INFORMATICS INSTITUTE OF TECHNOLOGY

In Collaboration with

ROBERT GORDON UNIVERSITY ABERDEEN

# MutliModal Fall Detection System

Group 20 Literature Review Document by:

Modarage Ethan Christoff Perera – 20221812 | 2331419

Senuli Laknara Wickramage – 20220950 | 2330973

Himansa Wathsiluni Jayasuriya – 20230903 | 2330903

Mevinu Induwara Gunaratne – 20232429 | 2330893

Supervised by

Mrs Vishmi Embuldeniya

Submitted in partial fulfilment of the requirements for the BEng/BSc in Artificial Intelligence and Data Science degree at the Robert Gordon University.

**October 2024**

# Table of Contents



# List of Tables



# List of Figures

# 1.0 Introduction

In terms of the tendency of an elderly person to fall in isolated conditions given the fact that they themselves may be experiencing issues and illnesses with joint related issues it may be seen that there has been a vivid increase in the rate at which elderly persons tend to retain injuries at their age due to being neglected in their given state, a study was conducted from the Departments of Medicine (M.E.T., S.F.G.) and Epidemiology and Public Health (M.S.) (Mary E. Tinetti, 1988) and it was found that of a group of 336 elderly persons over the age of 75, 32% (108 subjects) of them had fell at least once. 24% of them had experienced serious injuries, each of which had worsened their conditions. These studies were carried out within a controlled group of people as to where each of them had no chronic disease, thus proving the fact that elderly persons with disease as such may experience much more consequential aftereffects.

Regarding the Literature review provided here, it should be noted that each of the mentioned studies have some relevance to our project in terms of how we may utilize the resources they have developed and provided for their own projects. This is exclusive of utilizing the entire project but instead using small segments for each project as they each provide us with a key understanding into how we are to implement some of the components of out project.

# 2.0 Relevant Works

## 2.1 Posture Detection using Image Pre-Processing for fall detection

In today's world it has been found that many elderly people are affected by falls due to isolation from the presence of a more capable and caring individual. A study was conducted by a group of individuals to monitor and record the effects of social isolation on the quality of life in elderly adults (Roger D. Newman-Norlund, 2022). It was found that it depreciates rapidly due to the forced and induced isolation that was projected onto these individuals.

In terms of how posture detection will be used to predict a fall, it may be seen that an object detection API will first feed the algorithm with real time data that is brought in it from a device that may be staged as a camera. The first task that will take place in terms of data pre-processing will be that of how the real time data will be actively fed into the model as raw/unprocessed data. Furthermore, it may be seen that the tendency of persons over the age of 80 to fall is quite high given risk factors such as isolation that affect them (Norsk forening for epidemiologi, 2012).

Thereafter once the data has been uploaded into the machine learning algorithm it will first be cleansed and set to a limit of **24** recorded frames per second. Thereafter feeding it into the algorithm, the first process to take place is pose landmark projecting using "MediaPipe". What happens here is that the data being fed into the algorithm will first have each frame separated from one another and then processed separately. Thereafter, utilizing MediaPipe's pose landmark detection API, we will be projecting these points onto a person's detected joints.

Having projected these points onto them, the algorithm may then assume a series of thresholds that are to be surpassed to initialize a state where the person is about to fall. In other words, the algorithm will try to understand if a persons joints are surpassing a certain threshold (eg: Elbows are close to the Knees suggesting that the person may collapse), thereafter it will see if that threshold is maintained for a given period of time and then if it exceeded the necessary measure will be taken to ensure that the person falls safely while alerting the relevant authorities.

It is proposed that the peripherals utilized for this segment of the project may be cost-effective and affordable given the fact that most systems are mostly unaffordable to the necessary demographics (Eg: elderly people). So, we believe that through the use of a trained model we may be able to implement a cost-effective solution to the issue at hand.

In terms of how we are expected to train the posture detection model, even though we propose utilizing a dataset from google we intend on customizing it with new thresholds and extended images that capture certain poses which are to be "baked" into its memory such that it may immediately identify a pose as such which is associated with a fall.

A study for the mentioned process has already been carried out by (Saraswat & Malathi, 2024) who had already implemented a vision-based fall detection system utilizing "MediaPipe" as it's backend for pose detection. To conclude, we propose that by utilizing an object detection API for posture detection we may greatly improve the overall accuracy of the systems ability to predict whether the user is about to fall or not.

