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ORIGINAL RESEARCH

Subject variability in sensor-based activity recognition

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Abstract

Building classification models in activity recognition is based on the concept of exchangeability. While splitting the dataset into training and test sets, we assume that the training set is exchangeable with the test set and expect good classification performance. However, this assumption is invalid due to subject variability of the training and test sets due to age differences. This happens when the classification models are trained with adult dataset and tested it with elderly dataset. This study investigates the effects of subject variability on activity recognition using inertial sensor. Two different datasets—one locally collected from 15 elders and another public from 30 adults with eight types of activities—were used to evaluate the assessment techniques using ten-fold cross-validation. Three sets of experiments have been conducted: experiments on the public dataset only, experiments on the local dataset only, and experiments on public (as training) and local (as test) datasets using machine learning and deep learning classifiers including single classifiers (Support Vector Machine, Decision Tree, K-Nearest Neighbors), ensemble classifiers (Adaboost, Random Forest, and XGBoost), and Convolutional Neural Network. The experimental results show that there is a significant performance drop in activity recognition on different subjects with different age groups. It demonstrates that on average the drop in recognition accuracy is 9.75 and 12% for machine learning and deep learning models respectively. This confirms that subject variability concerning age is a valid problem that degrades the performance of activity recognition models.

Keywords Activity recognition · Deep learning · Machine learning · Subject variability

1 Introduction

The increased life expectancy together with declining birth rates led to an aged population structure. The population of the world is rapidly aging (Lee et al. 2020). Approximately all countries in the world are experiencing growth in the percentage of elderly in their population. For instance, the current number of elderly people (60 years and older) in the world is higher than the number of children younger than 5 years old. By 2050, it is expected that 1 in 6 persons in the globe will be over 65 years old (United Nations 2019). This increased longevity is a threat to the stability of every society due to its negative effects on elderly health and social care (Howdon and Rice 2018) including loss of physical, mental, and cognitive abilities causing impaired actions and greater vulnerability to morbidity and mortality (Chang et al. 2019).

Aged people are always vulnerable to many age-related problems including diabetes, stroke, Parkinson's, Alzheimer's, dementia, cardiovascular, osteoarthritis, and other chronic diseases (Vepakomma et al. 2015; Subasi et al. 2020). These diseases together with the weak cognitive and physical ability of the elderly prevent them from independent living and barriers them in performing daily activities (i.e. toileting, bathing, cooking, etc.) (Van Kasteren et al. 2010). To assist elderly people, some family members and governments provide high nursing spendings on elderly care (Vepakomma et al. 2015; Yao et al. 2018). However, with the increase of the elderly population, caregivers' assistance is becoming scarce and the caregivers become overburdened with the continuous monitoring responsibility (Piyathilaka and Kodagoda 2015; Richter et al. 2017).

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Therefore, there is a primary need for a system that can early detect elderly gradual cognitive changes and automatically recognize elderly activities to monitor their health conditions, and provide evidence-based nursing assistants (Nambu et al. 2000; Vijayaprabakaran et al. 2020). This has recently attracted many scientists who proposed activity recognition systems aimed at promoting and assisting the living independence of older people through developing techniques and systems that recognize the mobility, daily life activities, and physiological signs of elderly people (Khusainov et al. 2013). This is one reason why activity recognition is becoming a hot research area in sensor-rich and ubiquitous mobile devices (Zahin et al. 2019) that is specially applied in the elderly healthcare domain (Dinarević et al. 2019). Understanding the different kinds of human activities can also have an extensive contribution to solving other real-world problems such as security and military (Labrador and Yejas 2011; Lara and Labrador 2013), entertainment, surveillance, gaming, remote monitoring, intelligent environments (Hussain et al. 2019), health tracking and monitoring, rehabilitation and assisted living (Rezaie and Ghassemian 2018), home behavior analysis (Satapathy and Das 2016), gait analysis (Hammerla et al. 2016), gesture recognition (Kim and Toomajian 2016), assistive technologies and manufacturing. It may easily change the way we sense, monitor, recognize, and predict human physical activities and surrounding environments (Campbell et al. 2008; Chiang et al. 2019).

Activity recognition is the process of identifying predefined activities of interest performed by a human through monitoring human activities and/or surrounding environments using sensors (Chiang et al. 2019). Most of activity recognition systems follow four regular phases (data collection, data pre-processing, feature extraction, and training and activity classification or recognition (Nweke et al. 2018; Straczkiewicz and Onnela 2019) with slight variations based on the model (machine learning vs. deep learning), application domain, and dataset. Typically, during training and activity classification, the classification models are evaluated using public datasets or locally collected datasets. (Nweke et al. 2018).

The way human activities are performed and their durations vary from one person to another (Akbari and Jafari 2020). Subject variability can be caused by several factors such as age, sex, fitness level, and environmental state. This variation (referred to as subject variability) changes the pattern of the sensory data from one subject to another and limits the generalization of the classification models to new subjects, hence reduces the recognition accuracy of the models. Although subject variability is a real problem in activity recognition, it remains largely unexplored. This study is focusing on variation generated by age differences among subjects. It occurs whenever the classification models are trained with sensor data from one particular age group such as adults and tested the trained model with sensor data from another different age group e.g. elderly. The signals of elderly activities vary from the signals of adult activities even when the same activity is being performed. Typically, the acceleration (magnitude) is lower and the activity signals have a longer duration. This is because, elderly people have a lower intensity of dynamic (e.g. walking, running, jogging) and transitional activities and a less stable static activity (e.g. standing, sitting) than adults. This variation originates from the fact that adults are stronger, more confident, and active than elderly people in performing the activities. Consequently, a classification model that is trained on activity data that is collected from adults is not able to generalize to elderly's dataset.

