Fall Detection and Assessment Using Multitask Learning and Micro-sized LiDAR in Elderly Care

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Abstract. The increasing concern over the rapid aging population has brought to light a significant issue: the escalating number of falls among the elderly. As seniors grow older, they become more susceptible to physical ailments, leading to a higher frequency of falls. The lack of prompt assistance after a fall further compounds the problem, putting them at risk of severe consequences, including mortality. To address this pressing matter, the demand for fall detection systems in nursing homes and similar care facilities is on the rise. In response, our research proposes developing a point cloud-based fall detection system, complete with risk assessment capabilities, catering to the specific needs of the elderly. By employing advanced 3D LiDAR technology, we can scan the environment while preserving privacy. The algorithm employed then carefully analyzes this representation, extracting spatio-temporal discriminative features, thus enabling accurate fall detection. We have thoroughly evaluated the proposed system using collected data in our lab, and the results are promising, demonstrating its ability to detect fall events effectively. The successful implementation of this system could significantly enhance safety and improve the overall quality of life for the elderly population.

Keywords: Point cloud · LiDAR · Fall detection · Risk assessment · Healthcare

1 Introduction

Falls present a significant public health concern, particularly among the elderly. The World Health Organization (WHO) reports falls as the second leading cause of accidental or unintentional injury deaths globally, with adults aged 60 and above being at higher risk. In the United States, falls stand as the primary cause of injury-related deaths among those aged 65 and older, signifying an urgent issue that requires immediate attention. In Japan, a country recognized for its rapidly aging population, falls represent the most frequent cause of fatal accidents that occur within homes.

A. Zaslavsky et al. (Eds.): MobiQuitous 2023, LNICST 594, pp. 280–293, 2024.
https://doi.org/10.1007/978-3-031-63992-0_19

Falls have far-reaching consequences, often leading to severe injuries like fractures, head injuries, and traumatic brain injuries, which, in turn, can result in reduced independence, disabilities, and a decline in quality of life. For older adults, falls can even prove fatal due to their underlying health conditions, rendering them more susceptible to complications arising from such injuries. The increasing number of elderly individuals living alone adds further complexity to ensuring their safety and well-being, highlighting the urgent need to address fall-related risks. To protect the health and dignity of our aging population, it is crucial to develop robust fall detection systems. These systems should be capable of swiftly detecting falls and providing timely assistance, ensuring the well-being of seniors even when they are living independently. By addressing this pressing issue, we can significantly enhance the safety and quality of life for our elderly citizens.

In light of this critical challenge, researchers have been actively working on the development of diverse fall detection systems, utilizing a wide range of sensors and technologies. These include accelerometers [1–8], Wi-Fi [9], and video cameras [10–12]. By harnessing the potential of these tools, the systems can effectively detect falls by sensing sudden changes in acceleration or orientation or by analyzing images and video footage to recognize patterns commonly associated with falls.

Many of these systems utilize wearable sensors, such as smartwatches [3] or smartphones [7]. However, for older adults, the use of these devices can be inconvenient and uncomfortable, resulting in inconsistent or incorrect usage. Furthermore, fall detection systems that rely on visible cameras to capture videos [11,12] raise privacy concerns due to the sensitivity of the data, including images and location information. This concern holds particular importance for older adults, as they place a high priority on their privacy and are sensitive to issues of security and surveillance. Therefore, the installation of cameras for fall detection in their homes may encounter resistance, as it can be interpreted as an invasion of their privacy and a form of surveillance.

As a result, there exists a reluctance among certain older adults to fully embrace these systems, even if it means forgoing access to crucial fall detection services. However, there is a promising alternative in the form of radio-based fall detection, which ingeniously harnesses signals like WiFi RSSI or CSI [13], offering a privacy-conscious solution. This cutting-edge approach effectively mitigates the visual privacy concerns often associated with camera-based systems, presenting a more appealing option for those who prioritize their privacy. Nonetheless, radio-based fall detection is not without its challenges. It faces hurdles in terms of accuracy and the need for further refinement in technology for practical and widespread adoption.