## 2.2 Use of Accelerometers and Gyroscopes along with ML models for fall detection

In recent years, sensor-based systems have become evident as a powerful way of detecting falls. These systems, mainly the ones that use accelerometers and gyroscopes, have the potential to continuously monitor movements and orientation. They focus on measuring motion dynamics and provide real time data to detect falls when they happen. The ability to embed these in wearable devices have enabled continuous monitoring of at-risk individuals. This chapter covers how accelerometers and gyroscopes are used in fall detection in various systems.

Accelerometers and Gyroscopes are known to be the main tools for fall detection in the past projects since they have the ability to capture data related to motion. Accelerometers are mainly used to measure the change in velocity of an object. In fall detection devices, this is used to detect falls based on sudden changes in the acceleration. In (Palmerini, et al., 2020) , they have used accelerometers to detect falls based on sudden movements or impacts that might indicate a fall. Especially, if the large acceleration is followed by a still period, it triggers and alert.

When the accelerator was used alone some of the intentional motion types were also detected under falls. For example, sitting quickly. This is where the gyroscope comes in. The Gyroscopes are used to measure and maintain the orientation and angular velocity, which is most helpful in capturing data related to rotational movements of the person. A project done with the use of both sensors mentions clearly about this. (Li, et al., 2009) The combination of data from both sensors reduces the false positives that might get detected from accelerometers allows the system to distinguish between intentional motions from unintentional falls. The effectiveness of using these sensors in real world applications has been demonstrated and proved by many studies, making them valuable in elderly monitoring systems.

When it comes to processing the data that is collected from these sensors, there are mainly two types. Threshold based methods and more advanced machine learning based methods. A study about a comparison of these two types explains why machine learning is a better approach than the other. (Aziz, et al., 2017)

Threshold based methods lie in the earliest years, where predefined or calculated limits for acceleration and angular velocity were set and when the data exceeds them, trigger fall alert. This method resulted in a higher rate of false positives because they get triggered by non-fall activities like bending or standing up quickly.

On the other hand, machine learning algorithms like support vector machines and neural networks showed improved accuracy, due to the ability of learning patterns of real time data and hence distinguishing between everyday normal movements and fall movements.

A study (Zurbuchen, et al., 2020) has been conducted to compare the accuracy of a set of machine learning algorithms used for fall detection. They have used the dataset named 'Sisfall' (Sucerquia, et al., 2017) which is publicly available. The machine learning algorithms they have used include support vector machines (SVM), k-Nearest Neighbours (KNN), Decision Trees (DT), Random Forests (RF), and Gradient Boosting (GB). The results showed that gradient boosting outperformed other algorithms in terms of sensitivity and specificity. But it also mentions the need of high computational resources and carful parameter tuning. It also mentions the importance of simple algorithms such as random forests and k-nearest neighbours due to their balance of computational needs and classification power.

| Algorithm | Sensitivity [%] | Specificity [%] | Accuracy [%] | AUROC [%] |
|---|---|---|---|---|
| KNN | 97.26 | **99.31** | 98.41 | 99.45 |
| SVM | 87.93 | 93.78 | 91.20 | 96.43 |
| DT | 96.60 | 97.26 | 96.97 | 96.93 |
| RF | 98.00 | 98.94 | 98.52 | 99.90 |
| GB | **98.06** | 99.21 | **98.70** | **99.93** |

*Figure 1: Comparison of ML algorithms in a study (Zurbuchen, et al., 2020)*

## 2.3 Real-Time Data Analysis for Event Prediction in Fall Detection

Real-time data analysis is integral to modern fall detection systems, enabling immediate identification and prediction of fall events through sophisticated sensor technologies and advanced algorithms. These systems typically employ embedded sensors, including accelerometers, gyroscopes, and pressure sensors, to collect motion data from users. For instance, some systems integrate accelerometers and gyroscopes into footwear, which continuously monitor body movements (Qu, Huang, Ji, and Li, 2024). This data is transmitted to a mobile application via Bluetooth, where it is processed in real time using deep learning models, such as the FallSeqTCN, designed for analyzing time-series data (Qu et al., 2024)

In addition to using traditional motion sensors, some approaches leverage RGB-D sensors and skeleton data to detect falls (Nguyen and Le, 2024). This method analyzes human skeleton information extracted from video footage, allowing the system to track movements accurately. Other studies enhance existing algorithms, such as the improved YOLOv8 model, which incorporates an attention mechanism to improve object localization and detection accuracy, especially in cluttered environments (Khekan, Aghdasi and Salehpoor, 2024). By applying these advanced techniques, these systems can more effectively distinguish between falls and other movements.

