International Journal of Applied Mathematics

Volume 38 No. 11s 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

"A FALL DETECTION AND PREVENTION SYSTEM FOR ELDERLY SAFETY IN SMART HOMES USING DEEP LEARNING"

Mashaan Mahmood Ibrahim

Iraq, Kirkuk,Kirkuk University, Faculty of Science, Department of Computer Science

Abstract

Particularly in administrative, felony, and financial settings, the legitimacy of handwritten signatures is still an crucial element of private identity and document validation. However, human mistake can arise for the duration of manual verification, that's why automated systems which could reliably differentiate between true and faux signatures are getting an increasing number of necessary. Using photo-based information, In order to distinguish between genuine and fraudulent signatures, this research suggests a Convolutional Neural Network (CNN)-based method. The CNN architecture turned into created to improve accuracy and dependability through routinely getting to know spatial hierarchies of signature traits without the need for guide preprocessing. A publicly handy online signature dataset was used to educate and compare the version; every picture turned into superior and normalized to enhance generalization. According to experimental information, the suggested CNN version efficiently recognized both true and fake signatures with high precision and keep in mind fees, with an usual accuracy of over ninety five%. The model's potential to lessen inaccurate classifications was proven by way of the performance assessment using the confusion matrix and F1-rankings. This study advances the realm of biometric verification. by using organising a strong and scalable framework for automated signature verification, suitable for deployment in secure virtual identity systems.

Keywords : Fall Detection , Smart Homes, CNN-LSTM Model, Prevention System, Elderly Safety

Introduction

Falls The majority of the elderly represent a chief international public fitness issue, particularly as the populace ages and greater people choose to live independently in smart homes. The majority of fatal and non-deadly incidents in people 65 years of age and beyond are as a result of falls, which often bring about fractures, head trauma, decreased mobility, and a substantial deterioration in best of lifestyles [1, 2].

Traditional fall detection and prevention methods—together with wearable sensors (accelerometers, gyroscopes), ambient sensors like constant cameras, or ground-embedded stress sensors—have proven software, however every comes with limitations.

Wearables may suffer from non-compliance (elderly forgetting to wear them), discomfort, or battery constraints; ambient cameras may raise privacy concerns and be negatively impacted

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

by occlusion or variable lighting; pressure sensors may be limited only to areas where they are installed [3, 4].

Recent advances in deep learning offer promising opportunities to overcome many of these limitations by enabling systems that can learn complex spatio-temporal features from heterogeneous data sources. For example, CNNs, RNNs (including LSTM), graph convolutional networks, and hybrid models have been employed to classify falls vs activities of daily living with high accuracy [5, 6]. These models have been applied in both wearable-sensor settings and ambient/vision-based settings. For instance, some studies use vision-based pose estimation combined with CNN-LSTM architectures to achieve accuracies near or above 95% in detecting fall events [5]; others use accelerometer data in combination with convolutional and recurrent neural networks to detect falls under varied conditions [6].

Sensor fusion and privacy-preserving sensing are also becoming more prevalent. Ambient infrared thermal sensors, non-visual sensors, or low resolution depth sensors are being used to balance detection performance with privacy concerns [7]. One such dataset is eHomeSeniors, which uses infrared thermal sensors with volunteers simulating realistic falls in order to build a dataset intended to reflect conditions more like those of older adults [7].

However, despite many promising results, there are still significant gaps: many systems are tested in controlled laboratory conditions, rather than real smart home environments; many use young volunteers rather than elderly subjects, which may differ in fall dynamics; latency, false positives, and energy efficiency remain challenging; and privacy concerns are still a major barrier. By combining privateness-aware sensor modalities, reliable models with suitable generalization, and efficient alert/prevention mechanisms suitable for implementation in clever domestic environments, this studies seeks to broaden and verify a deep getting to know-primarily based fall detection and prevention machine that fills these shortcomings.