Additionally, current fall detection techniques often lack the ability to assess the severity of falls, leading to inappropriate system responses. This limitation must be addressed urgently to guarantee precise and targeted assistance for the safety and well-being of the elderly population. Sustained research efforts are essential to develop a privacy-preserving, non-intrusive approach that can accurately detect falls and assess their risk level.

In recent times, remarkable progress has been achieved in the field of 3D range scanning, particularly with the emergence of LiDAR technology. LiDAR finds diverse applications across a broad spectrum, including human identification [14], tracking in public spaces [15–18], and activity recognition [19], among many others. One of the inherent advantages of LiDAR is its ability to prioritize privacy. By utilizing a 3D point cloud data capture approach, LiDAR effectively solves common privacy concerns that are often associated with camera-based systems. The point cloud data comprises purely non-personal information, represented by three-dimensional coordinates, making LiDAR a privacy-conscious and secure alternative.

In this paper, we present a system for fall detection utilizing low-cost, non-invasive LiDAR tailored for healthcare applications. Specifically, our system is run on Hitonavi-μ which is composed of a compact-size LiDAR device, a processing unit, and a battery [14]. By scanning and representing the environment in a point cloud format, our system achieves real-time fall detection on Hitonavi-μ across various scenarios while prioritizing individual privacy. This characteristic makes it well-suited for deployment in privacy-sensitive settings, including restrooms, where ensuring privacy is of utmost importance. Furthermore, the system demonstrates exceptional proficiency in evaluating the corresponding risk level of detected falls from *non-fall*, *low*, *moderate*, and *high* levels, depending on the activity during the fall, as it impacts the speed of the fall. This distinctive capability empowers the system to initiate prompt and appropriate actions, such as reaching out to emergency response teams or notifying family members, depending on the severity of the fall event.

Nevertheless, the system proposed faces two challenges. Firstly, extracting significant context from variable-sized, unordered, and unstructured point cloud representations proves to be a complex task in comparison to 2D images. Secondly, considering the constrained computational power available at the edge device, additional considerations require careful attention.

To address these challenges, we have devised a series of modules, introducing resolution enhancement, and downsampling techniques. Additionally, we have incorporated a computationally efficient feature extraction method based on the Fisher vector, which generates fixed-size distinctive signatures of falls by leveraging its symmetric functions. These extracted features play a vital role in our multitask learning approach, training a model that can simultaneously recognize fall events and assess their severity levels without compromising efficiency.

The proposed system underwent a comprehensive evaluation, employing data gathered from a diverse group of participants over several days. We also addressed the data imbalance by upsampling minority data. Impressively, the system achieved remarkable accuracy rates, detecting falls with 95.2% and accurately assessing fall risk levels at 94.6%.

An essential strength of the system is its unwavering dedication to safeguarding the privacy of the elderly while ensuring their safety through prompt and suitable actions determined by the recognized risk level. This aspect emphasizes the system's ability to provide effective fall detection services without compromising the dignity and privacy of older adults, making it an ideal solution for maintaining their well-being in all settings. The impressive outcomes clearly highlight the revolutionary possibilities of Hitonavi-μ as the cutting-edge fall detection technology of the future.

The subsequent sections of this paper are organized as follows. In Sect. 2, we conduct a comprehensive literature review. Section 3 offers an overview of the proposed system, while Sect. 4 delves into its details. Moving on to Sect. 5, we explain the data collection process and the system's testing methodology. Lastly, we draw our conclusions in Sect. 6.

2 Related Work

Fall detection systems can be classified into three main types, depending on the sensing technology used: wearable-based, vision-based, and ambient-based systems.