Real-time data analysis not only aids in predicting falls but also facilitates immediate alerts to caregivers or medical personnel when a fall is detected. For example, certain systems employ GSM modules to send SMS notifications and make calls, ensuring that help is promptly dispatched to the user (Fitriawan, Purwiyanti, Faturrohman, Santoso, Darajat and Gunawan, 2024). This timely response can significantly mitigate the consequences of falls, which are often more severe due to delays in assistance.

The effectiveness of these systems is evaluated using various performance metrics, such as accuracy, precision, recall, and F1 score. For instance, one model achieved an accuracy of 98% and an F1 score of 0.90, demonstrating the robust capabilities of real-time data analysis in accurately predicting fall events (Khekan, Aghdasi and Salehpoor, 2024). These metrics reflect not only the reliability of the detection systems but also the potential for scalability and further optimization as additional data and models are incorporated.

Overall, the integration of real-time data analysis in fall detection systems highlights significant advancements in ensuring the safety and independence of elderly individuals. By leveraging cutting-edge technology and sophisticated algorithms, these systems provide vital support in preventing fall-related injuries and fatalities.

## 2.4 Monitoring Stress Levels through Blood Pressure and Relating It to Fall Risk

Stress is closely linked to cardiovascular health, and elevated blood pressure due to stress has been widely recognized as a risk factor for falls in elderly populations. Monitoring blood pressure as an indicator of stress levels is key for preventing cardiovascular events and predicting fall risks. Various studies have examined the link between psychological stress, hypertension, and ambulatory blood pressure monitoring, providing insights into how these factors can contribute to fall risk.

Ambulatory Blood Pressure Monitoring in the Elderly: Features and Perspectives
This study investigates the utility of ambulatory blood pressure monitoring (ABPM) in elderly populations, highlighting its importance in detecting blood pressure variability due to stress and predicting cardiovascular events. ABPM is crucial in capturing real-time variations in blood pressure, which may correlate with increased fall risks in elderly individuals, especially those prone to stress. The study emphasizes that timely monitoring of blood pressure can help in identifying early warning signs of stress-induced health deterioration, potentially preventing falls.

Stress and Hypertension: Examining the Relation between Psychological Stress
This research focuses on how psychological stress directly impacts hypertension, leading to sustained high blood pressure. It explores the physiological mechanisms that cause stress-induced blood pressure increases and their implications for cardiovascular health. For elderly individuals, prolonged high blood pressure from chronic stress is a significant risk factor for cardiovascular events and falls. The study suggests that continuous monitoring of stress levels through blood pressure could help predict and reduce fall-related incidents.

2013 Ambulatory Blood Pressure Monitoring Recommendations for the Diagnosis of Adult Hypertension, Assessment of Cardiovascular and other Hypertension-associated Risk, and Attainment of Therapeutic Goals
These recommendations provide a detailed guide on using ABPM to diagnose hypertension and assess cardiovascular risks. The report emphasizes how blood pressure monitoring, particularly in elderly adults, is essential in understanding how stress contributes to increased fall risk. By accurately tracking fluctuations in blood pressure, it is possible to predict cardiovascular events and develop therapeutic interventions that reduce fall risks in stressed individuals.

Study Links High Levels of Stress Hormones to Increased Blood Pressure, Cardiovascular Events
This study shows how stress hormones like cortisol and adrenaline cause blood pressure spikes, leading to cardiovascular events. It draws a direct connection between stress-induced blood pressure changes and health complications, which can be especially dangerous for elderly individuals at risk of falling. Monitoring stress through blood pressure provides an effective means of predicting falls due to sudden cardiovascular issues, further reinforcing the importance of blood pressure monitoring in fall prevention systems.

