The Smart Insole: A Pilot Study of Fall Detection

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Abstract. Falls are common events among human beings and raised a global health problem. Wearable sensors can provide quantitative assessments for fall-based movements. Automatic fall detection systems based on the wearable sensors are becoming popular in recent years. This paper proposes a new fall detection system based on the smart insole. Each smart insole contains pressure a pressure sensor array and can provide abundant pressure information during the daily activities. According to such information, the system can successfully distinguish the fall from other activities of daily livings (ADLs) using deep learning algorithms. To reduce the computational complexity through the classifiers, the raw data for each sensor in the time windows are utilized. Furthermore, the deep visualization approach is applied to provide an intuitive explanation of how the deep learning system works on distinguishing the fall events. Both quantitative and qualitative experiments are demonstrated in this paper to prove the feasibility and effectiveness of the proposed fall detection system.

Keywords: Pressure sensor array · Fall detection · Deep learning · Smart insole · Deep visualization

1 Introduction

Falls are the most common incident among human beings. It poses a global health problem. In the United States, more than 1.6 million adults receive treatment due to the fall-related accidents every year [7], and the financial costs associated with fall are rising in these years [10]. Approximately one-third of the aged population fall at least once a year, and the similar reports are also generated from other countries, such as Spain and Colombia [1]. With increasing age, the physical changes make people more prone to falls, and the fall injuries are exacerbated. Falls event leads to significant injuries including skin abrasions, upper limb and hip fractures, brain injuries and general connective tissue lesions [2,11]. Falls not

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only seriously threaten the health, but also cause the psychological problem like lowering the self-confidence and being afraid of independent life, which further weakens the quality of daily life [9]. In the past few decades, falls detection has attracted more attention from the public. Most of the time, the fallers might lose consciousness and are unable to call for help. Therefore, many automatic fall detection technologies have proposed in recent years [16].

It is generally known that the vision, sound, radar, and infrared sensors perform well to detect falls automatically [13]. However, these ambient sensor-based technologies have the problem of privacy and make the seniors face many constraints, for example, living in a restricted zone [12,14]. In the last decades, the development of the wearable sensor-device provides new chances for detecting fall-related accidents. The wearable sensor-based fall detection systems eliminate the space limitation compared with the systems based on the ambient technologies [12]. Due to the wearable accelerometers have the characters of small size and low price, many wearable fall detection systems are designed based on such sensors and place them on different positions on the subject of interest (SOI). However, in these ways, SOI have to wear many sensors during daily activities, which make them inconvenient. On the other hands, It is forgettable for the SOI to wear complicated wearable sensors, especially for seniors. Nowadays, smart insoles based on the wearable pressure sensors array placed in shoes can provide sufficient information for the gait analysis [8]. On the other hand, the characteristics of smart insole placed in the shoe are convenient and hard to be forgotten by the users.

In this article, we mainly focus on the fall detection based on the smart insole. To acquire the pressure information of an area, a high-spatial-resolution pressure sensor array has been developed over an individual pressure sensor. We extend smart insole with 48 pressure sensors array [8] to contain 96 pressure sensors for receiving more precise pressure information. The deep learning methods are applied to make the fall detection classifier. Besides, the comparison experiments of using the combinations of the smart insole with other wearable sensors including accelerometers and gyroscopes to perform the fall detection are also demonstrated. To further understand the deep learning model on distinguishing fall events, the saliency visualization [3] is introduced to present how the pressure information during the dynamic motion pattern contributes towards a fall classification.