To perceive subject variability, this study aims to investigate the effects of subject variability generated by age differences on activity recognition. It is an assessment study that focuses on proofing that subject variability is a valid problem in activity recognition that has a role in performance decline. This will be achieved via investigation on whether activity recognition models achieve better subject variability performance than subject similarity using adult and elderly datasets. The adult dataset is a public dataset and the elderly dataset was internally collected. The experiments are conducted in three stages whereby each stage is carried out in sequence using adult dataset only, elderly dataset only, and both adult and elderly datasets as a training set and a test set respectively. Machine learning and deep learning techniques are used for the activity recognition. The main contribution of this study is investigating the effects of subject variability on activity recognition using inertial sensors for the first time. The contributions of this research are summarized as follows:

a. To our best knowledge, we are the first to investigate the effects of subject variability generated by age difference on activity recognition.
b. We conduct comprehensive experiments to investigate the effects of subject variability in activity recognition using various machine learning and deep learning techniques.
c. We discuss the performance degradation caused by subject variability contributed by age differences in activity recognition.

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The remainder of this study is organized as follows. Section 2 discusses the related work of the study, Sect. 3 explains subject variability in detail, Sect. 4 provides the research methodology of this study, Sect. 5 contains experimental results, and Sect. 7 concludes the paper.

2 Related work

Wearable sensors including accelerometer and gyroscope have recently dominated activity recognition (Cornacchia et al. 2017). Despite that sensor-based activity recognition has recently achieved higher performance, one of the challenges confronting its task is subject variability generated by age differences as explained in Sect. 3. Current scientists do not pay any attention to the misclassification problems that can be caused by such kind of subject variability. This overlook can be observed from the existing HAR studies.

For instance, Xu et al. (2020) have proposed a new loss function named "harmonic loss" and label replication technique to improve the classification performance of activity recognition using Long Short Term Memory (LSTM) networks. They have individually trained their model using two public HAR benchmarks namely: OPPORTUNITY dataset and UCI HAR datasets. OPPORTUNITY Dataset contains daily morning activities. It was collected from 12 subjects based on a European research project called OPPORTUNITY. During the data collection, the participants performed 17 activities including eating a sandwich, drinking coffee, cleaning, opening fridge, closing fridge, opening dishwasher, and closing dishwasher for 6 h (Roggen et al. 2010).

UCI HAR dataset has been collected by 30 adults within an age bracket of 19–48 years. Participants perform six activities including standing, sitting, lying down, walking, walking downstairs, and upstairs. During the data collection, participants were wearing a smartphone embedded with accelerometer and gyroscope sensors on the waist. They also recorded the experiments to label data manually. This dataset was sampled in fixed-width sliding windows of 2.56 s and 50% overlap (128 readings/window) (Anguita et al. 2013).

In addition to that, Hashim and Amutha (2020) have proposed a dimensionality reduction technique called "fast feature dimensionality reduction technique" to reduce the number of features used in the UCI HAR dataset with less time consumption. Their work was proposed for less powerful systems. They have managed to reduce the number of features from 561 to 66. To recognize elderly activities, they also used locally collected elderly dataset and managed to reduce 76% of its features. Their elderly dataset was collected from 10 elder subjects aging 60+ years. The participants the elderly dataset performed five activities: sitting, upstairs, downstairs, standing, and walking. Similar to the above studies, activity recognition models in this study are trained and tested on the two datasets individually.

Other recent activity recognition approaches include the work of Khatun and Morshed (2018). They designed a transition activity recognition technique using a decision tree with an ensemble approach. They have used Mobile Health (mHealth) public dataset to evaluate the effectiveness of their work. mHealth dataset consists of 12 daily activities. The aim of collecting this data was health application (Banos et al. 2014).

Another work that has trained and tested their method using a single dataset is the study of Gil-Martín et al. (2020). They proposed an improved physical activity recognition using a new CNN architecture and post-processing techniques. They have trained their model on the PAMAP2 dataset. This dataset was collected from nine adults performing 18 different activities. The collected activities include lying, sitting, standing, walking, running, cycling, watching TV, and using computers (Reiss and Stricker 2012).

Xia et al. (2020) also evaluated their work on the same age group subjects as those used to train the model. These authors have developed a novel LSTM-CNN model for activity recognition. They have experimented with their work on the UCI-HAR, OPPORTUNITY, and WISDM datasets. WISDM dataset was collected from 29 young adults at Mining Lab Fordham University using a single android based mobile phone accelerometer sensor. During the data collection, participants performed simple ambulatory activities including sitting, standing, and jogging (Kwapisz et al. 2011). Other activity recognition studies that make use of the WISDM dataset for activity recognition include the work of Zhang et al. (2020). The authors of this study proposed an IoT-perspective activity recognition technique that utilizes multi-head CNNs and the attention mechanism for a better feature extraction and selection purpose.

Furthermore, Gani et al. (2019) have used datasets with the same age group. They have developed a computationally efficient activity recognition approach using dynamical systems and chaos theory. They have evaluated the performance of their work using self-collected and the UCI HAR Public Datasets. In their self data collection, they collected walking, walking upstairs, walking downstairs, running, sitting, standing, elevator up, and an elevator down from ten adults using an accelerometer. They have experimented with their method using Decision Tree, KNN, SVM, SVM-Gaussian, weighted KNN, and Bagged trees. All of the above studies indicate that the experiments are conducted with subjects from the same age group. The results show that the classification models perform well on subjects of similar age. However, it is not guaranteed that the classification models will generalize to new unseen subjects of different age groups.

