Transfer Learning Using Computer Vision Models for Fall Detection from UWB Radars

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Abstract

Detecting when a person falls poses a substantial challenge to researchers because of the risk of serious injuries like femoral neck fractures, brain hemorrhages, or burns, which can lead to significant discomfort and, in some cases, worsen over time, resulting in complications or even fatalities. The effectiveness of fall detection is linked to promptly alerting caregivers, such as nurses, upon detecting a fall. In our study, we present a technique for identifying falls within a 40-square-meter apartment using data collected from three ultra-wideband radars. Our approach integrates pre-trained computer vision models (ResNet, VGG, and AlexNet) for fall detection, which is a binary classification task aimed at distinguishing between fall and non-fall events. To refine the model's performance, we utilize data representing various fall scenarios simulated by 10 participants across three locations within the apartment. We evaluate the performance of the presented technique by using the leave-one-subject-out strategy. The results consistently demonstrate the superior performance of the ResNet model compared to the VGG and AlexNet models. Notably, our findings indicate an approximate 95% F1 score in fall detection, suggesting promising prospects for real-world deployment.

Keywords: Fall Detection; Classification; Ultra-wideband radar; Transfer Learning; Residual Neural Network

1. Introduction

The frequency of falls among elderly populations poses a significant concern for global public health, resulting in serious injuries, diminished quality of life, and escalated healthcare expenses. Prompt and accurate detection of falls

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is crucial for timely intervention and mitigating adverse consequences. Advances in technology have spurred the development of various fall detection systems, employing diverse sensor technologies and machine learning techniques (Shen et al. (2023)).

Within the technology domain, Ultra-Wideband (UWB) radar systems emerge as promising tools for fall detection. Their ability to penetrate barriers, operate in diverse settings, and provide precise sensing highlights their potential. UWB radars are characterized by their non-intrusive nature, privacy-respecting attributes, and ability to facilitate continuous monitoring, making them suitable for discreet fall detection applications both indoors and outdoors (Cheraghinia et al. (2024)).

While UWB radar-based fall detection systems show promise, there remain considerable challenges in accurately distinguishing falls from everyday movements and reducing false alarms. In this work, we address this issue by leveraging advanced machine learning techniques in computer vision, specifically employing pre-trained computer vision models: Visual Geometry Group (VGG) (Majib et al. (2021)), Residual Neural Network (ResNet) (Kiliç et al. (2020)), and AlexNet (Azhagiri and Rajesh (2024)). Our approach capitalizes on the distinct capabilities of these models to enhance the precision of fall detection using UWB radar signals (Ullmann et al. (2023)).

The following structure is presented in this paper: Section 2 offers a synopsis of pertinent literature, followed by Section 3 introducing the proposed methodology. Section 4 elaborates on the experimental setup, and Section 5 examines the results and analysis. Finally, Section 6 outlines the conclusions drawn from this study and suggests avenues for future research.

2. Literature Review

Studies on fall detection can be categorized into two primary groups: approaches using wearable technologies and those employing non-wearable solutions. Within the non-wearable category, methods vary based on the technologies utilized, such as vision sensors or non-vision sensors. Our study focuses specifically on the non-wearable approach utilizing non-vision sensors (Gharghan and Hashim (2024)).

The non-wearable strategy employs non-vision sensors that generate one-dimensional (2D) discrete-distance signals (Hu et al. (2024)). Unlike cameras, which provide 2D and 3D data, interpreting information from 1D signals presents a challenge for observers. Additionally, these technologies mitigate the shortcomings of wearable devices and cameras, such as battery management issues, data absence instances (when individuals fail to use the device), and privacy concerns related to cameras. According to available literature, various solutions for fall detection exist, including smart floors (comprising a network of seismic sensors) (Clemente et al. (2019)), acoustic sensors like ultrasonic arrays (Chen et al. (2023)), and infrared array sensors (He et al. (2023)).