2 Related Work

Most of the fall detection systems are designed by utilizing wearable devices [7,12,15,18]. The wearable devices are attached to clothes or part of the body of the SOI for detecting the falls [1,7,12]. The sensors as the main components of wearable devices measure the characteristics of the movements of SOI. The strategies of the fall detection system mainly monitor the variables of acceleration and speed primarily. The changes of the acceleration magnitude are utilized to detect the falls. When the value of accelerometers exceeds a specific threshold, the falls are recognized [15,19]. However, the threshold-based systems based on

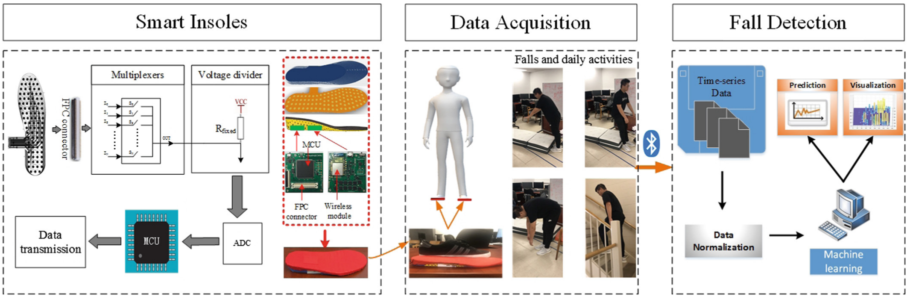

Fig. 1. The flowchart of the falls detection system. The data are collected from the pressure sensor array on the smart insoles that are attached to the SOI. The data are transmitted to the centralized data warehouse, and the machine learning algorithms are implemented for the falling recognition.

accelerometers are difficult to distinguish the falls from other activities that have similar characteristics in term of acceleration [1]. Some researchers enhance the system based on the accelerometers by applying more wearable sensors. The systems integrate the sensors that are placed on different positions such as the waist, ankle, and chest on the subject of SOI with data mining techniques [12,16–18]. Besides, the pressure sensor array designed on insole has been used in gait analysis and can provide sufficient information about the SOI movements [8]. In order to overcome the weakness of using a threshold, machine learning approaches are implemented including k-nearest neighbor (k-NN) [6], support vector machines (SVM) [7], decision tree [5] and artificial neural networks (ANNs) [1]. To understand the ANN-based classification models, several visualization techniques are used. Zeiler et al. [4] try to reconstruct the input of each layer from the output. Simonyan et al. [3] introduce a specific class saliency visualization approach to find the most influential part of a particular classification.

3 Methodology

The working flow of the proposed system is illustrated in Fig. 1. The smart insoles are applied in the proposed system to collect the data. The data are transmitted to a centralized data warehouse via Bluetooth. The fall detection movements are learned by the deep learning approaches and the deep learning visualization are applied for interpreting the deep learning classifier of the fall event.

3.1 Hardware Architecture of Smart Insole

The smart insole is applied in the proposed system for fall detection. Figure 1 shows the hardware architecture of smart insole utilized in the fall detection system. The smart insole is developed by integrating the circuit board and pressure sensor array through an insole shaped package. A high-performance Microcontroller Unit (MCU) is used for signal processing. Besides, twenty-four 12-bit

Digital Converter (ADC) channels are provided, which are used for measuring the pressure sensor array [8]. In this manuscript, each smart insole contains 96 pressure sensors. A Flexible Printed Circuit (FPC) connector connects the pressure sensor array with the signal processing circuit. Multiplexers are connected with all the pressure sensors and form a voltage divider circuit by connecting the selected pressure sensor with Rfixed, and the Analog could measure the voltage drop on the pressure sensor to ADC. The data can be transmitted via Bluetooth through the wireless module. The top layer is a fabric cover which guarantees the comfort of wearing and the pressure sensor array with insole shape is put into the middle layer. The bottom layer is an insole shaped package which is designed for settled battery and the circuit board.