# 3.0 Existing Works

*Table 1: List of all the exisiting works*

| Citation | Technology/Algorithm Used | Dataset | Advantages | Limitation | Metric |
|---|---|---|---|---|---|
| | **Posture Detection using Image Processing API for fall detection** | | | | |
| (Lin, et al., 2022) | Object Detection API using neuromorphic computing hardware and cameras | N/A | Able to accurately detect whether a person has fallen or is about to fall given the fact that it utilizes "emulated' brain tissue elements | **False Alarms**: Occlusion, especially when the subject's skin is blocked by clothing or background elements, leads to **false positives** | Fall Detection Rate: 91.01%<br><br>False Detection Rate: 0.3% |
| (Liaqat, et al., 2021) | Utilizes deep learning and machine learning (random forest, KNN, SVM, etc) for posture detection | N/A | Detects sedentary behaviour by detecting poor postures in real time and the alerts the user to move | The postures detected are only when the user is sitting or standing (not when they are in any other position) | N/A |
| (Ogundokun, et al., 2022) | Utilizes  Convolutional Neural Networks (CNNs) Which is normally used for human posture detection due to their ability to extract multiscale | MPII Human Pose Dataset | By using image data augmentation, the model reduces overfitting issues typically seen in deep | Deep CNN models like AlexNet and VGG16 require significant computational resources | **AlexNet:**<br>• **Accuracy: 91.2 %**<br>**VGG16:**<br>• **Accuracy:** |

| | | | | | |
|---|---|---|---|---|---|
| | high-level visual representations. | | learning when training on small datasets. | and time due to the millions of parameters involved making it cost inefficient | **90.2 %**<br>□ **CNN:**<br>• **Accuracy: 87.5 %**<br>□ **MLP:**<br>• **Accuracy: 89.9 %** |
| (G. Diraco, 2010) | | Synthetic Range Data | The use of geodesic distance as the Morse function ensures that the system is invariant to translation, scale, rotation, and isometric transformations, making it highly adaptable to different human postures. | The validation of the system was performed using synthetic range data, which may not perfectly replicate the noise and variability found in real-world scenarios. | N/A |
| (Yu, et al., 2012) | Utilizes background substraction which is may be utilized to extract the human body from the video by isolating the foreground from the background. | Small custom dataset of 15 people in a simulated home (controlled environment devoid of extraneous factors) | The system achieves a fall detection rate of 97.08%, making it highly reliable for monitoring elderly people in home care applications. | The system was tested with only 15 participants in a simulated environment. A larger and more diverse dataset, especially with real-world noise and variability, may be | Fall Detection Rate: 97.08%<br><br>False Detection Rate: 0.8% |

| | | | | | |
|---|---|---|---|---|---|
| | | | | needed to confirm its generalizability. | |
| (Feng, et al., 2014) | Utilizes a deep belief network where a deep learning model made up of multiple layers of restricted Boltzmann machines (RBMs) is used for unsupervised learning to extract features from the binary images. | Recordings from a real smart home care environment involving 15 participants creating **2904 postures**. This dataset is used for evaluating the fall detection models. | The use of deep learning methods such as Boltzmann Machines and Deep Belief Networks allows for better feature extraction from the binary images, leading to improved classification performance. | The use of deep learning models like Boltzmann Machines and Deep Belief Networks requires substantial computational resources and might be harder to deploy in real-time, resource-constrained environments. | N/A |
| **Use of Accelerometers and Gyroscopes along with ML models for fall detection** | | | | | |
| (Li, et al., 2009) | A threshold-based fall detection algorithm using tri-axial accelerometers and gyroscopes. Divides human activities into static postures and dynamic transitions. | The dataset includes activities of daily living (ADL), fall-like motions, and different types of falls (e.g., forward, backward, onstairs) | Reduces false positives and negatives. Low computational cost and real-time response. | Difficulty distinguishing between jumping into bed and falling against a wall with a seated posture. | Sensitivity: 91%<br>Specificity: 92% |
| (Aarathi & Sujitha, 2022) | Sensor and Image Data - Deep Convolutional Neural Network (CNN) for feature extraction and SVM (Support | validated using the UR Fall Detection (URFD) dataset | The integration of sensor data and video analysis makes the system more | The processing and joining of image and sensor data needs more | accuracy of **99.81%** on the UR Fall Detection dataset high sensitivity |