Wearable sensors include accelerometers, gyroscopes, magnetometers, and electromyography. They analyze changes in body movements related to falls. Among these wearable sensors, accelerometers have received considerable attention in various studies (Wang et al., 2020). Accelerometers present numerous advantages, including their compact size, portability, cost-effectiveness, and non-intrusive nature, which help avoid privacy concerns. Moreover, the prevalence of smartphones and smartwatches equipped with built-in sensors makes them promising resources for real-world fall detection applications. Accelerometers offer flexibility in their placement on various body parts, including the waist (i.e., waist [1], thigh [2], wrist [3], sole [4], torso [5], chest [6], ankle [8], etc.) For instance, [2] proposed a patient-specific fall detection system with a single sensor. In contrast to many existing research studies that solely focus on detection, the proposed approach goes beyond detection by also addressing the aspect of prediction. The system consists of two branches for fall prediction and detection individually. They adopted a threshold approach for prediction and a machine-learning approach for detection. This is because the fall prediction requires a low computational cost algorithm to alarm the patients before falls occur. They successfully reduced the false alarm rate by taking the fall prediction result into the detection process.

- *In contrast to the wearable-based approach, point cloud-based fall detection systems do not require individuals to wear sensors or devices, making them more user-friendly and suitable for scenarios where individuals may not be willing or able to wear sensors.*

Vision-based fall detection has been extensively explored and demonstrated promising performance. Common visual sensors used in this context include infrared cameras [10], RGB cameras [11,12], and RGB-D cameras [20]. [11] proposed a vision-based method using a monocular camera for monitoring elderly people. They first extract foreground objects and conduct segmentation. Then, they apply ellipse fitting for the approximation of human-body regions. The feature is extracted from those regions and fed into a multi-class support vector machine followed by a context-free grammar-based method that incorporates longer-range temporal constraints to validate the detected falls. [12] proposed an algorithm that determines regions of the human silhouette based on the centroids of different regions of the human body part instead of ellipses. This reduced the false alarm rate of fall-like movements, such as squatting and sitting, which had been a problem with ellipse-based detection. Images obtained from these types of sensors offer detailed scene information; however, they also raise concerns regarding privacy violations, as they may capture personal and environmental information in living spaces. RGB cameras are widely used due to advancements in computer vision technology. However, they face challenges related to their sensitivity to environmental conditions. In particular, their performance is significantly affected in low-light settings, making them less effective during nighttime. Additionally, distinguishing between real falls and certain behaviors like lying down can be difficult, leading to a higher rate of false detections.

– *Compared with visual sensors, point clouds are less intrusive in terms of privacy since they don't capture detailed color or texture information about individuals. Point clouds are also less affected by changes in lighting conditions, making them more reliable in scenarios with poor lighting.*

Ambient sensors offer a privacy-preserving approach for fall detection. Common examples of these sensors are pressure tiles, magnetic switches, seismic sensors, and Wi-Fi-based sensors [9], etc. The approach presented in the paper [9] utilized Wi-Fi signals and gained popularity due to its non-intrusive and widespread availability. Their proposal involved real-time, cost-effective indoor fall detection using CSI phase differences as the primary signal. However, the system's effectiveness is limited in multi-person scenarios, as it works effectively only when a single individual is in motion while others remain stationary. The benefit of using ambient sensors lies in their non-intrusive nature. These non-contact sensors do not require direct attachment to the body, allowing users to have a comfortable and unrestricted experience in their daily activities. In addition to being non-intrusive, ambient sensors can detect changes in the surrounding environment, providing a comprehensive monitoring approach. However, they are susceptible to interference from external factors such as walls, furniture, or other electronic devices, leading to poor detection. e.g., the pressure tile has the disadvantage of sensing all objects in its vicinity, resulting in an increased false alarm rate.