Among the few studies that have investigated variability in activity recognition is the work of Sakuma et al. (2019). As stated in their study, there is a variability that can be caused by the relationship between time and human activity. For instance, lack of movement in the bedroom might show a sleeping activity at night, but trouble at the day. To address such kind of variability and reduce the calculation cost of activity recognition, they have proposed three contextual (Spatio-temporal, spatial, and temporal) approaches as well as context-free, online CluStream, and offline Minibatch k-means techniques. The authors managed to approximately reduce 20% in calculation cost and improve 20% recognition accuracy. However, the focus is the contextual variability rather than subject variability. Furthermore, the authors trained their models on a dataset with the same age group. Mannini and Intille (2019) have proposed supervised fine-tuning classification layers and unsupervised retraining of feature extraction layers to experiment on how uncertainties in activity recognition could be measured. Unlike the focus of this research, the authors focused on intra-subject variability that occurs when the same person performs the same activity differently. By using individual datasets from adults and youth, they found out that recognition accuracy varies from 80.8 to 96.5% in youth and 70.7–95.0% in adults. Similar to the above study, the authors trained and tested their models with subjects from the same age group, one time for adults and another for youth. In this study, we investigated the effects of subject variability on activity recognition. Three stages of experiments are performed: activity recognition using adult dataset only, activity recognition using elderly dataset only, and activity recognition using adult dataset as training and elderly dataset as testing. The purpose of these experiments is to prove that subject variability caused by age differences among subjects is a valid problem in activity recognition that has a role in performance decline.

3 Subject variability in activity recognition

Subject variability in activity recognition refers to the variations in the activity signals. Subject variability of human activities is generated by the physical patterns' difference of humans due to many factors including age, sex, fitness level, and environmental state. There are two known types of subject variability: inter-subject variability and intra-subject variability.

Intra-subject variability occurs when a given activity performed by the same subject at different times shows variations. This could be contributed by the mood and emotion of the person such as sad versus happy, energetic versus tired, etc. For example, the physical activities of a sleepy or tired person are different from the walking style of the same person in an active and fresh mood. In other words, the walking activity can be more dynamic in the morning after a nice sleep than in late evening after a full day working.

Inter-subject variability also known as cross-subject variability, on the other hand, is observed when the activities vary from subject to another subject. For example, the jogging activity of a subject is normally different from the jogging activity of another subject. Subjects' physical activities can also vary, given different age groups.

This subject variability is mainly due to the variation in the body acceleration of the subjects while performing the activities, especially the dynamic and transitional activities. This is to say that elderly activities vary from the adult activities in which the magnitude of the acceleration is relatively lower and the length of the signals is relatively longer.

To clarify the subject variability of an age difference, visual imagery of the signal variations (2 s) for an elderly subject and an adult subject are provided in Figs. 1, 2 and

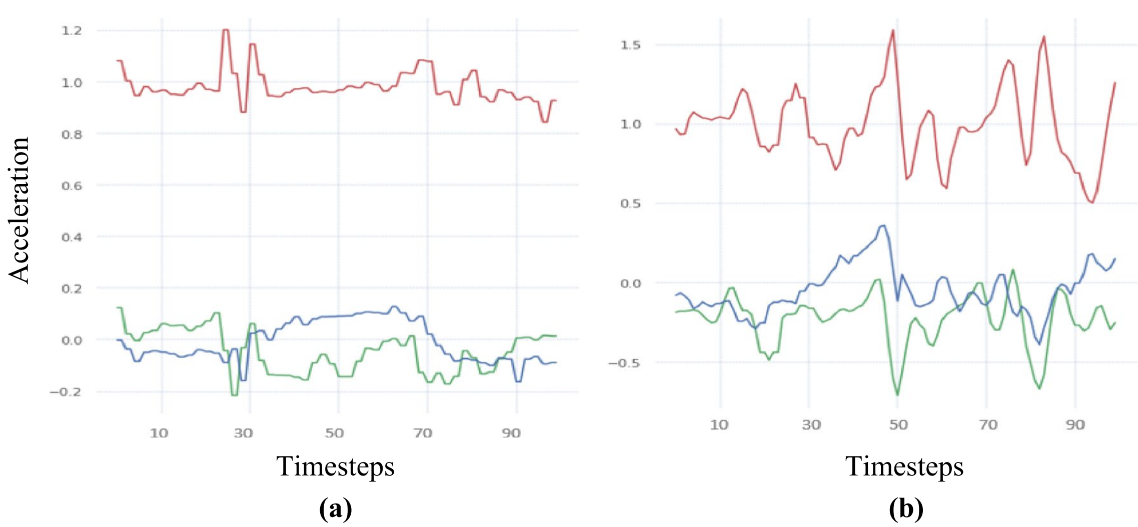

Fig. 1 Comparison of walking activity signals of an **a** elderly subject and **b** adult subject

