence. Video systems are informative but raise privacy concerns and depend on lighting and an unobstructed line of sight. Floor, acoustic, and infrared sensors usually cover a limited area and do not always distinguish a fall from an intentional postural transition [5-8].

Radar sensors register reflected electromagnetic signals and can estimate range, radial velocity, direction of movement, and micromotions of body segments. They require no wearable device, operate in darkness, and do not generate a conventional photographic image. Potential applications include hospital wards, nursing homes, rehabilitation settings, and home monitoring [9-13].

High laboratory accuracy is not equivalent to clinical reliability. Real falls may be rapid, slow, interrupted by furniture, or associated with syncope and weakness. Because such events are rare relative to ordinary activity, even a small false-positive rate can cause alarm fatigue. Key performance indicators should therefore include event-level sensitivity, false alarms per patient-day, notification delay, and the proportion of time during which the system functions correctly [5, 7, 9]. The aim of this review is to summarize the physical principles, algorithms, experimental evidence, and requirements for the clinical implementation of radar-based fall detection.

2. Literature Search Strategy

PubMed/MEDLINE, Scopus, Web of Science, and Embase were searched primarily for the period from January 2020 to July 2026; earlier publications were included to describe fundamental principles and key prototypes. Search terms were used in combinations including "fall detection," "patient fall," "radar fall detection," "Doppler radar," "FMCW radar," "UWB radar," "mmWave radar," "micro-Doppler," "range-Doppler," "point cloud," "machine learning," "deep learning," "hospital," "older adult," and "home monitoring." Priority was given to original studies, reviews, guidelines, and medical-device documents. Studies without human fall events or an adequate description of methods were excluded. This article is a narrative review; no meta-analysis, formal risk-of-bias assessment, or PRISMA flow diagram was performed.

3. Clinical and Technological Foundations

3.1. A Fall as a Sequence of Events

A clinically useful system should recognize not only the final position near the floor but also the dynamic sequence: pre-fall activity, loss of balance, reduction in body height, contact with a surface or interruption of the fall, and the post-fall state. A person may intentionally lie on the floor, whereas sliding from a bed or falling onto furniture does not always end in a horizontal position. An algorithm based only on height or immobility will therefore inevitably produce missed events and false alarms [5-11]. The direction of movement relative to the radar affects Doppler velocity: movement across the line of sight produces a weaker signal than movement toward or away from the sensor. A slow descent caused by weakness may not produce a pronounced velocity peak. The most robust approach combines velocity, changes in range and height, the spatial distribution of reflections, and behavior after the event.

3.2. Physical Principles and Radar Types

Range is determined from the round-trip signal propagation delay, whereas radial velocity is derived from the Doppler shift. Movements of the trunk and limbs generate micro-Doppler components that form characteristic time-frequency spectrograms. Measurements are affected by body orientation, distance, static reflections, and multipath propagation from walls and furniture [11-15].

Continuous-wave Doppler radar is simple and sensitive to movement, but a conventional single-frequency system does not measure range. FMCW radar uses frequency-modulated chirps and estimates range and velocity simultaneously. UWB radar provides high range resolution. Millimeter-wave MIMO systems additionally estimate azimuth and elevation and generate three-dimensional or four-dimensional point clouds [14, 16-22].

Multiple radars reduce blind spots and directional dependence but require synchronization and increase cost. One properly positioned sensor may be sufficient for a small single-occupancy room; multi-bed wards or shared spaces require multi-target tracking and robust separation of reflections.

3.3. Signal Representation and Processing

A typical processing pipeline includes channel calibration, static-clutter suppression, estimation of range, velocity, and angle, target detection, clustering, tracking, and classification. Data may be represented as range-time matrices, range-Doppler maps, micro-Doppler spectrograms, range-angle maps, or point clouds. Each representation preserves different motion characteristics and introduces its own errors [9, 10, 16-22].

Point clouds make it possible to estimate centroid height, vertical velocity, and the spatial extent of the body, but they remain sparse and depend on distance and the detection threshold. Errors arising at early stages propagate to the classifier: loss of the trunk reflection may create a false trajectory, while merging a patient and a staff member may mimic a change in target size or velocity. Clinical evaluation should therefore cover the entire pipeline rather than the neural network alone.