| | | | | | |
|---|---|---|---|---|---|
| | Vector Machine) for classification of falls and non-falls | | effective. System has reduced fall positives and negatives. | computational power and speed. | and specificity |
| (Saleh & Jeannès, 2019) | Support Vector Machines (SVM) with both linear and quadratic kernels to detect falls in the elderly based on triaxial accelerometer data. | Sisfall dataset | Low computational cost, suitable for embedding in wearable devices. Efficient feature extraction using a novel two-segment method, enhancing classification accuracy. | **False positives** may occur during fast ADLs like jogging. **False negatives** might happen in slow falls, such as falling backward while sitting | accuracy of **99.9%**, with a sensitivity of **99.50%** and **99.44%** in two different feature extraction methods |
| (Wisesa & Mahardika, 209) | **Recurrent Neural Networks (RNN),** specifically Long **Short-Term Memory (LSTM) networks**, to analyse time-series data from accelerometer and gyroscope sensors to distinguish between falls and Activities of Daily Living (ADL). | **UMA Fall Dataset** (sensor data from 746 samples). Sensors placed on various body parts (waist, ankle, wrist, chest), capturing data for ADL and fall scenarios | High accuracy in distinguishing between falls and ADL using only accelerometer data.<br><br>Cost-effective and easy to set up wearable sensors | Lower performance when combining multiple sensor data streams.<br><br>Some false positives when ADL was misclassified as a fall | **92.31% validation accuracy** using X-axis accelerometer data |
| Real-Time Data Analysis for Event Prediction in Fall Detection | | | | | |
| (Nguyen, et al., 2024) | Non-vision-based (wearable sensors) vs Vision-based (image sequences, skeleton modeling). | RGB-D images and skeleton sequences captured by Kinect sensors. | High detection accuracy with YLOv3-tiny and DeepSort | RNNs used struggle with long sequences<br><br>Falls lasting 400 to 1600ms | over 99% accuracy on both standard and custom datasets for fall detection. |

| | | | | | |
|---|---|---|---|---|---|
| | YOLOv3-tiny (for real-time object detection) and DeepSORT (for human tracking).<br><br>AlphaPose for high-accuracy skeleton | | Preprocessing reduce false posistives | require prcise timing | |
| (Liu & Shi, 2024) | MoveNet for 2D human pose estimation and LSTM for temporal sequence modeling. | UR Fall Detection dataset | Real-time performance<br><br>Efficient pose<br><br>estimation High accuracy | Limited to 2D pose estimation<br><br>Future work needed: needs validation in multi-scene, multi-view, and multi-fall scenarios | MoveNet achieves superior frame rate performance (2.68x faster than OpenPose) with a significantly reduced number of parameters (27% of OpenPose's). |
| (Fitriawan, Purwiyanti, Faturrohman, Santoso, Darajat and Gunawan, 2024) | Arduino UNO, MPU-6050 accelerometer and gyroscope, GPS module, and GSM module | 15 participants who performed controlled falls in indoor and outdoor environments | Low-cost: Real-time alerts: Portable and lightweight | GPS accuracy: Errors<br><br>Threshold customization needed for individual based on movement pattern | The system achieves acceptable fall detection accuracy based on real-time performance, but the GPS accuracy varied due to environmental factors, with an average error of 9.23 meters. |
| (Khekan, Aghdasi and Salehpoor, 2024) | Improved YOLOv8 algorithm for fall detection | CAUCAF all dataset | Increased detection speed and reduced | Potential limitations regarding the | Detection accuracy is measured using mean Average |

| | | | | | |
|---|---|---|---|---|---|
| | | | misclassificat ions | complexity of senarios | Precision (mAP), which considers both precision and recall across various classes and IoU thresholds. |
| (Qu, et al., 2024) | Accelerometers, gyroscopes, and pressure sensors embedded in footwear.<br><br>FallSeqTCN, a Temporal Convolutional Network (TCN) for time-series prediction. | UMAFall dataset Own Dataset: collected using the system | Real-time Analysis<br><br>High Accuracy with the FallSeqTCN model Scalable | Noise Sensitivity<br><br>User Discomfort<br><br>Limited Dataset | 98% accuracy in detecting falls<br><br>8% accuracy prediction falls<br><br>F1 score 0.90 |
| **Monitoring Stress Levels through Blood Pressure to Predict Fall Risk** | | | | | |
| (M.D, 2016) | Ambulatory Blood Pressure Monitoring (ABPM) | N/A | Real-time monitoring of blood pressure variability, useful for detecting stress-induced fall risk. | Limited to elderly subjects, may miss transient events | N/A |
| (Mediavilla García, et al., 2011) | Continuous Blood Pressure Monitoring | Clinical trial data on hypertension | Demonstrates clear link between psychological stress and sustained high blood pressure | May not generalize beyond clinical settings | N/A |
| (Hermida, et al., 2012) | ABPM for hypertension diagnosis | Data on adult hypertension and cardiovascular risk | Establishes best practices for diagnosing hypertension and identifying | Focuses on diagnosis rather than direct fall risk | Accuracy in predicting hypertension progression |