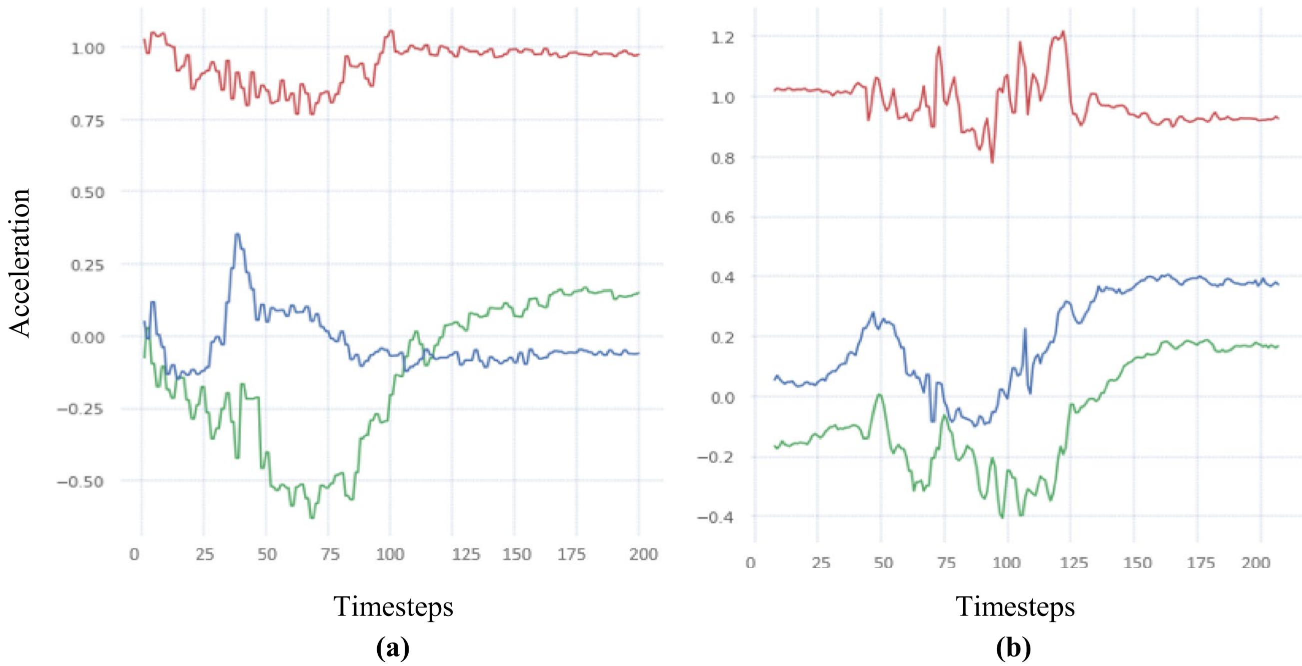

Fig. 2 Comparison of stand-to-sit activity signals of an **a** elderly subject and **b** adult subject

3. Figure 1 illustrates two walking activity signals that were collected from the elderly and adult subjects. As can be seen in Fig. 1, the walking activity signal of the elderly has a lower acceleration than the walking activity signal of the adult people where the peak-to-peak amplitude of the elderly walking activity signal is just one-third of the adult's walking activity signal. This is due to the elderly has a slower walking speed than the adult and this also applies to other dynamic activities i.e. jogging, running and jumping.

Figure 2 shows a comparison of transitional activity signals of the elderly and adult subjects. It shows that the length of transitional activity signals (stand-to-sit) of the elderly (as shown in Fig. 2a) is longer compared to the length of transitional activity signals of the adult (as shown in Fig. 2b). The elderly took approximately 4 s (from 0 to 200) to complete the activity while the adult took about 3.18 s (from 0 to 159) to do so. This applies to other transitional activities such as sit-to-stand, sit-to-lie and lie-to-sit.

Figure 3 shows a comparison of standing activity signals of the elderly and adult subjects. Normally, elderly people perform less stable static activities such as standing due to their weakened muscles, and other age-related problems. This compromises their balance ability to remain steady on their feet. So, the activity signals often contain more random, irregular and sparse spikes compared to the ones generated by adults.

All the aforementioned issues create a data distribution gap between the training set and the test set that causes a significant recognition performance degradation if the trained HAR models are tested on subjects not included in the training set. Although subject variability degrades the recognition performance when the HAR model is trained with an adult dataset and tested with an elder dataset, this kind of subject variability which can eliminate the classification of HAR models and reduce the generalization performance of a learning algorithm is overlooked (Lv et al. 2020). Due to the absence of techniques for investigating subject variability, activity recognition for inter-age problems is still not robust enough for real-world deployment (Hossain and Roy 2019). This study investigates the performance degradation caused by subject variability contributed by age differences in activity recognition. The next section is the research methodology and experimental setup of this study.

4 Methodology and experimental setup

The section presents the systematic plan implemented to conduct this research. The methodology of this study is divided into three main phases: Experimental datasets collection and pre-processing, model training and testing, and classification and evaluation.