Table 1. Principal Radar Technologies for Contactless Fall Detection

Technology	Measurement principle	Typical output data	Fall-related features	Main advantages	Main limitations	References
Continuous-wave	Continuous transmission with	Doppler signal, phase signal,	High radial velocity, micro-	Simple hardware	No direct range measurement,	[11, 15, 20]

Technology	Measurement principle	Typical output data	Fall-related features	Main advantages	Main limitations	References
Doppler radar	measurement of Doppler shift and phase change	time-frequency spectrogram	Doppler motion of the trunk and limbs, reduced movement after a fall	implementation, high sensitivity to motion	directional dependence, difficulty with multiple people	
FMCW radar	Frequency-modulated chirps for measuring range and velocity	Range profile, range-time map, range-Doppler map	Reduction in body position, velocity impulse, trajectory toward the floor	Simultaneous estimation of range and velocity, localization capability	Processing complexity, multipath effects, need for calibration	[9, 10, 14, 16, 17]
Ultra-wideband radar	Use of a signal with a wide bandwidth	High-resolution range profiles, range-time images	Rapid change in the distribution of the reflected signal and body position	High range resolution, contactless observation	Dependence on room materials and interference, complex background reflections	[18]
Millimeter-wave MIMO radar	FMCW measurement with a virtual antenna array	Range, velocity, and angle maps; three-dimensional point clouds	Reduction in height, change in the point-cloud centroid, fall velocity, immobility near the floor	Compact size, spatial localization, three-dimensional analysis	Sparse point clouds, computational complexity, dependence on body position	[9, 10, 21, 22]
Multi-radar system	Fusion of sensor data acquired from different directions	Synchronized maps, trajectories, features, or decisions	More complete reconstruction of the fall trajectory	Reduced blind spots and directional dependence	Cost, synchronization, calibration, and maintenance	[17]
Radar with additional sensors	Fusion of radar with bed, pressure, infrared, or acoustic sensors	Multimodal temporal features	Confirmation of bed exit, impact, immobility, or staff presence	Potential reduction in false alarms and improved contextual assessment	Greater system complexity and additional privacy and cybersecurity concerns	[5, 8-10]