| | | | | | |
|---|---|---|---|---|---|
| | | | cardiovascular risks | | |
| (Inoue, et al., 2021) | Hormonal impact on blood pressure | Stress hormone analysis in adults | Shows direct impact of cortisol and adrenaline on blood pressure, correlating with cardiovascular events and falls | Focuses on hormonal effects rather than direct monitoring | N/A |

# 4.0 Summary

To conclude what our project is and what it aims to achieve, it may be condensed into the following paragraph. Our project is a multi-modal fall detection system that utilizes the IOT (Internet of Things) to detect whether a person is about to fall or not. It aims to utilize a gyroscope, accelerometer and externally placed image processing device (camera) that is to monitor the posture of a person into the algorithm to predict whether a person is about to fall or not such that emergency measure may be taken to alert the relevant authorities and initiate an airbag to be released behind the mounted device such that the user does not sustain any injuries. Our model aims to use a posture detection API with customized thresholds and a trained model to understand which values retained by the peripherals are to assume an urgent and risky state.

# 5.0 Bibliography

Aarathi, S. M. & Sujitha, J., 2022. Intelligent Fall Detection System based on Sensor. *IEEE explore.*

Aziz, O. et al., 2017. A comparison of accuracy of fall detection algorithms (threshold-based vs. machine learning) using waist-mounted tri-axial accelerometer signals from a comprehensive set of falls and non-fall trials. *Springer.*

Feng, P., Yu, M., Naqvi, S. M. & Chambers, J. A., 2014. *Deep learning for posture analysis in fall detection.* [Online]
Available at: https://ieeexplore.ieee.org/abstract/document/6900806
[Accessed 11 October 2024].

Fitriawan, H. et al., 2024. *Development of a Low-Cost Fall Detection System for the Elderly with Accurate Detection and Real-Time Alerts.* [Online]
Available at: https://ieeexplore.ieee.org/abstract/document/10675589
[Accessed 10 October 2024].

G. Diraco, A. L. P. S., 2010. *An active vision system for fall detection and posture recognition in elderly healthcare.* [Online]
Available at: https://ieeexplore.ieee.org/abstract/document/5457055
[Accessed 11 October 2024].

Hermida, R. C. et al., 2012. *2013 Ambulatory Blood Pressure Monitoring Recommendations for the Diagnosis of Adult Hypertension, Assessment of Cardiovascular and other Hypertension-associated Risk, and Attainment of Therapeutic Goals.* [Online]
Available at: https://www.tandfonline.com/doi/full/10.3109/07420528.2013.750490#d1e686
[Accessed 11 October 2024].

Inoue, K. et al., 2021. *Urinary Stress Hormones, Hypertension, and Cardiovascular Events: The Multi-Ethnic Study of Atherosclerosis.* [Online]
Available at: https://www.ahajournals.org/doi/10.1161/HYPERTENSIONAHA.121.17618
[Accessed 11 October 2024].

Khekan, A. R., Aghdasi, H. S. & Salehpoor, P., 2024. *Fast and High-Precision Human Fall Detection Using Improved YOLOv8 Model.* [Online]
Available at: https://ieeexplore.ieee.org/abstract/document/10697972
[Accessed 11 October 2024].

Liaqat, S. et al., 2021. *A Hybrid Posture Detection Framework: Integrating Machine Learning and Deep Neural Networks.* [Online]
Available at: https://ieeexplore.ieee.org/abstract/document/9343347
[Accessed 10 October 2024].