3.2 Deep Learning Algorithms and Evaluation Metrics

To distinguish falls from other daily activities based on the data collected from smart insoles, Artificial neural networks (ANN) model is designed. Before the data are fed into the model, the data normalization is implemented. ANN has been proved to be efficient due to the promising results on the sensor data [1]. Hidden features are extracted from the input data through the Artificial neural networks, and more abstract features are calculated by deeper layers. Multi-Layer Perceptron (MLP) and convolutional neural network (CNN) are two primary subcategories of Artificial neural networks. To take advantage of the characteristic of time-series data dependency, the sliding window is employed in MLP and CNN for the falls detection. The performance can be validated by the following success criteria. *Sensitivity (Se)* represents the capacity of the automatic system on fall detection, $Se = TP/(TP + FN)$. *Precision (Pr)* is the precision of the system for detecting falls, $Pr = TP/(TP + FP)$. *Specificity(Sp)* measures the ability of the system for identifying ADLs, $Sp = TN/(TN + FP)$. Accuracy (Ac) clearly describe the correct differentiation between falls and non-falls, $Ac = (TP+TN)/(TP+FP+FN+TN)$. Here, TP (a fall occurs and the system recognizes it as a fall), TN (a fall does not occur and the system does not recognize it as a fall), FP (a fall does not happen but the system recognizes it as a fall), and FN (a fall happens but the system misses it) are used in the calculation of sensitivity, precision and accuracy.

3.3 Deep Learning Visualization

The deep neural network has made enormous progress over the last several decades and got tremendous attention from academia, industry, and health-care community. Many researchers have been considered about improvements in the knowledge of how to create high-performing architectures and learning algorithms. Historically, deep learning models have been thought of as "black boxes", meaning that the inner workings were different to understand or interpret. In order to shine the light into the "black boxes" to better understand exactly what the deep learning has learned, the deep learning visualization approach is applied.

In this section, the technique for the deep learning model visualization [3] is introduced. Saliency map is a quick way to tell which variation of the sensor data influenced the classification decision made by the network. Given a trained classification CNN, a specific activities class ac of interest, an sensor data I_s and the class score function $S_{ac}(I)$. The value of every single sensor I_s are sorted according to the influence on the score $S_{ac}(I_s)$. Take the linear score model as the example,

$$S_{ac}(I) = w_{ac}^T I + b_{ac} \tag{1}$$

where the I is the input sensor data, and w_{ac} and b_{ac} are the parameters in the model. The magnitude of elements w determines the importance though sensor I for the specific class. In CNN scenario, it is a highly non-linear problem. According to the first-order Taylor expansion, the $S_{ac}(I)$ can be approximated expressed with a linear function in the neighborhood of I_s.

$$S_{ac}(I) \approx w^T I + b,\ where\ w = \frac{\partial S_{ac}}{\partial I}|_{I_s} \tag{2}$$

Current deep learning Visualization is mostly focused on image-based system [4]. However, in the sensor-based system, it lacks efficient methods to know what the changes in movements make the models arrive at a certain classification decision. Here, exploring the deep learning visualization for the sensor-based system are mainly discussed. To acquire the saliency map from the time-series pressure sensor array, a two-dimension matrix should be utilized. The time is represented over one dimension while another dimension is expected to be related to the value of the pressure sensor array. The class saliency map $S \in R^{m \times n}$ can be calculated through the back-propagation process in the CNN and according to the derivative w. Researchers can elicit a particular interpretation using deep learning visualization for fall detection.

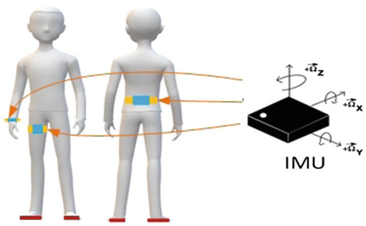

Fig. 2. The position where IMUs are attached.

4 Experiments

4.1 Dataset and Experimental Settings

It is commonly acknowledged that most of the falls occur with the directions of forwards, backward or sideways [20]. The experiments are designed with a

Table 1. The comparison experimental results of using smart insoles and wearable sensors placed on SOI for fall detection, W-waist, H-hand, T-thigh, I-smart insole, with k-nearest neighbor ($k$nn), support vector machines (svm), decision tree (dt), discriminant (dc), Multi-Layer Perceptron (mlp) and convolutional neural network (cnn).