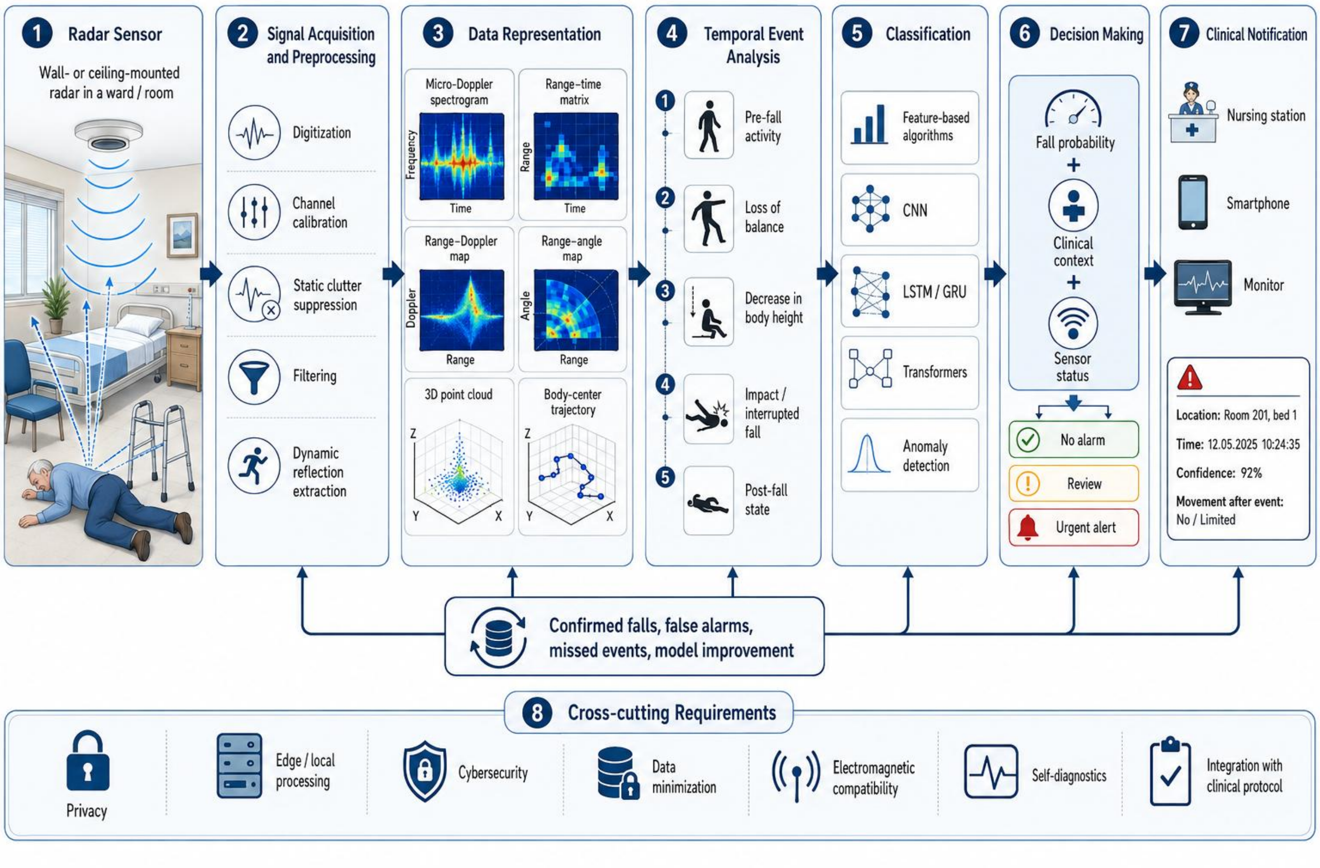

Figure 1. Conceptual architecture of a contactless patient fall detection system using radar sensors.

4. Algorithmic Approaches

4.1. Threshold-Based Methods and Classical Machine Learning

Early systems used maximum velocity, velocity-pulse duration, change in range, and post-fall immobility. Threshold rules are interpretable and computationally simple but transfer poorly across patients and installation geometries. Support vector machines, random forests, and other classical methods combine several features, although they depend on manual feature selection [11, 15].

Segmentation of the continuous data stream is also critical. A window that is too short does not capture all phases of a fall, whereas a long window delays the alarm. In practice, systems use sliding windows, a separate activity detector, or a sequential model that updates the probability as each frame arrives.

4.2. Deep Learning and Spatiotemporal Models

Convolutional neural networks automatically extract features from spectrograms and range-Doppler maps. LSTM, GRU, and temporal convolutional networks model the sequence of instability, reduction in height, and the post-fall state. PointNet-like architectures process point clouds directly, while autoencoders and anomaly-detection methods reduce dependence on large numbers of labeled falls [16, 19-21, 23-37].

A complex model does not guarantee clinical benefit. Performance depends on image formation, point-cloud quality, the composition of negative examples, and the data-splitting strategy. If adjacent fragments of the same recording are included in both training and testing, accuracy is substantially inflated. Participant-level separation is a minimum requirement; evaluation in a new room and an independent institution provides stronger evidence [9, 23].

Transformers and attention mechanisms are promising for slow events and long temporal contexts but require large datasets. Quantization and lightweight networks are important for edge devices, although optimization must address not only the classifier but also angle processing, clustering, and signal transmission.

4.3. Converting a Prediction into an Alarm

Model output must be converted into a clinical action. A high probability of a rapid fall followed by immobility may trigger an immediate notification, whereas an uncertain event may prompt a voice check or confirmation by a second sensor. The notification should include the location, time, and information about movement after the event.

Specificity measured on short laboratory segments does not reflect the operational burden. The most important indicators are false alarms per patient-day, notification delay, and the proportion of technically unavailable time. The system should include self-diagnostics and report power loss, communication failure, sensor obstruction, or calibration failure. Radar initiates an assessment but does not determine the cause of the fall and does not replace evaluation of consciousness, injury, vital signs, or medication history [2, 3, 5, 7, 9].

5. Experimental Evidence

Key studies confirm the technical feasibility of Doppler, FMCW, UWB, and millimeter-wave fall detection. Wavelet and micro-Doppler analyses identified differences between falls, walking, and postural transitions; CNN and LSTM models enabled automatic extraction of spatiotemporal features; and four-dimensional radars and PointNet-based methods allowed analysis of changes in height and point-cloud configuration [15-40].

Accuracy above 90-95% is frequently reported in controlled datasets. Comparisons are nevertheless limited by differences in participant numbers, fall directions, rooms, and negative activities. The strongest designs separated new participants and new environments, assessed slow falls, or tracked multiple people. Even in these studies, intentional falls by healthy volunteers predominated, while long-term clinical observations remained uncommon [21, 23-37].