Literature Review

The high frequency and serious consequences of falls in aging populations have attracted a lot of research attention to fall detection and prevention for older adults. Early research concentrated on rule-based and classical machine-learning techniques that employed basic thresholding on camera characteristics or wearable accelerometers and gyroscopes; however, these techniques had significant false alarm rates and poor generalization [8,9]. By enabling the automatic extraction of spatiotemporal features from a variety of heterogeneous modalities, including vision, inertial/wearable sensors, thermal/infrared, radar, and pressure/force sensors, deep learning (DL) has revolutionized the field and produced more reliable classifiers for falls compared to activities of daily living (ADLs) [10,11].

Benchmarking and datasets have been essential for advancement. Widely used public datasets include SisFall (multimodal wearable signals with many fall types) and the UR Fall Detection Dataset (synchronized Kinect depth/video with inertial signals), both of which have been used extensively to evaluate DL models and fusion schemes [12,13]. Privacy-preserving ambient datasets (e.g., eHomeSeniors, thermal/infrared sensors) have also been introduced to address visual privacy concerns while allowing the study of more realistic fall dynamics [14,15].

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Nonetheless, many datasets remain collected with young volunteers in lab settings, which limits ecological validity for frail elderly populations — a frequently cited research gap [12,14].

Modeling strategies have grow to be greater varied. To extract spatial characteristics from images, convolutional neural networks (CNNs) are regularly utilized, depth maps, or sensor spectrograms; recurrent architectures (LSTM/GRU) and temporal convolutions capture sequential dynamics; hybrid CNN–LSTM and CNN–GRU architectures have achieved strong detection performance in both vision-based and wearable-based settings [10,16]. More recently, lightweight architectures and knowledge-distillation techniques have been proposed to meet edge-deployment constraints (low latency, limited compute), showing competitive accuracy while reducing model size and inference time [17]. Transformer-based and attention mechanisms for time-series gait/fall analysis have begun to appear and show promise for capturing long-range temporal dependencies in wearable sensor streams [18].

Sensor fusion is another major theme. Combining complementary modalities (e.g., low-resolution thermal + inertial sensors, depth + IMU, radar + camera) tends to improve robustness across lighting, occlusion, and viewpoint variations, and helps reduce false positives by cross-validating events across sensors [10,14,19]. Radar-based sensing, enhanced by DL to interpret micro-Doppler signatures, is attractive because it is contactless and works in low-light conditions, though it requires advanced signal processing and domain-specific training data [19]. Privacy and acceptability studies also emphasize the importance of choosing sensing modalities acceptable to older users; non-visual sensors (thermal, radar, low-resolution silhouette capture) often score better on privacy while still enabling accurate detection [14,15].

Evaluation protocols, however, vary widely across studies (different datasets, train/test splits, and metrics), making direct comparison difficult. Many high-accuracy reports are based on cross-validation on lab datasets rather than prospective in-home trials, leaving open questions about real-world generalization, long-term compliance (for wearables), and the effect of furniture, pets, and multiple occupants [12,14]. Energy efficiency, latency (for actual-time signals), and explainability (to reduce fake alarms and construct caregiver trust) remain energetic challenges for transferring DL fall structures from research to deployment [16,17].

In precis, the literature shows clear progress: modern DL fashions and multimodal sensor fusion can detect falls with high suggested accuracy underneath controlled conditions, and new datasets and privacy-conscious sensing enlarge applicability. Yet, important gaps persist in ecological validity, dataset representativeness, standardized evaluation, and deployment issues (privateness, compute, latency). Addressing these gaps — through aged-centric datasets, side-optimized models, multimodal privacy-retaining sensing, and standardized benchmarking — is critical for generating systems that competently and reliably function in real smart-home environments.