– *On the contrary, point clouds are less affected by changes in lighting, temperature, or other environmental conditions compared to ambient sensors, which can be sensitive to variations in their surroundings.*

3 System Overview

The proposed system consists of two main stages: **the sensing stage** and **the intelligence stage**. In the sensing stage, our innovative proprietary device,

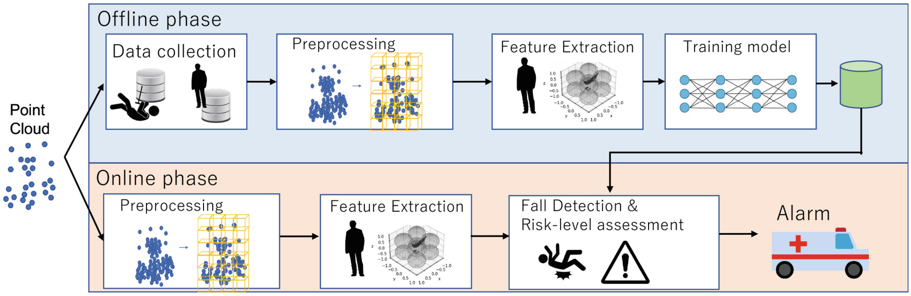

Fig. 1. System overview

referred to as Hitonavi-μ introduced in our previous work [14], plays a central role. This device has been ingeniously designed to support various applications in smart environments. By simply plugging in Hitonavi-μ, the system gains the impressive capability to scan its surroundings and create a detailed 3D point cloud representation of the scene. The main goal of this sensing functionality is to create a signature database for detecting falls. This is done by gathering point cloud scans of individuals in simulated falling scenarios. These captured point clouds are then efficiently processed within the Intelligence stage. The intelligence has two different phases (i.e., offline phase and online phase) as shown in Fig. 1. The offline phase involves model training, which includes gathering data, preprocessing, and extracting features. On the other hand, during the online phase, the system detects falls and assesses the risk level when it's operating in real-world settings. If a fall happens, the system alerts healthcare services, ensuring prompt treatment and preventing severe damage.

4 The System Details

In this section, we offer a detailed explanation of the different modules in the proposed system. These modules cover the stages of sensing and intelligence including multiple modules.

4.1 The Sensing Stage

This section provides an overview of the key features of the proposed sensing device, referred to as Hitonavi-μ. Hitonavi-μ is a compact, battery-equipped version of Light Detection and Ranging (LiDAR), accompanied by its computing unit. LiDAR, in general, is a remote sensing technology used to measure the distance to the surface of surrounding objects. It achieves this by calculating the time taken for a laser pulse to travel from the sensor to the objects/surfaces and back, thus estimating the distance. LiDAR technology has found extensive applications, including obstacle detection in autonomous cars [21], as well as human and robot detection, tracking, and navigation in public indoor environments [18]. However, the existing LiDAR systems used in these applications are typically large and expensive, making them more suitable for commercial environments like malls and museums. This restricts their widespread adoption as privacy-preserving vision technology, especially in private settings.

To address this limitation, we employ a micro-sized LiDAR sensor[1] This sensor is relatively smaller and lighter compared to consumer-grade LiDAR devices, with dimensions of 44 mm width, 24 mm depth, and 16 mm height. The design rationale behind Hitonavi-μ is to enable its deployment in any indoor environment, including homes where camera-based systems may not be suitable. This paves the way for the next generation of privacy-preserving vision technology.

The LiDAR sensor is linked to a battery-equipped computing unit, specifically the Raspberry Pi 4 Model B [22], which serves as the processing platform for our algorithms. The Raspberry Pi 4 Model B is a compact single-board computer suitable for mobile devices. It features an ARM Cortex-A72 quad-core CPU running at 1.5 GHz and is equipped with 4 GB of RAM. Figure 2 illustrates the composition of Hitonavi-μ, consisting of the small-sized sensor and the Raspberry Pi compute module. The sensor operates at an average frame rate of approximately 30 frames per second.

4.2 The Intelligence Stage

In this section, we describe the process shown in Fig. 1, including data collection, preprocessing, feature extraction, and classifier.

The Data Collection. During this phase, we collect 3D point cloud data from individuals to create a unique database. This is done by using the sensor to record the scene and then sending the collected point cloud to our server using the built-in WiFi on Hitonavi-μ. Figure 3 and Fig. 4 show the scene of data collection and corresponding point cloud captured by the sensor. We position the sensor on a tripod, which allows it to capture objects and people around it within a distance of up to 3 m. As can be seen in visualization of point cloud, it is challenging to know the attribute (e.g., gender, age) of people by direct observation, making it suitable in privacy-related situations.