Table 2. Principal Experimental Studies of Radar-Based Fall Detection

Study	Sensor and data representation	Algorithmic approach	Principal reported results	Key limitations
Su et al., 2015 [15]	Doppler radar; time-frequency characteristics	Wavelet transform and feature extraction	Demonstrated the ability to distinguish falls from activities of daily living	Controlled falls; limited spatial information
Jokanovic, Amin, 2018 [16]	Range-Doppler maps	Deep convolutional network	Demonstrated the feasibility of automatic feature extraction from range-Doppler maps	Laboratory dataset; limited evaluation in a clinical environment
Tian et al., 2018 [32]	Radio-frequency reflections; spatiotemporal maps	CNN and state machine	More than 140 participants and 57 environments; recall 94%, positive predictive value 92%	Not a typical commercial FMCW radar; controlled activities
Sadreazami et al., 2019 [31]	UWB radar; range-time data	Capsule neural network	Demonstrated classification of falls using UWB signals	Simulated events; limited external validation
Jin et al., 2022 [21]	4D mmWave radar; point cloud and body centroid	Hybrid variational recurrent autoencoder	Detected 98% of 50 falls with two false alarms	Small number of falls; experimental apartment; no long-term clinical observation
Wang et al., 2022 [29]	mmWave FMCW; contour-confined Doppler-time maps	Contour processing and classification	Demonstrated recognition of sudden and slow falls	Technical definition of a slow fall; laboratory volunteers

Study	Sensor and data representation	Algorithmic approach	Principal reported results	Key limitations
Wang et al., 2023 [30]	FMCW; range and velocity maps and an energy curve	Two CNNs with feature fusion	High reported performance for sudden and soft falls	Independent evaluation in a clinical population is required
Cardenas et al., 2023 [34]	Doppler characteristics of a CW signal	CNN and LSTM	Fall-detection accuracy of approximately 92.1% in 11 participants	Small sample; simulated falls; limited environmental diversity
Rezaei et al., 2023 [37]	mmWave; spatial and motion features	Data-driven methods	Confirmed the feasibility of contactless fall recognition	Laboratory data; no assessment of clinical outcomes
Alhazmi et al., 2024 [26]	IWR6843ISK-ODS; point clouds	PointNet on Jetson Nano	Overall accuracy of 99.5% across five activity classes; alarm transmission implemented	Overall rather than fall-specific clinical metric; limited sample
Liang et al., 2024 [23]	24 GHz FMCW; enhanced 3D point clouds	GRU point-enhancement model and lightweight CNN	Accuracy of 99.1% in new participants and 98.9% in new participants in a new environment	Small dataset; time-consuming angle processing; no real patient falls
Shen et al., 2024 [24]	Three mmWave radars; multi-person point clouds	Dynamic DBSCAN, tracking, and state prediction	Fall-detection accuracy of 96.3%; tracking of one to three targets	Controlled environment; complexity of synchronizing and installing multiple radars
Li et al., 2024 [25]	Doppler radar; frequency spectra	CNN and bidirectional LSTM	High accuracy, sensitivity, and specificity were reported	External and prospective validation is required
Cho et al., 2025 [35]	CW radar; time-frequency data	Binarized neural network	Accuracy of 93.1% for binary classification; lightweight implementation demonstrated	Differences between offline and real-time tests; small number of participants
Ahn et al., 2025 [36]	4D radar; normalized and clustered point clouds	CNN, web dashboard, and three-dimensional avatar	Posture-classification accuracy of 98.66%; fall-detection accuracy of 95%	Experimental evaluation; no long-term observation of older patients

6. Clinical and Practical Significance

In hospitals, radar can continuously register bed exit, standing, and a rapid reduction in body height, particularly at night. Its potential value lies in shortening the interval between an event and clinical assessment rather than replacing nursing observation. Prospective studies should compare time to assistance, duration of time on the floor, and complications, rather than technical accuracy alone.

Slow falls and sliding from a bed or chair are especially important in long-term care facilities. In the home, advantages include the absence of a wearable device and the ability to operate in a bedroom or bathroom without conventional video recording. Remaining limitations include coverage of multiple rooms, a backup communication channel, and selection of the alarm recipient. A practical approach is a staged workflow consisting of a voice check, notification of a relative or staff member, and subsequent escalation.

Multi-occupancy rooms require zoning and robust tracking of several people. The clinical interface should display a brief explanation, such as a rapid reduction in height followed by immobility, and allow the user to label a true fall, controlled lowering, staff assistance, or a technical error. Such feedback is useful for audit, but automatic retraining without expert review may be unsafe.