	pr($k$nn)	se($k$nn)	sp($k$nn)	ac($k$nn)	pr(svm)	se(svm)	sp(svm)	ac(svm)
W	0.9385	0.9423	0.9896	0.9828	0.9458	0.9342	0.9910	0.9828
H	0.8566	0.8601	0.9758	0.9592	0.8477	0.8477	0.9744	0.9562
T	0.9336	0.9259	0,9889	0.9799	0.8943	0.9053	0.9820	0.9710
I	0.9555	0.9712	0.9924	0.9893	0.9874	0.9712	0.9979	0.9941
WI	0.9916	0.9753	0.9986	0.9953	0.9797	0.9918	0.9965	0.9959
HI	0.9872	0.9547	0.9979	0.9917	0.9917	0.9877	0.9986	0.9970
TI	0.9958	0.9794	0.9993	0.9964	0.9917	0.9877	0.9986	0.9970
WHTI	0.9958	0.9835	0.9993	0.9970	0.9918	0.9918	0.9986	0.9976

	pr(dt)	se(dt)	sp(dt)	ac(dt)	pr(dc)	se(dc)	sp(dc)	ac(dc)
W	0.9540	0.9383	0.9924	0.9846	0.9751	0.8066	0.9965	0.9692
H	0.8611	0.8930	0.9758	0.9639	0.8942	0.7253	0.9862	0.9503
T	0.9461	0.9383	0.9910	0.9834	0.9760	0.8354	0.9965	0.9734
I	0.9833	0.9712	0.9972	0.9935	0.9736	0.9095	0.9959	0.9834
W	0.9918	0.9877	0.9986	0.9970	0.9793	0.9753	0.9965	0.9935
HI	0.9833	0.9671	0.9972	0.9929	0.9706	0.9506	0.9952	0.9888
TI	0.9795	0.9835	0.9965	0.9947	0.9787	0.9465	0.9965	0.9835
WHTI	0.9836	0.9877	0.9972	0.9959	0.9756	0.9877	0.9959	0.9947

	pr(cnn)	se(cnn)	sp(cnn)	ac(cnn)	pr(mlp)	se(mlp)	sp(mlp)	ac(mlp)
W	0.9575	0.9783	0.9889	0.9911	0.9362	0.9565	0.9889	0.9852
H	0.9333	0.9130	0.9889	0.9793	0.8750	0.9130	0.9779	0.9704
T	0.9545	0.9348	0.9924	0.9852	0.8936	0.9130	0.9820	0.9734
I	0.9876	0.9794	0.9979	0.9953	0.9793	0.9660	0.9965	0.9921
WI	0.9959	0.9877	0.9993	0.9976	0.9862	0.9728	0.9976	0.9941
HI	0.9836	0.9877	0.9972	0.9959	0.9755	0.9835	0.9958	0.9941
TI	0.9916	0.9793	0.9986	0.9959	0.9714	0.9794	0.9952	0.9929
WHTI	0.9918	0.9918	0.9986	0.9976	0.9876	0.9835	0.9979	0.9959

group of falls containing backward falls, forward hard falls, forward soft falls, left falls and right falls. Note that, during the hard fall, SOI falls from vertical standing to the ground directly. A soft fall refers to the SOI fall to their knee before impacting on the ground. Regarding activities of daily livings (ADLs), activities can be divided into 9 groups with 12 most common activities: sit down, sitting (sitting on the chair and sitting on the sofa), walking (walking, walking upstairs and walking downstairs), bending, bend to pick up items, standing, squatting, squat to pick up items and laying. In this paper, the sample rate of the whole pressure sensor array is 30 Hz. Data obtained from the wearable devices accompanied with timestamps and videos which record the movements and provide a precise determination of each event (ground-truth). The counter is a kind of time stamp used for checking the synchronization and missed data. The fall detection system is validated on ten subjects with performing a set of movements including 12 ADLs and 5 falls. Each experiment trail is performed twice to ensure sufficient quantity and consistency. About 1.5 s sliding windows are utilized in the system to process the time-series sensor data. The time-series data which have inherent local dependency characteristics and can represent the activities such as gait, balance, and posture are collected by the smart insoles. In the system, the time-series data are collected from the smart insoles on two feet and are transmitted to a centralized data warehouse. For evaluating the performance of the machine learning algorithms, the 5-fold cross validation as the evaluation protocol is applied. As for the CNN architecture, it contains two convolutional layers, two max-pooling layers, and three fully-connected layers. six fully-connected layers build the MLP architecture in this paper.