Preprocessing. This section describes modules to handle input point clouds for system stability and improvement. There are two modules for frame integration, downsampling.

Frame Integration. In this module, frame integration serves two primary purposes. Firstly, it combines multiple successive frames to enhance the sensor's resolution, resulting in a more intricate representation of the captured scene. While commercial LiDAR systems typically gather a substantial number of points (around $\sim 100k$ points) within a single point cloud, our Hitonavi-μ sensor averages just $0.8k$ points. This lower point density preserves privacy but poses

[1] The sensor used in this study was manufactured by MagikEye company.

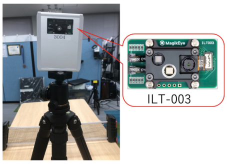

Fig. 2. Hitonavi-μ

Fig. 3. Scene of Data Collection

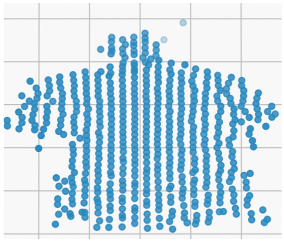

Fig. 4. Point cloud as captured by the sensor

recognition challenges. To address this, we utilize the sensor's high sampling rate to boost its resolution by merging m consecutive frames into a single frame with higher point density. This strategy enhances visual clarity and data accuracy.

Secondly, frame integration allows us to capture the temporal changes within the time sequences. This capability is crucial for fall detection, which involves capturing sequences of events that happen over time. Falls often unfold gradually, involving a series of movements, shifts, and changes in position. By observing these changes across a sequence of frames, we can more accurately identify and differentiate a fall from other activities or situations.

Downsampling. This module serves two primary objectives. Firstly, we aim to reduce the computational cost by removing some points from the point clouds. Processing point clouds using machine learning requires substantial computational resources, which can be challenging, especially when deploying the system on edge devices with limited processing power. Downsampling points is one approach to address this challenge. Secondly, we aim to mitigate sampling biases. Point cloud representations often exhibit non-uniform distribution, resulting in varying densities across the scene. Certain areas may have denser point clouds due to factors like sensor-object distances. This non-uniform density can impact the performance of our system, as areas with more points contain more information compared to areas with lower density. Our second goal is to address this issue.

To accomplish these goals, we utilize Voxel downsampling. This approach involves dividing the 3D space into grids, creating individual boxes known as 'Voxels.' Each voxel then generates a single point by averaging all the points within it. These processes can be easily performed using the distributed open3D library.

Feature Extraction. This section introduces our proposed feature extraction technique based on Fisher Vector (FV) representations. Before we delve into the feature extraction technique, we discuss the challenges associated with representing a 3D point cloud. The primary challenge stems from the fact that a 3D point cloud lacks a structured grid, unlike images that have a fixed grid arrangement. This variance in the number of points within a point cloud makes it challenging to apply traditional computer vision techniques. To address this issue, voxelization is commonly employed, which involves discretizing the 3D space into cells to facilitate the application of Convolutional Neural Networks (CNNs). However, voxelization introduces quantization loss and imposes high computational resources. Additionally, there is a challenge related to the ordering of points within the point cloud. It is crucial for models to produce consistent results regardless of the order in which the data points are presented.

To address these challenges, we utilized the FV representation. The FV representation is employed to create distinctive signatures for the data of different activities including fall, which can vary in size, such as 3D point cloud frames. This representation inherently captures the spatial locality of the points. It defines the signature as the deviation of the 3D points from a generative model, such as a Gaussian Mixture Model (GMM). This is achieved by calculating the gradients of the sample's log-likelihood with respect to the model parameters, including weight, mean, and covariance. Furthermore, the FV maintains a fixed-size grid structure, making it a convenient input for any classifier.

The key advantage of the Fisher vector representation is its independence from the sample size, making it a suitable choice for representing point cloud data.