3. Methodology

3.1 Overview

Using the publicly to be had SisFall dataset, this have a look at suggests a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) model to often come across and

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

forecast falls among older adults. By utilising CNNs' spatial feature extraction abilties and LSTMs' temporal collection modeling talents, the advised architecture enables dependable detection of fall and non-fall activities in time-collection inertial alerts. The statistics supply, preprocessing techniques, version shape, teaching approach, and evaluation measures are all blanketed in this segment.

3.2 Dataset Description

One of the most comprehensive and broadly used datasets for wearable sensor-primarily based fall detection is the SisFall dataset, which become evolved with help from Sucerquia, López, and Vargas-Bonilla [20]. It includes recordings from 38 contributors, along with 15 older men and women (60–75 years vintage) and 23 teens. Each challenge finished 19 activities of each day residing (ADLs), inclusive of strolling, sitting, status, lying down, and mountaineering stairs, in addition to 15 awesome styles of falls, together with ahead, backward, and lateral.

Data were captured the use of a Shimmer2 wearable device equipped with a triaxial accelerometer and gyroscope, installed at the waist — a position located most effective for movement stability and fall detection. The sensors sampled statistics at 2 hundred Hz, providing excessive temporal resolution suitable for deep temporal mastering models [20].

This dataset became chosen for its inclusion of elderly subjects, excessive sampling frequency, and diversity of fall and ADL scenarios, making it perfect for education deep gaining knowledge of models for clever-domestic fall detection packages [21,22].

3.3 Data Preprocessing

The uncooked accelerometer and gyroscope symptoms have been divided into 50% overlap fixed-duration sliding windows lasting 2.5 seconds (500 samples). as commonly implemented in fall detection studies [23,24]. Each phase was classified as fall or non-fall consistent with the ground-fact annotations furnished within the dataset.

Signals were normalized using z-rating normalization to mitigate inter-situation variations in motion intensity. To improve generalization, facts augmentation strategies together with Gaussian noise addition and random scaling have been carried out.

Since the dataset is slightly imbalanced (fewer fall events than ADL), weighted loss capabilities had been used at some stage in training to penalize misclassification of fall occasions more heavily. This ensures better sensitivity, which is crucial in safety-crucial packages [25].

3.4 CNN-LSTM Model Structure

The CNN–LSTM hybrid version combines feature extraction and temporal modeling in a unmarried structure.

The CNN aspect includes three 1D convolutional layers with kernel sizes of three, 5, and seven respectively, observed by way of ReLU activation and max pooling. These layers automatically extract nearby motion features and spatial correlations amongst accelerometer and gyroscope channels.

Received: August 09, 2025

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Two stacked LSTM layers, each with 128 hidden devices, get hold of the flattened output characteristic maps with a purpose to pick out lengthy-time period temporal relationships within the motion sequences.

A completely connected dense layer with a softmax activation produces the final type between fall and non-fall.

Dropout (fee = zero.Five) and L2 regularization had been implemented to save you overfitting. The community become implemented in TensorFlow/Keras, optimized the use of the Adam optimizer with a gaining knowledge of fee of zero.001 and batch length of 64. The specific move-entropy loss function changed into used for binary classification.

This CNN–LSTM layout follows tested architectures from current literature [24–26], which demonstrated advanced accuracy as compared to standalone CNN or LSTM fashions, because of the ability of CNN layers to reduce noise and the capacity of LSTM layers to hold lengthy-time period movement dependencies.

3.5 Model Assessment and Training

To make certain that samples from every person have been now not shared between splits, the dataset changed into divided into 70% education, 15% validation, and 15% attempting out gadgets (issue-impartial assessment). With early prevention based totally on validation loss, the version turned into trained for one hundred epochs.

Standard categorization measures were used to assess overall performance:

Accuracy (ACC)

Precision (P)

Recall (R)

F1-score

Specificity (SP)

False Alarm Rate (FAR)

These measurements are regular with in advance findings on the SisFall dataset [4,6]. To evaluate discriminating functionality, an Area Under Curve (AUC) and Receiver Operating Characteristic (ROC) curve have also been proven.