Radar data remain personal medical information even when they contain no photographic image. Local processing, transmission of only the alarm event, limited retention periods, and patient information are preferable. Economic evaluation should include the cost of equipment, installation, maintenance, and management of false signals; convincing evidence of improved outcomes and reduced costs is still insufficient.

7. Diagnostic Applications and Digital Biomarkers

Continuous monitoring can assess not only an actual fall but also walking speed, step length and cadence, variability, sit-to-stand time, and nighttime activity. Radar-derived walking speed and step length have been compared with instrumented systems, and micro-Doppler characteristics have been used to analyze pathological and assisted gait [39-48].

Fall detection, identification of risky behavior, and long-term risk assessment should be distinguished. Detecting a severely mobility-impaired patient sitting on the edge of the bed may allow assistance to be called before walking begins; however, early warning alone does not prove that the number of falls is reduced. No single gait parameter replaces a comprehensive assessment of history, medications, cognitive status, vision, and muscle strength [3, 45, 49-61].

For a parameter to be recognized as a digital biomarker, analytical validation of the measurement, a clinical association with a condition or outcome, and evidence of usefulness for decision-making are required. Reproducibility, the minimal meaningful change, the proportion of unusable episodes, and the effects of trajectory, furniture, and software updates must be determined.

8. Current Limitations and Controversial Issues

The principal limitation of the evidence base is the use of small, unrepresentative samples. Numerous repetitions by a few volunteers are not equivalent to the diversity of older patients. An intentional fall onto a mat differs from syncope, seizures, slipping, and gradual collapse due to weakness. There is no uniform definition of a complete, interrupted, slow, or near fall.

Random splitting of frames causes information leakage. Data from one participant and one session should appear in only one dataset partition. Evaluation in a new room and an independent center is more convincing. Because of the severe class imbalance, false alarms per patient-day and positive predictive value at the real event frequency should be reported.

Differences in frequency, bandwidth, antenna count, and firmware limit model transfer across sensors. Repositioning a bed, metallic equipment, opening doors, and multipath propagation alter the background. In the presence of several people, clusters may merge, particularly when a staff member supports a patient.

False alarms cause alarm fatigue and may delay staff response [72-74]. Improving specificity through post-fall immobility or a second sensor must not create a dangerous delay. The model may also perform less effectively in patients with unusual anthropometry, wheelchair use, amputation, or very slow gait.

Deep models may exploit room-specific features rather than physiologically meaningful movement. Interpretability and uncertainty estimation are important but do not replace external validation. The most substantial evidence gap is the lack of convincing proof that the system reduces complications, time spent on the floor, or mortality. Radar does not replace comprehensive prevention measures, including exercise, environmental modification, medication review, and mobility assistance [49-57].

A clinical device should comply with requirements for risk management, the software life cycle, usability, and electromagnetic compatibility; connected systems require authentication, encryption, signed updates, and vulnerability management [62-71].

9. Future Directions

The priority is multicenter prospective research in hospitals, long-term care facilities, and homes. Mandatory endpoints include confirmed falls, event-level sensitivity, false alarms per patient-day, delay, technical availability, time to assistance, and duration of time on the floor.

Standardized datasets are needed with labels for initial position, direction, speed, final surface, contact with furniture, assistance by another person, and ability to stand up. Negative examples should include rapid lying down, exercise, kneeling, and controlled lowering. Real events can be accumulated through prolonged, ethically approved observation; synthetic data should be used only as a supplement.

Self-supervised learning, semi-supervised models, and personalization can use the large volume of ordinary activity, but adaptation must not normalize recurrent dangerous behavior. Federated learning and edge processing may reduce transmission of raw data. Multimodal integration should remain functional when one channel fails.

Clinical trials of artificial intelligence should prespecify the model version, error handling, interaction with staff, and software changes. The principles of responsible medical AI and the CONSORT-AI, SPIRIT-AI, and DECIDE-AI guidelines should be followed [75-80].

10. Conclusion

Radar sensors enable contactless measurement of range, velocity, and the spatiotemporal structure of movement and represent a promising alternative to wearable and video systems. Laboratory studies confirm high technical feasibility, but clinical readiness is limited by simulated falls, small samples, hardware heterogeneity, and the absence of operational metrics. Safe implementation requires independent prospective validation, self-diagnostics, data protection, and integration with a clear response workflow. Radar should complement, rather than replace, fall prevention and clinical observation.

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