Classifier Training. In this section, we explain our approach to constructing a classification model capable of accurately identifying falls and assessing associated risks using the extracted Fisher representations.

We employed multi-task learning for our classifier, which involved fall detection and risk assessment tasks. Multi-task learning is an approach in machine learning where a single model is trained to perform multiple related tasks simultaneously. Instead of training separate models for each task, the multi-task learning model shares information and parameters across tasks to exploit their inherent relationships.

The motivation for utilizing multi-task learning is to have a simplified model that can efficiently run on edge devices. By training multiple tasks with a single model, we eliminate the need for separate models for each task. This reduces the complexity of the model and allows for efficient utilization of memory and computational resources. Moreover, multi-task learning enables us to train multiple related tasks simultaneously, even with less data compared to training separate models for each task. The sharing of features and parameters promotes information exchange between tasks, leading to improved data efficiency. This advantage is crucial due to the difficulty of collecting fall data.

The architecture of the network is shown in Fig. 5. We used three layers of fully connected neural layers for the shared components with 512, 256, and 128 units, respectively. As for the subsequent branches, both fall detection and risk-level detection consist of two fully connected layers with 64 and 32 units. The activation function used throughout the model is Rectified Linear Unit (ReLU). Finally, the output layers of each branch are designed with a number of neurons

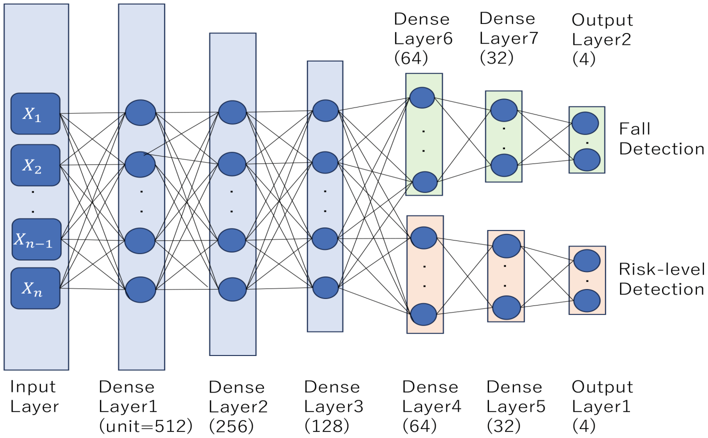

Fig. 5. Model architecture

corresponding to the number of fall classes and risk levels under consideration, with a Softmax activation function.

The term "risk level" specifically refers to the severity of falls that have occurred while engaging in various activities. Our categorization comprises four classes: non-fall, low, moderate, and high, which are labeled by experts in our lab who were familiar with fall events in their research [23]. The "non-fall" classification pertains to activities of daily living (ADLs) where the risk of falling is minimal. However, the other categories relate to instances of falls, indicating different levels of risk associated with each. Our classification of fall-related events is primarily determined by the particular activities being performed during the fall. Specifically, falls that occur during standing activities or transitioning from standing to sitting are labeled as "low risk." Falls that happen during activities of picking up objects or sitting down are categorized as "moderate risk." Conversely, falls that occur while walking or transitioning from sitting to standing are considered "high risk." These are basically associated with the poses, particularly the positions of heads. Generally, higher head positions lead to higher risks when falls happen.

5 Evaluation

In this section, we conduct an evaluation of the proposed system's end-to-end performance. To ensure a thorough assessment, we considered various activities of daily life (ADL), encompassing standing, walking, sitting, sit-to-stand, stand-to-sit, and picking up objects. The dataset utilized for these experiments was collected from seven subjects, each exhibiting different attributes such as height and body shape, among others. To gather fall events data, we recorded falls occurring in different directions – front, right, left, and back – a total of ten times for each direction. Note that we consider only front falls for the walking activity.