Baik and Shin (2024) devised an algorithm to categorize falls by identifying human movements utilizing frequency modulation continuous wave radar. It introduced an innovative feature to mitigate detection inaccuracies, which was derived from the range-velocity map of the 2D Fourier transform. This feature was evaluated utilizing supervised machine learning techniques such as support vector machines and linear discriminant analysis, achieving an accuracy surpassing 91%.

Some works have leveraged UWB radar for fall detection from various angles. For instance, Sadreazami et al. (2019) employed a solitary UWB radar for fall detection, employing a CNN architecture yielding an accuracy of 92.72%. However, their research encountered several constraints. Specifically, the dataset they collected demonstrated limited diversity, comprising only five subjects. Moreover, their methodology lacked validation through the leave-one-subject-out strategy.

Arnaoutoglou et al. (2024) developed an innovative non-contact radar technique for detecting falls among elderly individuals residing at home. The novelty lies in utilizing a 1D effective acceleration obtained through Short Time Fourier Transform (STFT). Their method was evaluated using a 2.45 GHz Continuous Wave (CW) Radar system built with readily available, affordable components and Software Defined Radio (SDR) technology. Test results are presented, demonstrating the system's ability to classify incidents as falls or non-falls in situations with clear line-of-sight. These results were compared to data obtained from a commercially available marker-based optoelectronic motion capture system comprising multiple cameras, showing strong correlation. Real-time scenarios were also conducted to assess the accuracy and false alarm rate of their method.

Yang et al. (2024) introduce a method for fall detection that relies on spatio-temporal features to accurately identify falling incidents by leveraging the spatio-temporal relationships within the skeleton. Regarding network architecture, thier approach involves two key steps. Firstly, they propose a novel spatial graph convolution technique aimed at capturing spatial features of the skeleton. This method directs the network's attention towards potential connections between joint points that are not physically linked in the human skeleton structure. Secondly, they enhance the network's ability to capture temporal information by integrating temporal features of various scales using multi-scale temporal graph convolution. Additionally, to account for the spatio-temporal correlations inherent in actions, they incorporate a spatio-temporal attention mechanism to capture more intricate spatio-temporal characteristics.

Moreover, a fall detection method leveraging Channel State Information (CSI) (He et al. (2024)) is devised to address the drawbacks of conventional fall detection systems such as compromised privacy, elevated expenses, and limited cross-domain applicability. Utilizing data from standard WiFi devices, the approach scrutinizes alterations in indoor CSI induced by human movements, enabling non-intrusive fall detection. Initially, a blend of Discrete Wavelet Transform (DWT), phase disparity analysis, and Moving Average Filter (MAF) is employed to mitigate the influence of ambient noise on detection accuracy. Subsequently, the variance of CSI amplitude and phase disparity is computed to guide subcarrier selection, while moving variance aids in delineating active intervals of chosen subcarriers, thereby diminishing data complexity and extracting time-frequency attributes. Lastly, Genetic Algorithm (GA) optimizes parameter selection for Random Forest (RF), enhancing classifier model performance.

Interestingly, no research examined in the literature utilized the leave-one-subject-out approach for assessing generalization or monitored activities across various sites. Moreover, our investigation suggests that the orientation of the radar's angle of operation could influence recognition outcomes. These findings underscore the importance of our study, as it faithfully replicates real-world conditions for fall detection and implements the leave-one-subject-out technique alongside advanced technology to showcase its applicability to novel participants.