Lin, B. S. et al., 2022. *Fall Detection System With Artificial Intelligence-Based Edge Computing.* [Online]
Available at: https://ieeexplore.ieee.org/abstract/document/9667467
[Accessed 10 October 2024].

Li, Q. et al., 2009. Accurate, Fast Fall Detection Using Gyroscopes and. *virginia.edu.*

Liu, S. & Shi, C., 2024. *A Real-Time Fall Detection System Based on MoveNet and LSTM.* [Online]
Available at: https://link.springer.com/chapter/10.1007/978-3-031-70235-8_2
[Accessed 11 October 2024].

M.D, V. G. M. :. W. B. W., 2016. *Ambulatory Blood Pressure Monitoring in Older Persons.* [Online]
Available at: https://link.springer.com/chapter/10.1007/978-3-319-22771-9_11
[Accessed 11 October 2024].

Mediavilla García, J. D. et al., 2011. *Ambulatory Blood Pressure Monitoring in the Elderly.* [Online]
Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3249829/
[Accessed 11 October 2024].

Nguyen, T.-B., Nguyen, D.-L., Nguyen , H.-Q. & Le, T.-L., 2024. *A Real-Time and Continuous Fall Detection Based on Skeleton Sequence.* [Online]
Available at: https://link.springer.com/chapter/10.1007/978-981-97-5504-2_11
[Accessed 11 October 2024].

Norsk forening for epidemiologi, 2012. *Fall risk factors in community-dwelling elderly people.* [Online]
Available at: https://oda.oslomet.no/oda-xmlui/handle/10642/1474
[Accessed 10 October 2024].

Ogundokun, R. O., Maskeliūnas, R. & Damaševičius, R., 2022. *Human Posture Detection Using Image Augmentation and Hyperparameter-Optimized Transfer Learning Algorithms.* [Online]
Available at: https://www.mdpi.com/2076-3417/12/19/10156
[Accessed 11 October 2024].

Palmerini, L., Klenk, J., Becker, C. & Chiari, L., 2020. Accelerometer-Based Fall Detection Using Machine Learning: Training and Testing on Real-World Falls. *mdpi.*

Qu, Z., Huang, T., Ji, Y. & Li, Y., 2024. *PHYSICS SENSOR BASED DEEP LEARNING FALL DETECTION.* [Online]
Available at: https://arxiv.org/pdf/2403.06994
[Accessed 11 October 2024].

Roger D. Newman-Norlund, S. E. N.-N. S. ,. C. M. R., 2022. *Effects of social isolation on quality of life in elderly adults.* [Online]
Available at: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0276590
[Accessed 11 October 2024].

Saleh, M. & Jeannès, R. L. B., 2019. Elderly Fall Detection Using Wearable Sensors: A Low Cost Highly Accurate Algorithm. *IEEE explore.*

Saraswat, S. & Malathi, G., 2024. *Pose Estimation based Fall Detection system using MediaPipe.* [Online]
Available at: https://ieeexplore.ieee.org/abstract/document/10543522
[Accessed 11 October 2024].

Shuxin Liu, C. S., 2024. *A Real-Time Fall Detection System Based on MoveNet and LSTM.* [Online]
Available at: https://link.springer.com/chapter/10.1007/978-3-031-70235-8_2
[Accessed 11 October 2024].

Sucerquia, A., López, J. D. & Vargas-Bonilla, J. F., 2017. SisFall: A Fall and Movement Dataset. *mdpi.*

Thuy-Binh Nguyen, D.-L. N. H.-Q. N. T.-L. L., 2024. *A Real-Time and Continuous Fall Detection Based on Skeleton Sequence.* [Online]
Available at: https://link.springer.com/chapter/10.1007/978-981-97-5504-2_11
[Accessed 11 October 2024].

Wisesa, W. W. & Mahardika, G., 209. Fall detection algorithm based on accelerometer. *IOP Science.*

Yu, M. et al., 2012. *A Posture Recognition-Based Fall Detection System for Monitoring an Elderly Person in a Smart Home Environment.* [Online]
Available at: https://ieeexplore.ieee.org/abstract/document/6279483
[Accessed 11 October 2024].

Zurbuchen, N., Bruegger, P. & Wilde, A., 2020. A Comparison of Machine Learning Algorithms for Fall Detection using Wearable Sensors. *IEEE explore.*