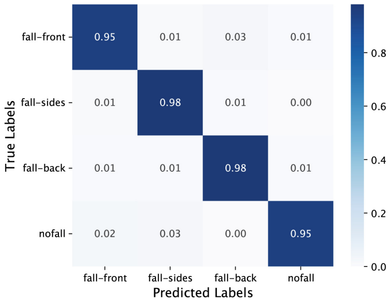

Fig. 6. Fall detection

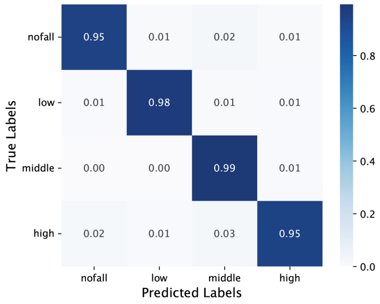

Fig. 7. Risk-level detection

Additionally, for the collection of ADL data, we recorded stationary activities (i.e., standing and sitting) for a duration of 30 s, while mobility activities (i.e., walking, sit-to-stand, and stand-to-sit) were recorded ten times each.

For the purpose of evaluation, we split the data into an 80% training set and a 20% testing set.

5.1 System Parameters

The default parameters of each module are selected (based on the performance obtained by grid search) as follows: Number of frames integration = 9 and Downsampling voxel grid size = 5. The details of the grid search are summarized in Table 1.

Table 1. Details of the grid search

Target module	Parameter	Value
Frame integration	Number of integrated frames	1, 3, 5, 7, 9, 11
Voxel Downsampling	Grid length(r)	5, 15, 30, 50

5.2 Results

In this section, we present the outcomes of the system's performance evaluation. The confusion matrices for fall and risk-level detection are illustrated in Fig. 6 and Fig. 7, respectively, showing accuracies of 95.2% and 94.6%.

These promising outcomes highlight the effectiveness of our point cloud-based fall detection system. Its ability to achieve such high accuracies in detecting falls and assessing risk levels reaffirms its credibility and potential for real-world healthcare applications.

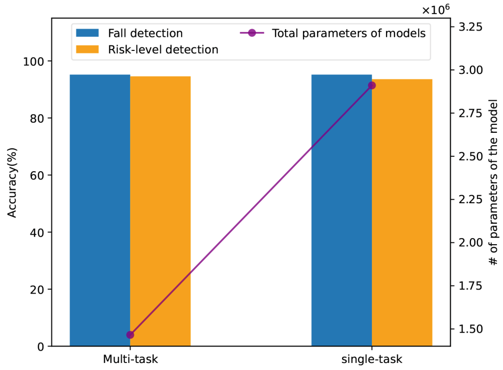

Fig. 8. Comparison between single-task and multi-task learning

Comparison with Single Task Model. This section investigates the performance comparison with the single-task model to show the efficacy of multi-task learning. Figure 8 shows the results, including the accuracy and memory consumption. The system built with a single-task-based model incurs twice the burden in memory consumption compared to the multi-task-based one. Implementing this on edge devices with limited computational power and memory capacity is not suitable. Additionally, it is notable that the model with multi-task learning achieves slightly better accuracy compared with that with single-task learning. i.e., both 95.2% for fall detection, while 94.6% and 93.6% for risk detection. As such, the multitask learning model is a better choice than the single-task model as described in Sect. 4.2.

6 Conclusion

In this paper, we introduced a novel fall detection system with risk-level assessment, utilizing privacy-preserving point clouds. Our system includes modules to achieve accurate recognition while minimizing computational overhead. These modules enhance point cloud resolution, downsample point clouds, and learn salient representations through the Fisher vector. To optimize the recognition of falls and simultaneously assess the associated risk level, we employed a multi-task learning approach. Our evaluation showed remarkable results: 95.2% accuracy in fall detection and an outstanding 94.6% accuracy in risk-level assessment, with strong generalization across diverse scenarios. These findings highlight Hitonavi-μ's potential as a transformative plug-and-play healthcare support device with far-reaching implications for assistive technology. Future plans involve large-scale deployment in residential and hospital settings, aiming to positively impact healthcare outcomes.

Acknowledgment. This work was supported by JST, A-STEP Grant Number JPMJTR20RV, Japan.

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