3. Methodology

This study presents a technique utilizing a pre-trained computer vision model to enhance the precision of fall event detection through the utilization of data collected from three UWB radars. The phases of this technique are illustrated in Fig. 1, and further elaborated in the following paragraphs.
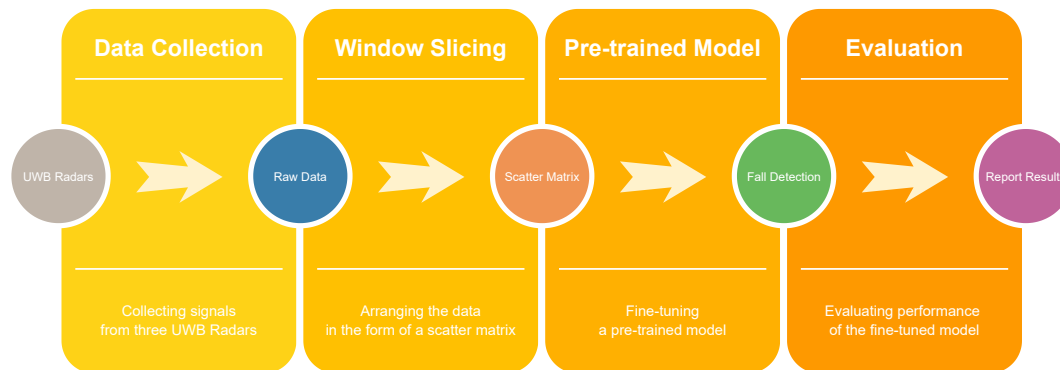

Fig. 1. Phases of the presented technique.

Initially, raw data is gathered as signals from UWB radar systems. This data, obtained from each radar, is organized into scatter matrices. The matrix's horizontal axis denotes a consistent size, equivalent to 184 real values recorded at each time instance, while the vertical axis signifies the duration of data collection. In our examination, every scatter matrix is viewed as a time series. Furthermore, we implement a data augmentation technique by employing overlapping along the scatter matrix's vertical axis. In this work, we employ data augmentation to enhance the accuracy of fall event detection.

Fig. 2 illustrates the initial organization of data extracted from the three UWBs following signal acquisition. Each set of data captured by individual radars is presented as a scatter matrix, as demonstrated in Fig. 3. These scatter

matrices serve as input channels for the deep learning models employed. We partition the scatter matrices into time slots for the purpose of emulating time series analysis, with each time slot consisting of 200 frames, corresponding to a four-second duration along the vertical axis of the scatter matrix. To enhance the dataset, we apply a 90% overlap between consecutive time slots. It is important to note that no data balancing is performed in this study, as the dataset does not display significant imbalances.
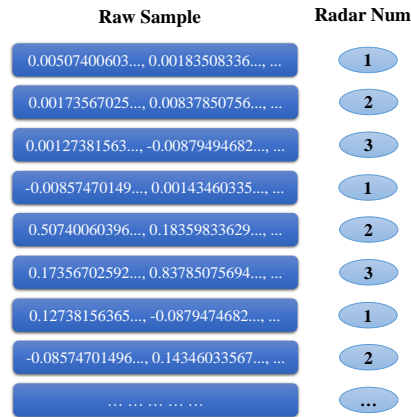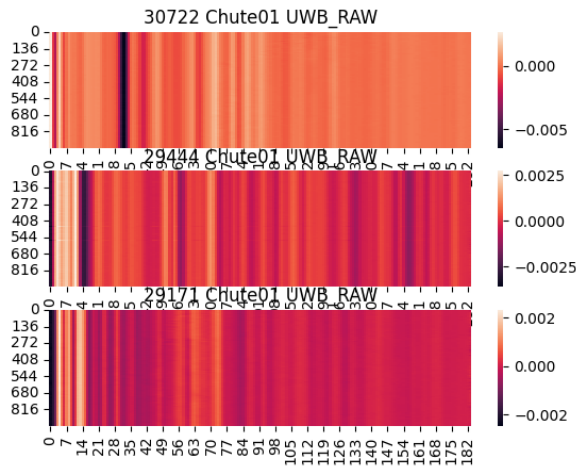

Fig. 2. The raw data format.

Fig. 3. The Scatter Matrix for raw data.

Subsequently, we fine-tune a pre-trained model by employing the data generated from the overlapping process. We treat this data structure as visual patterns, incorporating each scatter matrix as a separate channel into the pre-trained models. The model was trained over 20 epochs, utilizing data segments sourced from the corresponding datasets utilized in our study. The choice of 20 epochs was deliberate, aiming to balance training efficacy with time constraints. To ensure fairness in our comparisons, we consistently applied all models to identical data segments across each evaluation round, encompassing train, validation, and test sets. This approach mitigates bias stemming from the random selection of data segments from the primary datasets. Our analysis focuses on the predictive performance of the trained model that demonstrated the highest validation accuracy during the training process.