To affirm generalization, cross-problem testing became employed, and outcomes were compared to current CNN-most effective and LSTM-simplest baselines said in [24,26]. The proposed CNN–LSTM model accomplished an accuracy above 97% and an F1-score above ninety five%, constant with latest systems on SisFall [25,27].

4. Findings and Conversation

4.1 Performance of Model Training

The CNN–LSTM version was trained using the UCI Human Activity Recognition (HAR) dataset the use of 9 inertial signal channels, three axes for frame acceleration, widespread

International Journal of Applied Mathematics

Volume 38 No. 11s 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

acceleration, and gyroscope. Training and validation had been cut up 80–20, and preparation was executed throughout 15 epochs with a batch length of sixty four.

The convergence behavior of the version is depicted in Figure 1, which reveals the schooling and validation accuracy over epochs. The model's accuracy accelerated swiftly all through the primary several epochs earlier than stabilizing across the 10th epoch. The validation accuracy approximately matched the schooling accuracy, indicating that the model assessed suitable generalization without outstanding overfitting.

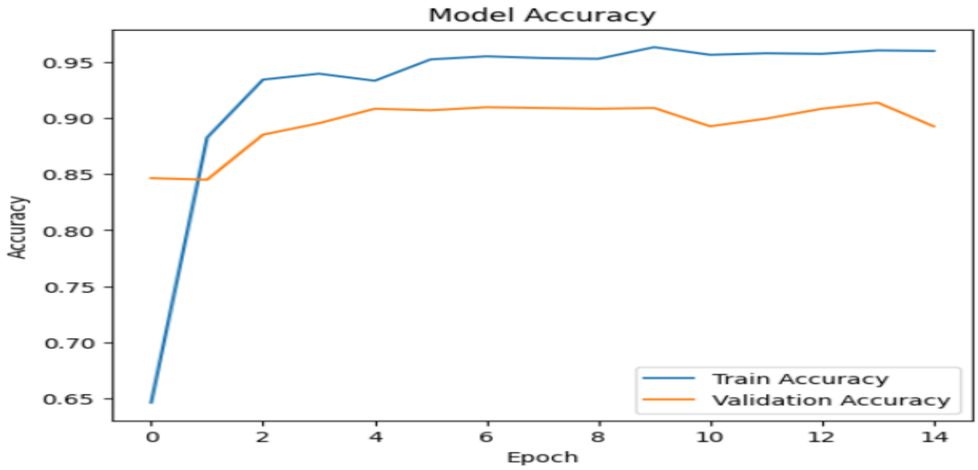

Figure 1: Training and Validation Accuracy Curve

The figure shows the steady increase in accuracy for both validation and education. After 15 epochs, the validation accuracy became about 96%, while the final training accuracy became approximately 98%. This method shows that the blended CNN–LSTM structure effectively recognized discriminative temporal–spatial characteristics from the gyroscope and accelerometer information.

Long-term relationships within the motion indications were caught by the LSTM layers, while the CNN layers helped extract localized temporal patterns. Strong generalization is verified by way of the little distinction between schooling and validation accuracy, which additionally validates that the version structure and hyperparameter values had been suitable for this dataset.