Besides, the device that combines a 3-axis gyroscope, 3-axis accelerometer, 3-axis magnetometer is also applied through contrast experiments which are placed to thigh, waist, and hand as shown in Fig. 2. To acquire more precise information, the orientation is calculated by the raw sensor data from the accelerometer and the magnetometer. To further demonstrate the effectiveness of the system, four machine learning algorithms, the k-nearest neighbor, the support vector machines, the decision tree, and the discriminant are used for evaluating the system.

4.2 Results and Analysis

Both quantitative and qualitative experiments are demonstrated in this paper to prove the feasibility and effectiveness of the proposed fall detection system. As shown in Table 1, the comparisons of sensor combinations through six machine learning algorithm?s performances are illustrated. The input data are collected from the smart insoles and the predictions are 2 classes, fall or no fall. In the fall detection scenario, Using the Smart Insoles based on CNN achieve to the higher accuracy than using a single device (3-axis gyroscope, 3-axis accelerometer, 3-axis magnetometer) placed on the waist, right-hand or right-thigh with the widely-used machine learning algorithms. It is obvious that combining smart insoles with other sensors can achieve a better performance than using one single sensor units. The smart insoles can improve the performance of fall classification system. The smart insoles can acquire a higher precision than other single sensor units, which indicates that the system based on smart insoles guarantees a low risk regarding the daily activities as the fall.

This work proves that it is possible to achieve a high accuracy using smart insoles. Using only smart insoles can achieve to a high performance on fall detection (98.76% precision, 97.94% sensitivity, 99.79% specificity and 99.53% accuracy), which is better than using one single device placed on the waist, hand or thigh. Besides, for the combination scenarios, the best performance (99.59% precision, 98.77% sensitivity, 99.93% specificity and 99.76% accuracy) is achieved using the combination of smart insoles with the devices that placed at the waist. The waist sensor is close to the trunk. It has better performance than from the