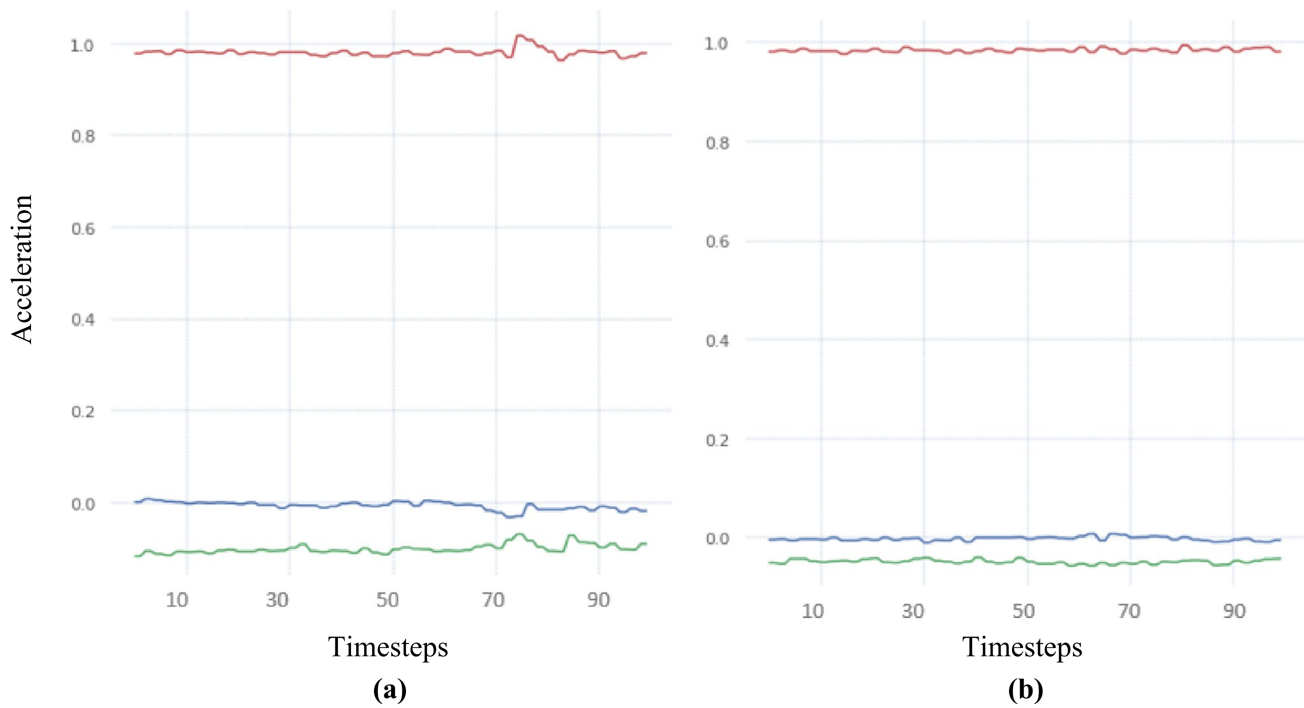

Fig. 3 Comparison of standing activity signals of an **a** elderly subject and **b** adult subject

4.1 Experimental datasets collection and pre-processing

In this study, two activity recognition datasets are used which are internally collected (local) dataset and a public dataset.

4.1.1 Local dataset

The local dataset contains accelerometer and gyroscope measurements that are collected from fifteen (15) elderly people. The inertial sensor is configured to generate samples at 50 Hz. The mean age of the subjects is 64.8 with the standard deviation of 8.79. Each subject wore three inertial sensors, one on the chest, one on the right waist and one on the right ankle. The subjects were asked to perform a set of activities such as walking, standing, sitting, lying down and the transitional activities in their own preferred style and pace. No specific instructions were given about how to perform the activities. The activities were performed continuously for a single trial in the elderly house. Previous studies have shown that the waist is the best location for a single-sensor activity recognition because the acquired sensor data represent the major body movement (Attal et al. 2015). Therefore, only data from the sensor on the waist is used in the actual recognition. The other sensors are used as references for data labeling in the experimental analyses. Written informed consent was obtained prior to data collection in accordance with the approval by the human research ethics committee of Universiti Sains Malaysia (USM/JEPeM/18040205). Although this dataset is specifically designed for this project, it can be extended to other future projects for elderly action recognition. Table 1 shows the number of windows (samples) for each activity.

4.1.2 Public dataset

The Smartphone-Based Recognition of Human Activities and Postural Transitions (UCI HAPT) dataset of (Reyes-Ortiz et al. 2016) has been chosen as the adult dataset in this study for several reasons. First, the dataset is the first large dataset for activity recognition which was collected using inertial sensors (accelerometer and gyroscope) embedded in

Table 1 Counting activities of the local dataset

Activity	Number of samples
Walking	48,428
Sitting	31,613
Standing	25,492
Lying down	17,413
Stand-to-sit	7724
Sit-to-stand	6082
Sit-to-lie	2703
Lie-to-sit	2321

mobile phones. Second, it is used in the recent state-of-the-art studies and is the only dataset that contains transitional activity signals. Finally, it is similar to our dataset in terms of the activities performed and the sensor placements (on the waist). Other related datasets such as those discussed in the related work are not used in this study since they contain only dynamic and static activities. This dataset has been collected by 30 adults within an age bracket of 19–48 years. Participants perform 12 activities including walking, walking upstairs, walking downstairs, sitting, standing, lying down, stand-to-sit, sit-to-stand, sit-to-lie, lie-to-sit, stand-to-lie, lie-to-stand. However, only walking, standing, stand-to-sit, sitting, sit-to-stand, sit-to-lie, lying down, and lie-to-sit are considered for models training as the other four activities are not present in the local dataset. During the data collection, participants were wearing a smartphone embedded with accelerometer and gyroscope on the waist. Table 2 shows the number of windows (samples) for each activity.

4.2 Model training and testing

This study applies machine learning and deep learning techniques for activity recognition. The single machine learning classifiers are Logistic Regression, Support Vector Machine (SVM), and Decision Trees. The ensemble classifiers are Random Forest (RF), Adaboost, and Extremely Gradient Boosting Trees (XGBoost). Both single and ensemble classifiers follow five universal phases: activity sensing, feature extraction, feature selection, model training, and activity recognition. We have selected six statistical features for model training namely mean, median, variance, maximum, minimum, and skew. Table 3 contains the descriptions of each feature. Each feature is extracted from each axis of accelerometer (A_x, A_y and A_z) and gyroscope (G_x, G_y and G_z) signals. Then, the feature set is reduced using random forest feature importance to select the most relevant features. Third, selected features are used to train the classification models. In this study, the experiments are carried out in three stages. First, the adult dataset is used to train and test the classification models. In the second stage, only the elderly dataset is used to train and test the classification models. Finally, the classification models are trained using the adult dataset and tested on the elderly dataset. All of these experiments are performed to investigate the effects of subject variability on activity recognition.

Deep learning technique has been recently applied in activity recognition for automatic feature extraction and activity classification. Convolutional Neural Network (CNN) is considered to be one of the state-of-the-art deep learning models in activity recognition. In this study, two CNN with different architectures have been experimented to investigate the subject variability. As shown in Table 4, the first CNN contains four convolutional layers with rectified linear unit (ReLU) followed by dropout and max pooling respectively as the feature learning pipeline. The classification pipeline consists of a single dense layer with a softmax activation function. Adam optimizer with a learning rate of 0.0002 and a categorical cross-entropy loss function has been utilized to train the CNN model.