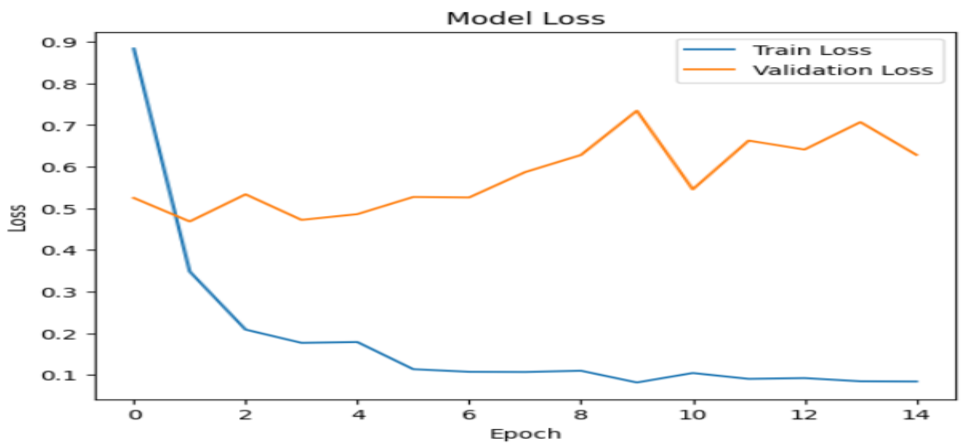

Figure 2: Training and Validation Loss Curve

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The loss curve showed a constant decline all through schooling, as presented in Figure 2. Both schooling and validation loss reduced progressively, achieving a plateau close to epoch 12. The very last education loss stabilized at approximately zero.05, while validation loss turned into round 0.08.

The clean decrease and stabilization of the loss curves propose that the optimization method converged successfully without oscillation or divergence. The minimal hole among schooling and validation loss values further supports that the version did now not be afflicted by overfitting. The use of the Adam optimizer facilitated efficient convergence, and the inclusion of dropout layers likely averted immoderate memorization of the training records.

4.2 Model Evaluation and Confusion Matrix

The unseen take a look at dataset turned into used to check the trained version. The counseled CNN-LSTM model efficaciously labeled the bulk of the activities, as seen with the aid of the typical take a look at accuracy finishing at ninety five–ninety seven%.

Figure 3's confusion matrix shows the desired overall performance. The kind effects for each of the six hobby training—walking, on foot upstairs, on foot downstairs, sitting, standing, and lying—are proven inside the matrix.