All experiment results are reported by using leave-one-subject-out strategy. Hence, for every iteration, we designate the data gathered from one subject as the test set, while the data chosen from the remaining participants form the training set. Then, the validation set is chosen from the initial training data by employing 10-fold cross-validation to the initial training set. Finally, we report the results obtained by calculating the average performance values across test sets corresponding to the all subjects.

4. Experimental Setup

We conducted numerous experiments to evaluate the effectiveness of the method presented from different perspectives. Our experiments were carried out on a workstation equipped with an NVIDIA GPU and 24GB of memory. Python, along with the PyTorch library and additional Python modules, was employed for all experimentation. Specifically, the torchvision package was utilized for constructing VGG, AlexNet, and ResNet models. Our utilized ResNet model has a depth of 18 layers (ResNet-18), while the VGG model consists of 16 layers (VGG-16).

4.1. Datasets

This research introduces a fall detection system that relies on Ultra-Wideband (UWB) radars installed within an apartment situated at the Laboratory of Ambient Intelligence for Activity Recognition (LIARA). The LIARA lab, situated within the University of Quebec at Chicoutimi, comprises a typical apartment layout of 40 square meters, featuring a kitchen, living room, bedroom, and bathroom, as illustrated in Fig. 4.

Three UWB radars, mounted on walls, were employed to collect data as shown in Fig. 5. The radars are positioned at a standard elevation of 36 centimeters above the ground level, which corresponds to the typical height of electrical outlets frequently encountered in Canada. The radar model utilized is the Xethru X4M200, manufactured by Novelda. It has the capability to receive electrical power directly from standard electrical outlets. The radar receiver operates within the 6.0 to 8.5 GHz range for low frequencies and between 7.25 and 10.2 GHz for high frequencies. The UWB radar operates at a pulse repetition frequency (PRF) of 15.875 MHz, detecting the reflected wave pulses emitted by objects or humans. The radar's resolution measures 5.14 cm.

Fig. 4. The LIARA's smart home.

The data, which is accessible online[1], is gathered from ten participants aged between 23 and 39, each experiencing three different fall positions (Maitre et al. (2020)). The experiments included simulating four categories of falls: backward, forward, sideways (left or right), and falling while trying to take a seat on a chair. Each category of falls was

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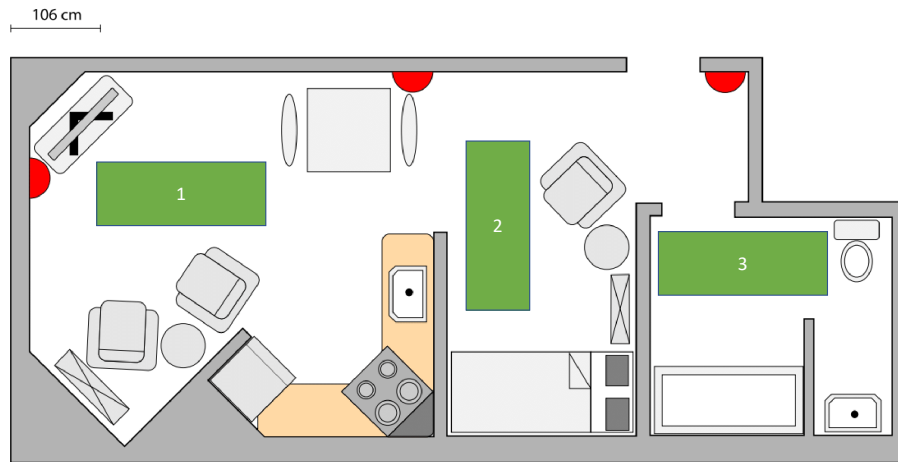[1] https://kevinbouchard122764662.wordpress.com/projets-de-recherche

Fig. 5. Layout of the LIARA apartment showing three UWB radars highlighted in red. The simulated falls are marked by green rectangles.

performed five times in three separate locations within the apartment, identified by green rectangular markers shown in Fig. 5. Consequently, we have three distinct datasets covering all potential fall positions. Within each dataset, data from individual participants are separated into fall and non-fall events. In our binary classification setup, the label '1' denotes fall occurrences (positive instances), while '0' denotes non-fall activities (negative instances).