The second CNN architecture contains two convolutional layers followed by dropout and max pooling as the feature learning pipeline. The classification pipeline consists of two dense layers with ReLU and softmax activation functions. Adam optimizer with a learning rate of 0.0002 and categorical cross-entropy loss function has been utilized to train

Table 2 Counting activities of the UCI HAPT dataset

Activity	Number of samples
Walking	187,069
Lying down	137,296
Standing	135,896
Sitting	124,712
Sit-to-lie	15,728
Sit-to-stand	13,675
Lie-to-sit	12,209
Stand-to-sit	11,790

Table 3 Feature description

Feature	Description	Equation
mean	Mean value of each activity signal $A_x, A_y, A_z, G_x, G_y, G_z$	$\mu_X = X = \frac{1}{n}\sum_{i=1}^{n} X_i$
median	The median value of each activity signal $A_x, A_y, A_z, G_x, G_y, G_z$	$i_m = \begin{cases} \frac{n+1}{2}, & if\ n\ is\ odd \\ \frac{n}{2}, & if\ n\ is\ even \end{cases}$
variance	The variance of each activity signal $A_x, A_y, A_z, G_x, G_y, G_z$	$\sigma_X = \left(\frac{1}{n}\left\{\sum_{i=1}^{n} X_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} X_i\right)^2\right\}\right)$
max	The maximum value of each activity signal $A_x, A_y, A_z, G_x, G_y, G_z$	-
min	The minimum value of each activity signal $A_x, A_y, A_z, G_x, G_y, G_z$	-
skew	The skewness of each activity signal $A_x, A_y, A_z, G_x, G_y, G_z$	$sk_{est} = \frac{3(\mu - \mathrm{M})}{\sigma}$

Table 4 CNN1 architecture

Layer (type)	Configuration	Output shape
1D convolution	Filters = 16 Kernel size = 7 Activation = ReLU	94, 16
Dropout	Rate = 0.3	94, 16
Max pooling	Pool size = 2	47, 16
1D convolution	Filters = 32 Kernel size = 5 Activation = ReLU	43, 32
Dropout	Rate = 0.3	43, 32
Max pooling	Pool size = 2	21, 32
1D convolution	Filters = 64 Kernel size = 3 Activation = ReLU	19, 64
Dropout	Rate = 0.2	19, 64
Max pooling	Pool size = 2	9, 64
1D convolution	Filters = 128 Kernel size = 3 Activation = ReLU	7, 128
Dropout	Rate = 0.2	7, 128
Max pooling	Pool size = 2	3, 128
Flatten		384
Dense	Num_classes Activation = softmax	8

Table 5 CNN2 model summary

Layer (type)	Configuration	Output shape
1D convolution	Filters = 16 Kernel size = 5 Activation = ReLU	96, 16
Dropout	Rate = 0.4	96, 16
Max pooling	Pool size = 2	48, 16
1D convolution	Filters = 32 Kernel size = 3 Activation = ReLU	46, 32
Dropout	Rate = 0.4	46, 32
Max pooling	Pool size = 2	23, 32
Flatten	Not applicable	736
Dense	Dense = 50 Activation = ReLU	50
Dense	Num_classes Activation = softmax	8

the second CNN model. Table 5 shows the CNN2 model summary.

In the classification and evaluation phase, the eight physical activities are classified. An evaluation is also carried out to validate the research findings using recognition accuracy. The ten-fold cross-validation is used to avoid bias in the results.

Table 6 Activity recognition results using single classifiers

Models	UCI HAPT dataset (%)	Local dataset (%)	UCI HAPT and local datasets (%)
Logistic regression	79	79	64
Linear SVM	79	82	71
Kernel SVM	78	77	72
Decision tree	77	78	67
KNN	77	79	67

Table 7 Activity recognition results using ensemble classifiers

Models	UCI HAPT dataset (%)	Local data-set (%)	UCI HAPT and local datasets (%)
Random forest	80	79	75
AdaBoost	77	77	69
XGBoost	85	80	70

5 Experimental results

The experimental results confirm that subject variability is an issue in activity recognition as explained in Sects. 5.1 and 5.2. It provided that subject variability contributed by age differences degrades the recognition performance of activity recognition models.

5.1 Activity recognition using machine learning

In general, the results of the activity recognition using machine learning indicate that there is a significant performance drop when two different datasets (UCI HAPT and local datasets) with different age groups are used for model training and testing respectively. Table 6 shows the recognition accuracy for the single classifiers where each column represents the three stages of the experiments. Overall, the activity recognition using UCI HAPT dataset only achieved an average of 78% whereas the average accuracy of activity recognition using the local dataset only is 79%. The performance of the classifiers drops significantly when the UCI HAPT dataset and local dataset are used for training and testing respectively. The average recognition accuracy is only 68.2%.

A similar performance drop is observed in ensemble classifiers while using two different datasets (UCI HAPT and local datasets) with different age groups for model training and testing respectively. Table 7 provides the recognition accuracy for the ensemble classifiers where each column represents one of the three stages of the experiments. On average, the activity recognition using UCI HAPT dataset only is 81%, the activity recognition using the local dataset only is 79%, and the activity recognition using UCI HAPT dataset for training and local dataset for testing is 71%. These results indicate that that the average recognition accuracy using UCI HAPT dataset for training and local dataset for testing is 8 and 10% lower than the average recognition accuracy of using Local Dataset only or UCI HAPT only.