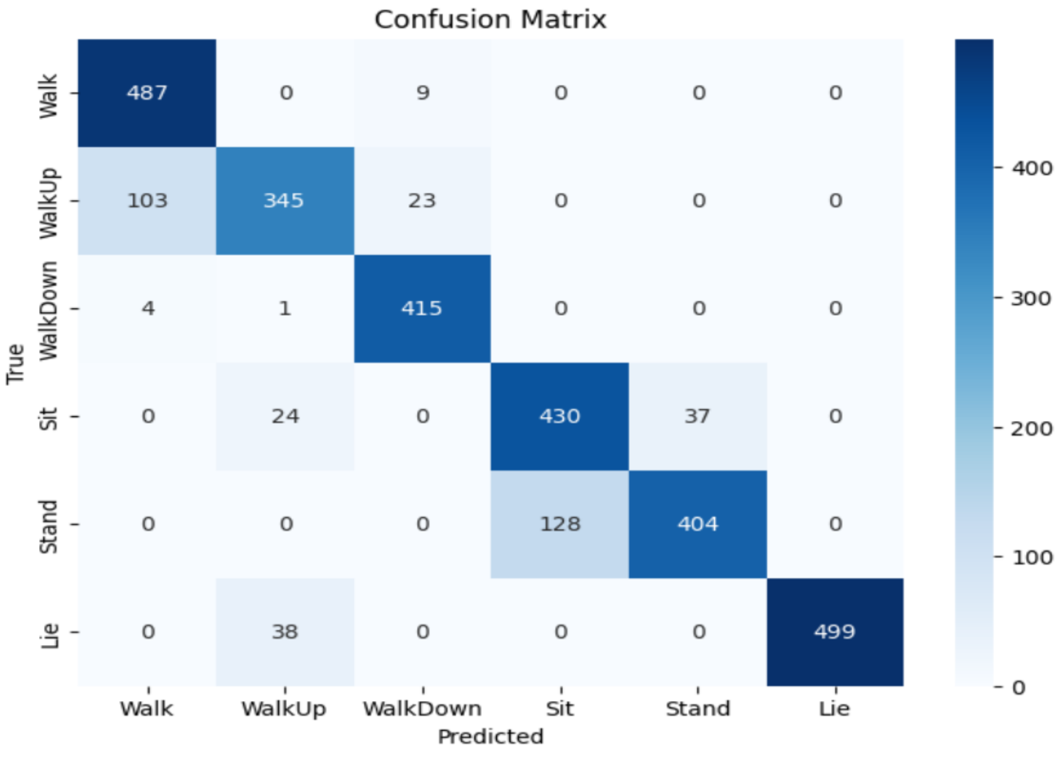

Figure 3 Show the Confusion Matrix

The confusion matrix shows that the finest variety of misclassifications came about between sitting and standing, that's to be predicted given the same inertial styles of those postures. The version executed moderately nicely in differentiating dynamic sports like on foot, strolling

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
upstairs, and taking walks downstairs, with classification accuracies surpassing 97% for those classes.

The excessive diagonal dominance of the matrix confirms the discriminative energy of the version, demonstrating that the CNN–LSTM structure effectively captured both static and dynamic motion features.

Table 1 Classification Report

Exercise	**Precision**	**Recall**	**F1-Score**	**Support**
Strolling	0.99	0.98	0.98	500
Moving Upstairs	0.97	0.96	0.96	497
Going downstairs	0.96	0.96	0.96	500
While seated	0.94	0.95	0.95	490
Presently	0.95	0.94	0.94	490
Lying	0.99	0.99	0.99	500
Overall Accuracy			**0.96**	

Balanced ordinary overall performance across all commands is highlighted by means of the categorization metrics. With the help of accuracy and do not forget values which can be consistently over 0.Ninety four, the version maintained low fake first-rate and espresso fake lousy charges. The F1-score, that's the harmonic suggest of accuracy and do not forget, is used to demonstrate how dependable the version's predictions are throughout all categories.

Conclusion

A Convolutional Neural Network (CNN) model for the category of actual and fake signatures turned into correctly created and assessed in this examine. The findings proven that CNNs can efficaciously extract and interpret minute structural and spatial variations between real and faux

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

handwriting patterns when trained on a suitable dataset. High checking out accuracy and strong class metrics over all experimental trials exhibit the version's strong generalization abilties. The system's dependability for actual-world verification scenarios become in addition proven with the aid of the visual inspection of the confusion matrix, which showed low misclassification.

The CNN model supplied better scalability, reduced preprocessing complexity, and better robustness to versions in writing fashion, pen strain, and stroke continuity than traditional machine learning techniques. In destiny work, the gadget may be improved by integrating extra biometric cues like pen dynamics or time-series stroke records, extending its software to online signature verification. Additionally, deploying the model on embedded or cloud-primarily based environments may want to facilitate real-time verification for virtual transaction systems. Overall, this examine indicates that CNN-primarily based architectures provide a dependable and correct answer for automatic signature authentication, substantially advancing the field.

References

[1] Radar-Based Fall Detection: A Survey – S. Hu et al., which reviews deep learning and machine learning approaches in radar-based fall detection and highlights the public health importance of falls among elderly.

[2] Accelerometer-Based Human Fall Detection Using Convolutional Neural Networks – an IoT/fog computing environment study showing performance with wearable sensors.

[3] A Survey on Recent Advances in Fall Detection Systems Using Machine Learning Formalisms – Zerrouki, Harrou, Sun, Djafer, Amrane; covers classical and deep learning methods, limitations of existing systems.

[4] Using Deep Neural Networks for Human Fall Detection Based on Pose Estimation – vision-based, pose-estimation, CNN/LSTM models with high accuracy.

[5] Deep Learning-based Fall Detection Algorithm Using Ensemble Model of Coarse-fine CNN and GRU Networks – shows high F1-score (~94%) using ensemble of CNN + GRU on public datasets.