4.2. Evaluation Measures

The practical outcomes obtained from experiments furnish a reliable method for gauging the effectiveness of the techniques introduced for fall detection. To evaluate these methods, we utilize metrics such as classification accuracy and F1-score. Accuracy denotes the percentage of correctly categorized samples, while the F1-score, also known as F-score or F-measure, encapsulates the balanced average of precision and recall, with a scale from 0 (poorest) to 1 (optimal). Recall, also termed sensitivity or true positive rate, expresses the proportion of accurately classified positive samples to the total positive samples, while precision signifies the ratio of accurately classified positive samples to all samples identified as positive (Yacouby and Axman (2020)).

5. Results and Analysis

We conducted a study to assess how well the chosen models performed in identifying instances of falls within the dataset utilized. Table 1 shows the performance of the evaluated pre-trained models with all used datasets. It is evident that not all pre-trained models exhibit strong performance in fall detection tasks. ResNet demonstrates notably superior performance compared to VGG and AlexNet.

As ResNet demonstrates superior performance, we presented additional evaluation metrics to underscore the importance of utilizing this model for fall event detection in UWB radar signals. Fig. 6 shows accuracy, F1-score, sensitivity, and precision. It is evident that no single dataset is superior in all aspects, as each possesses unique strengths. When scenarios demand high sensitivity, Datasets 1 and 2 are preferable. On the other hand, for situations where precision is the main concern, Dataset 3 is the best choice.

Fig. 7 shows the confusion matrix for the ResNet model when applied to the three datasets. It is clear that Dataset 1 demonstrates strong accuracy in forecasting "Fall" incidents, but it frequently misidentifies non-fall events as falls. Dataset 2 appears balanced, with high precision in predicting both "Fall" and "Non-fall" occurrences. Dataset 3 is exceptional at correctly identifying "Non-fall" events but struggles significantly with "Fall" predictions.

Table 1. Performance of the pre-trained models

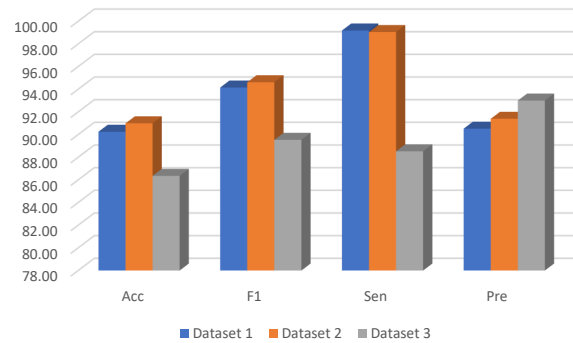| Fold	Dataset 1						Dataset 2						Dataset 3					
	ResNet		AlexNet		VGG		ResNet		AlexNet		VGG		ResNet		AlexNet		VGG	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1
1	0.99	0.99	0.72	0.84	0.72	0.84	0.71	0.83	0.72	0.84	0.72	0.84	0.83	0.88	0.72	0.84	0.72	0.84
2	0.65	0.79	0.70	0.82	0.70	0.82	0.71	0.83	0.72	0.84	0.72	0.84	0.66	0.72	0.71	0.83	0.71	0.83
3	0.75	0.85	0.71	0.83	0.71	0.83	0.88	0.92	0.70	0.83	0.70	0.83	0.62	0.67	0.74	0.85	0.74	0.85
4	0.95	0.97	0.70	0.82	0.70	0.82	0.99	0.99	0.71	0.83	0.71	0.83	0.80	0.88	0.71	0.83	0.71	0.83
5	0.70	0.82	0.70	0.83	0.70	0.83	1.00	1.00	0.68	0.81	0.68	0.81	0.82	0.85	0.69	0.82	0.69	0.82
6	0.99	1.00	0.75	0.86	0.75	0.86	1.00	1.00	0.69	0.81	0.69	0.81	0.99	1.00	0.72	0.84	0.72	0.84
7	1.00	1.00	0.70	0.82	0.70	0.82	0.99	1.00	0.73	0.84	0.73	0.84	0.92	0.95	0.73	0.84	0.73	0.84
8	1.00	1.00	0.73	0.84	0.73	0.84	0.82	0.89	0.72	0.84	0.72	0.84	1.00	1.00	0.70	0.82	0.70	0.82
9	1.00	1.00	0.73	0.84	0.73	0.84	1.00	1.00	0.72	0.84	0.72	0.84	1.00	1.00	0.74	0.85	0.74	0.85
10	1.00	1.00	0.72	0.84	0.72	0.84	1.00	1.00	0.72	0.84	0.72	0.84	1.00	1.00	0.73	0.84	0.73	0.84
Avg	0.90	0.94	0.72	0.83	0.72	0.83	0.91	0.95	0.71	0.83	0.71	0.83	0.86	0.90	0.72	0.84	0.72	0.84