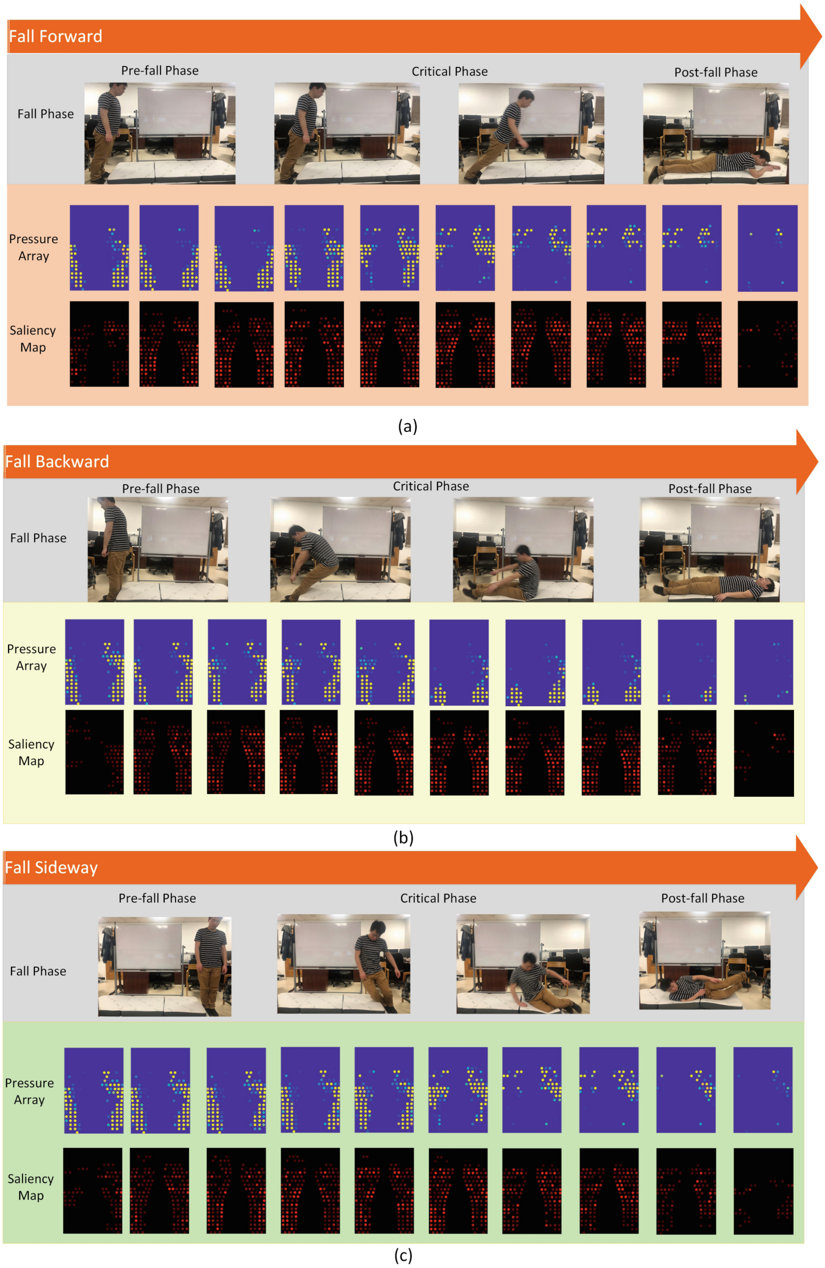

Fig. 3. The pressure changes and deep learning visualization for the time-series data of smart insole inside one window. For each fall events, the top is the fall in real life, the middle is the pressure changes of the smart insoles and the bottom is the corresponding saliency maps.

limbs because it is not easy to be affected by the interpersonal differences in the body movement during the daily activities. The smart insole can provide the pressure changes in various activities as shown in Fig. 3, the "pressure Array" reflects such changes when the fall forward, fall backward and fall sideways occurred.

As for the machine learning algorithms based on the input collected from the pressure insoles, the ANN algorithm is approved and satisfactory due to the high accuracy performance. The class of ANN covers several architectures including the CNN and the MLP. CNN can get the highest accuracy of 99.53% in all algorithms when using smart insoles. For the other machine learning algorithms, the k-NN algorithm produces 98.93% classification accuracy for the smart insoles and 98.28% accuracy with the single device that placed at the waist (the best performance of single device attached to SOI's waist, hand, and thigh). The SVM and Decision Tree have similar results as the k-NN. The best result of SVM can achieve to 99.41% when smart insoles units are used and Decision Tree can achieve to 99.35%. Discriminant gives 98.34% for using smart insoles to detect the fall. It is worthy to note that, CNN is more suitable for using only smart insoles on fall detection.

Fig. 4. The major change of disciminative area during the critical phase in fall forward, fall backward and fall sideways.

To further explain how the system based on smart insoles with CNN algorithm works in fall detection, the deep learning visualization approach is applied. The saliency map gives the most discriminative part of the pressure array on the smart insole through the whole fall events. As shown in Fig. 3, in the fixed-length time-series data window, the "saliency map" is generated according to the input ("pressure array"). 10 frames in a window (total 40 frames) is selected to represent the variability in one fall incidents. Based on the results of combining the "pressure array" and "saliency map", the critical phase shows the most significant evidence among the entire falling process. During the critical phase, the discriminative area has changed. When the SOI falls forward, the discriminative area is changing roughly from the heel to the forefoot. As for the fall backward and fall sideways (e.g. right fall), the discriminative area is changing from the forefoot to the heel and from left to right. It is worthy to note that, "saliency map" shows the first few frames (Pre-fall phase) has less effect on the model to detect the falling incidents. The changes in the pressure array during the falls become an important part for the CNN models to recognize the falls. To make such changes more intuitive, the saliency map distribution for the critical phase with a wire-frame mesh in a foot-shaped 3-D map is illustrated as shown in Fig. 4. The deep learning visualization gives a good explanation of how the deep learning model recognizes fall during the fall detection. The change of the discriminative area indicates that the deep learning model can learn the pressure changes during the fall. From the result, to recognize the fall, CNN is based on the identification of the variability in the pattern and the pressure distributions under the foot through the foot-shaped sensor array. That is to say, the CNN model can learn the trend of pressure changes during the falling process.