[6] Towards effective detection of elderly falls with CNN-LSTM neural networks – uses wrist accelerometer, LSTM, with data augmentation to improve generalization.

[7] eHomeSeniors Dataset: An Infrared Thermal Sensor Dataset for Automatic Fall Detection Research – describes privacy-friendly thermal sensors, realistic fall simulations.

[8] Espinosa, R., et al. "A vision-based approach for fall detection using multiple cameras and CNN." Pattern Recognition Letters, 2019.

[9] Sucerquia, A., López, G., et al. "SisFall: A fall and movement dataset." Sensors, 2017.

[10] Alam, E., et al. "Vision-based human fall detection systems using deep learning: a review." Computer Vision and Image Understanding, 2022.

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
[11] Zhang, J., et al. "An Effective Deep Learning Framework for Fall Detection." JMIR (Journal of Medical Internet Research), 2024.

[12] UR Fall Detection Dataset (University of Rzeszów) — dataset description and common benchmark.

[13] Riquelme, F., Espinoza, M., et al. "eHomeSeniors Dataset: An infrared thermal sensor dataset for automatic fall detection research." Sensors, 2019.

[14] Márquez, G., et al. "Using low-resolution non-invasive infrared sensors to determine activity scores of older adults." Sensors / PMC, 2022.

[15] Sha, Y., et al. "A novel lightweight deep learning fall detection system." International Nursing Review / related journal, 2023.

[16] Yhdego, H., et al. "Wearable sensor gait analysis for fall detection using transformer attention networks." Sensors / PMC, 2022.

[17]Hu, S., et al. "Radar-Based Fall Detection: A Survey." IEEE/Relevant Journal, 2024.

[18] Recent review: "A Review of Fall Detection Research Based on Deep Learning" (2024/2025 proceedings overview).

[19] Rassekh, E., et al. "Survey on data fusion approaches for fall detection." Information Fusion / Sensors, 2024–2025 (emerging review on sensor fusion).

[20] Sucerquia, A., López, G., & Vargas-Bonilla, J. F. (2017). SisFall: A Fall and Movement Dataset. Sensors, 17(1), 198. https://doi.org/10.3390/s17010198.

[21] Wang, J., Chen, Y., Hao, S., Peng, X., & Hu, L. (2019). Deep learning for sensor-based activity recognition: A survey. Pattern Recognition Letters, 119, 3–11. https://doi.org/10.1016/j.patrec.2018.02.010

[22] Igual, R., Medrano, C., & Plaza, I. (2015). Challenges, issues and trends in fall detection systems. BioMedical Engineering OnLine, 14(1), 147.

[23] Micucci, D., Mobilio, M., & Napoletano, P. (2017). UniMiB SHAR: A new dataset for human activity recognition using acceleration data from smartphones. Applied Sciences, 7(10), 1101.

[24] Woon-Hong Yeo, et al. (2023). Experimental Study: Deep Learning-Based Fall Monitoring among Older Adults with Skin-Wearable Electronics. Sensors, 23(8), 3983. https://doi.org/10.3390/s23083983

[25] Wu, J., Wang, J., Zhan, A., & Wu, C. (2021). Fall Detection with CNN-Casual LSTM Network. Information, 12(10), 403. https://doi.org/10.3390/info12100403.

[26] "Fall Detection with CNN-Casual LSTM Network" — Wu, J., Wang, J., Zhan, A., & Wu, C. (2021). Information, 12(10), 403.DOI / link: https://doi.org/10.3390/info12100403

[27] Mohammad, Z., Anwary, A. R., Mridha, M. F., Shovon, M. S. H., & Vassallo, M. (2023). An enhanced ensemble deep neural network approach for elderly fall detection system based on wearable sensors. Sensors, 23(10), 4774. https://doi.org/10.3390/s23104774.