Fig. 6. Performance of pre-trained ResNet for fall detection from UWB signals.
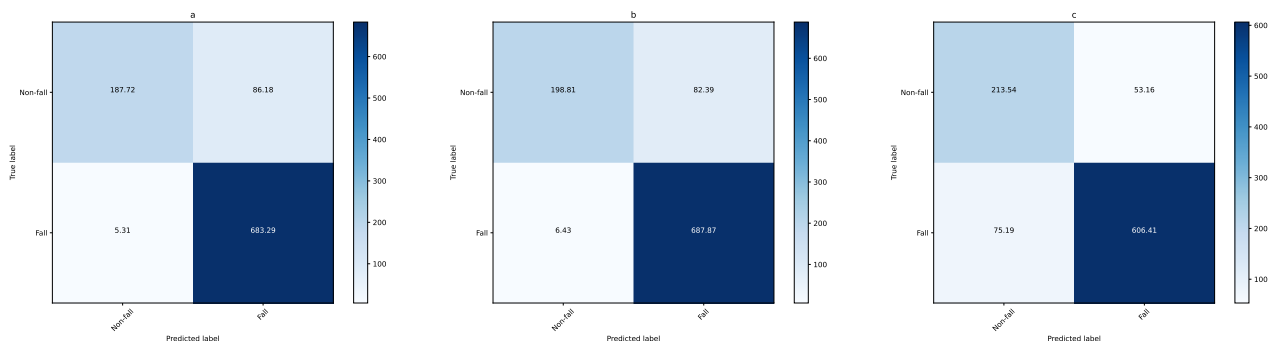

Fig. 7. Confusion matrix with ResNet: (a) Dataset 1; (b) Dataset 2; (c) Dataset 3.

6. Conclusion and Future Work

Through extensive experimentation and assessment, we showcase the effectiveness of employing computer vision models and the capacity of the pre-trained models to propel the cutting-edge in fall detection technology. This work has the potential to significantly enhance healthcare outcomes and elevate the quality of life for elderly individuals and vulnerable populations. Our pioneering approach not only showcases innovation and originality in the presented

technique but also demonstrates its uniqueness by seamlessly translating a state-of-the-art computer vision method into an equally advanced fall detection method from UWB Radars.

There are several potential avenues for extending this work. One promising direction involves assessing the efficacy of more computer vision networks in detecting falls from UWB signals. Another intriguing possibility is to explore data prepossessing techniques. For instance, evaluating the performance of applying more data augmentation methods for fall detection holds considerable promise. Moreover, investigating various combinations of computer vision models with diverse late fusion techniques could lead to valuable insights.

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