In general, the ensemble classifiers have a better performance than the single classifiers. Table 8 shows the average accuracy of ensemble classifiers is 3% higher than the average accuracy of single classifiers in activity recognition using UCI HAPT and UCI HAPT and local datasets respectively. This is due to the superior prediction power of ensemble classifiers that combine multiple classification models to make better decisions.

To better understand the performance of the classifiers, Tables 9 and 10, and Table 11 show the confusion matrices of activity recognition (with linear SVM) using UCI HAPT dataset, local dataset, and UCI HAPT and local datasets respectively. As shown in Table 9, in general, most of the activities are well classified except for sit-to-lie activity

Table 8 The average accuracy of machine learning models

Classifiers/experiments	UCI HAPT dataset (%)	Local dataset (%)	UCI HAPT and local datasets (%)
Single classifiers	78	79	68
Ensemble classifiers	81	79	71

Table 9 Confusion matrix of linear SVM using UCI HAPT only

	Walking	Standing	Stand-to-sit	Sitting	Sit-to-stand	Sit-to-lie	Lying down	Lie-to-sit
Walking	0.95	0.00	0.05	0.00	0.00	0.00	0.00	0.00
Standing	0.01	0.82	0.12	0.01	0.01	0.01	0.01	0.01
Stand-to-sit	0.05	0.20	0.72	0.00	0.00	0.01	0.01	0.01
Sitting	0.06	0.02	0.00	0.89	0.00	0.00	0.01	0.02
Sit-to-stand	0.22	0.12	0.10	0.00	0.50	0.03	0.00	0.03
Sit-to-lie	0.22	0.08	0.40	0.00	0.06	0.23	0.01	0.00
Lying down	0.19	0.03	0.00	0.23	0.04	0.00	0.50	0.01
Lie-to-sit	0.04	0.07	0.17	0.05	0.04	0.01	0.00	0.62

Table 10 Confusion matrix of linear SVM using local dataset only

	Walking	Standing	Stand-to-sit	Sitting	Sit-to-stand	Sit-to-lie	Lying down	Lie-to-sit
Walking	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Standing	0.00	0.79	0.20	0.01	0.00	0.00	0.00	0.00
Stand-to-sit	0.04	0.10	0.82	0.02	0.02	0.00	0.00	0.00
Sitting	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
Sit-to-stand	0.36	0.07	0.04	0.00	0.30	0.19	0.00	0.04
Sit-to-lie	0.31	0.03	0.07	0.00	0.07	0.48	0.00	0.03
Lying down	0.00	0.00	0.00	0.67	0.00	0.00	0.22	0.11
Lie-to-sit	0.12	0.00	0.00	0.50	0.12	0.12	0.00	0.14

Table 11 Confusion matrix of linear SVM using UCI HAPT and local datasets

	Walking	Standing	Stand-to-sit	Sitting	Sit-to-stand	Sit-to-lie	Lying down	Lie-to-sit
Walking	0.94	0.00	0.02	0.00	0.01	0.00	0.01	0.02
Standing	0.00	0.79	0.09	0.04	0.00	0.00	0.00	0.08
Stand-to-sit	0.04	0.36	0.47	0.02	0.01	0.00	0.00	0.10
Sitting	0.00	0.19	0.00	0.77	0.00	0.00	0.01	0.03
Sit-to-stand	0.41	0.12	0.08	0.06	0.18	0.02	0.08	0.05
Sit-to-lie	0.25	0.05	0.08	0.13	0.14	0.16	0.06	0.13
Lying down	0.02	0.07	0.00	0.44	0.00	0.00	0.40	0.07
Lie-to-sit	0.11	0.11	0.00	0.45	0.04	0.04	0.06	0.19

and lying down. Specifically, walking, standing and sitting achieved a true positive rate of 0.82 and above. It is observed that 0.4 of sit-to-lie samples are misclassified as stand-to-sit. This is because, the fixed sliding window segmentation techniques used and limited samples of the activity. Fixed sliding window technique cannot produce perfect segmentation for transitional activity signals as the length of its signals varies depending on the time to perform the activity.

In Table 10, the classifier performs well on classifying most of the activities except sit-to-stand and lie-to-sit activities using the local dataset only. The misclassification of these transitional activities is contributed by two factors: fixed sliding window segmentation and the short duration characteristics of transitional activities. In particular, only a smaller amount of transitional activity examples per activity samples can be collected from elderly people at a time.

As shown in Table 11, the classification performance of the classifier drops significantly for most activities using UCI HAPT dataset for training and local dataset for testing. For instance, the true positives of walking, sitting, stand-to-sit, sit-to-stand, and sit-to-lie activity using the local dataset only drop to 0.94, 0.79, 0.47, 0.18, and 0.16 respectively. In particular, the results indicate that transitional activities have less than 50% true positive rate. This is due to the fixed sliding window segmentation technique that cannot perfectly segment transitional activity signals since the length of transitional activity signals varies between elderly and adults. Depending on the time to perform the transitional activities, the length of the activity signals for the elderly people is relatively longer compared to the adults. For example, the elderly took about 4 s to complete stand-to-sit activity while the adult took about 3.18 s to do so as shown in Fig. 2. This is reflected in Table 11 where 0.36 of stand-to-sit activity is misclassified as standing activity while 0.25 of sit-to-lie activity is misclassified as walking and 0.45 of lie-to-sit activity is misclassified as a sitting activity. The same applies to other transitional activities. Table 11 shows that 0.12 and 0.41 of sit-to-stand activity samples are misclassified as standing activity and walking activity respectively. This confirms that subject variability (concerning age) performance degradation applies to machine learning models.

5.2 Activity recognition using deep learning

There is about a 10% performance drop when the deep learning models are trained and tested using UCI HAPT dataset and local dataset respectively. Table 12 shows that the activity recognition using UCI HAPT dataset only achieved an average of 80.5% while the average accuracy of activity recognition using the local dataset only is 82.5%. The average accuracy of activity recognition drops to 69.5% when UCI HAPT dataset is used as training set and the local dataset is used as test set.

