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In Collaboration with

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**MutliModal Fall Detection System**

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# 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](https://ai.google.dev/edge/mediapipe/solutions/vision/pose_landmarker) 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.

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 Neighbors (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.

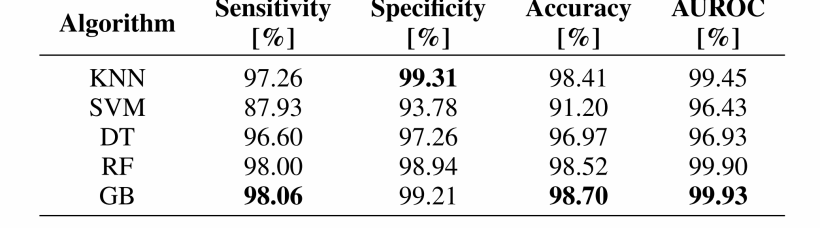


Figure 1: Comparison of ML algorithms in a study (Zurbuchen, et al., 2020)

# 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%  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 high-level visual representations. | MPII Human Pose Dataset | By using image data augmentation, the model reduces overfitting issues typically seen in deep learning when training on small datasets. | Deep CNN models like AlexNet and VGG16 require significant computational resources and time due to the millions of parameters involved making it cost inefficient |  **AlexNet:**   * **Accuracy: 91.2%**    **VGG16:**   * **Accuracy: 90.2%**    **CNN:**   * **Accuracy: 87.5%**    **MLP:**   * **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 needed to confirm its generalizability. | Fall Detection Rate: 97.08%  False Detection Rate: 0.8% |
| (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%  Specificity: 92% |
| (Aarathi & Sujitha, 2022) | Sensor and Image Data - Deep Convolutional Neural Network (CNN) for feature extraction and SVM (Support Vector Machine) for classification of falls and non-falls​ | validated using the UR Fall Detection (URFD) dataset | The integration of sensor data and video analysis makes the system more effective. System has reduced fall positives and negatives. | The processing and joining of image and sensor data needs more computational power and speed. | accuracy of **99.81%** on the UR Fall Detection dataset  high sensitivity 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.  Cost-effective and easy to set up wearable sensors | Lower performance when combining multiple sensor data streams.  Some false positives when ADL was misclassified as a fall | **92.31% validation accuracy** using X-axis accelerometer data |
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|  |  |  |  |  |  |

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# 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.

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