5 Discussion

To demonstrate the effectiveness of the smart insole, the confusion matrix of the CNN of 13 classes including 9 ADLs-movement groups and a fall-movement group. We can see that the proposed system has achieved high recognition performance in the aspect of fall detection. Through entire movements, most of the movements have been well recognized. The fall detection system based on smart insole ensures the user's convenience and is proved to be effective in the classification of dynamic and static movements. To further demonstrate the effectiveness of smart insoles, the comparison experiment is designed. In the experiment, we mainly discuss the fall detection system based on paired smart insoles compared to the system with only one smart insole for ten classes. As shown in Tables 2 and 3, the experimental result based on CNN for fall detection is summarized. Generally speaking, the system with two insoles has better performance than the system with only one insole. The system with two insoles has better accuracy, specificity, precision, and sensitivity for the fall detection and can classify the ADLs movement more accurate. The system based on only one smart insole is more likely to classify the "confounding activities" such as suddenly sitting down into fall and identify the walk as fall, while two smart insoles mitigate this

Table 2. The confusion matrix using CNN with only **one** smart insole as inputs. CM-confusion matrix, Fa-Falling, SD-Sit Down, Wa-Walking, BP-Bend to Pick up, St-Standing, Be-Bending, Si-Sitting, Ly-Lying, Sq-Squatting and SP-Squat to pick up

Confusion matrix	Fa	SD	Wa	BP	St	Be	Si	Ly	Sq	SP
Falling	0.96	0.01	0.01	0.01	0	0	0	0.01	0	0
Sit Down	0.04	0.84	0.04	0.04	0.02	0.02	0	0	0	0
Walking	0.01	0	0.97	0.01	0.01	0	0	0	0	0
Bend to Pick	0	0	0	0.84	0.02	0.14	0	0	0	0
Standing	0	0	0	0.03	0.96	0.01	0	0	0	0
Bending	0	0	0	0.01	0	0.99	0	0	0	0
Sitting	0	0	0	0	0	0	0.99	0.01	0	0
Lying	0	0	0	0	0	0	0.10	0.90	0	0
Squatting	0	0	0	0	0	0	0	0	0.92	0.08
Squat to pick	0	0	0.04	0	0	0	0	0	0.17	0.79

Table 3. The confusion matrix using CNN with **two** smart insole as inputs.

Confusion Matrix	Fa	SD	Wa	BP	St	Be	Si	Ly	Sq	SP
Falling	0.98	0.01	0.01	0	0	0	0	0	0	0
Sit Down	0.04	0.88	0	0	0.04	0.04	0	0	0	0
Walking	0	0	0.99	0	0.01	0	0	0	0	0
Bend to Pick	0	0	0	0.72	0.08	0.2	0	0	0	0
Standing	0	0	0	0	0.99	0.01	0	0	0	0
Bending	0	0	0	0.01	0	0.99	0	0	0	0
Sitting	0	0	0	0	0	0	0.99	0.01	0	0
Lying	0	0	0	0	0	0	0	1	0	0
Squatting	0	0	0	0	0	0	0	0	0.88	0.12
Squat to pick	0	0	0	0	0	0	0	0	0.09	0.91

problem. The results show that using two paired smart insole for identifying fall and ADLs is more desirable.

6 Conclusion

In this paper, we evaluate the effectiveness and feasibility of using smart insole and ANN for fall detection. As expected, the experimental results show that the smart insoles with the pressure sensor array make good performance on fall detection. The advantage of capturing the pressure changes shows the huge potential for using smart insoles to recognize the fall. Besides, the deep learning visualization approach is applied to further demonstrate what model has learned and show the discriminative area as the fall event occurred. The results of deep learning visualization provide potential hints for the future application design not only the classification algorithm improvement but also the hardware upgrade.

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