Table 12 Activity recognition results using deep learning

Models	UCI HARPT dataset (%)	Local dataset (%)	UCI HAPT and local datasets (%)
1D CNN1	80	81	69
1D CNN2	81	84	70

To better describe the performance of the deep learning models, Tables 13 and 14, and 15 show the confusion matrices for deep learning classification models (with CNN2) using UCI HAPT dataset, local dataset, and UCI HAPT and local datasets respectively. As shown in Table 13, the recognition performance of the CNN2 model is high using the UCI HAPT dataset only. More than 0.50 true positive is observed except for sit-to-lie activity. The classes that achieve the best true positive include walking, sitting, standing, and sit-to-stand. Similarly, as shown in Table 14, the confusion matrix of the CNN2 model using the local dataset only shows fewer misclassification errors and high classification performance. All activity classes achieve a true positive of 0.50 and above. Walking (1.00), sitting(0.99), sit-to-lie (0.79), stand-to-sit (0.76), and lie-to-sit (0.75) activity have the best true positive rate respectively while lying down activity has the worst true positive of 0.50. This is due to the nature of static and transitional activities.

Conversely, the performance of the classification models drops while using the UCI HAPT dataset as training set and the local dataset as test set. Table 15 shows the confusion matrix of CNN2 model using the UCI HAPT dataset as training and the local dataset as testing. Although CNN performed better than machine learning models, there are no great improvements observed. As can be seen, the classification performance of walking, stand-to-sit, sitting, sit-to-stand, and lie-to-sit activities have a relatively lower true positive rate compared to the activity recognition using UCI HAPT dataset only and local dataset only. Similar misclassification pattern can be seen in the table whereby the transitional activities have the highest misclassification rates. The fixed sliding window segmentation method failed to segment the transitional activity signals due to their relatively longer length compared to the adults. This is reflected in Table 15 whereby 0.28 of stand-to-sit activity is misclassified as standing activity, 0.24 of sit-to-stand is misclassified as walking, 0.21 of sit-to-lie is misclassified as walking, 0.27 of lying down is misclassified as sitting, and 0.30 of lie-to-sit activity is misclassified as lying down.

Overall, the classification models did not achieve state-of-the-art performance. This is due to the limited size of the training set. The training samples were reduced after eliminating null classes, and other non-related activities in the training set. The performance of the models was also

Table 13 Confusion matrix of CNN2 using UCI HAPT dataset only

	Walking	Standing	Stand-to-sit	Sitting	Sit-to-stand	Sit-to-lie	Lying down	Lie-to-sit
Walking	0.95	0.00	0.05	0.00	0.00	0.00	0.00	0.00
Standing	0.01	0.84	0.08	0.01	0.03	0.01	0.01	0.01
Stand-to-sit	0.09	0.24	0.63	0.00	0.00	0.01	0.02	0.01
Sitting	0.06	0.02	0.00	0.88	0.00	0.00	0.02	0.02
Sit-to-stand	0.08	0.00	0.02	0.00	0.75	0.02	0.03	0.10
Sit-to-lie	0.25	0.12	0.31	0.00	0.04	0.24	0.00	0.04
Lying down	0.15	0.03	0.00	0.19	0.05	0.00	0.55	0.03
Lie-to-sit	0.01	0.09	0.17	0.02	0.02	0.00	0.01	0.68

Table 14 Confusion matrix of CNN2 using local dataset only

	Walking	Standing	Stand-to-sit	Sitting	Sit-to-stand	Sit-to-lie	Lying down	Lie-to-sit
Walking	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Standing	0.00	0.69	0.19	0.12	0.00	0.00	0.00	0.00
Stand-to-sit	0.07	0.09	0.76	0.00	0.04	0.02	0.02	0.00
Sitting	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.01
Sit-to-stand	0.17	0.04	0.00	0.00	0.68	0.04	0.07	0.00
Sit-to-lie	0.10	0.00	0.04	0.00	0.07	0.79	0.00	0.00
Lying down	0.00	0.00	0.00	0.38	0.12	0.00	0.50	0.00
Lie-to-sit	0.12	0.00	0.00	0.00	0.00	0.13	0.00	0.75

Table 15 Confusion matrix of CNN2 using UCI HAPT and local datasets

	Walking	Standing	Stand-to-sit	Sitting	Sit-to-stand	Sit-to-lie	Lying down	Lie-to-sit
Walking	0.84	0.00	0.01	0.01	0.00	0.00	0.04	0.10
Standing	0.00	0.75	0.07	0.05	0.00	0.00	0.06	0.07
Stand-to-sit	0.07	0.28	0.50	0.00	0.01	0.03	0.01	0.10
Sitting	0.00	0.07	0.00	0.85	0.00	0.00	0.02	0.06
Sit-to-stand	0.24	0.06	0.04	0.01	0.35	0.05	0.17	0.08
Sit-to-lie	0.21	0.03	0.02	0.03	0.16	0.36	0.11	0.08
Lying down	0.00	0.02	0.13	0.27	0.00	0.00	0.55	0.03
Lie-to-sit	0.02	0.04	0.04	0.12	0.09	0.11	0.30	0.28

affected by the class imbalances available in both benchmark and local datasets. Nevertheless, the results confirmed that subject variability occurs when classification models are trained and tested on datasets with different age groups. The results also indicate that subject variability degrades the performance of activity recognition.

We analyze the activity signals of the elderly and adult subjects to determine the performance degradation. The performance degradation is mainly caused by the variation of the length of transitional activity signals which indicate the completion time of the activity, the speed of walking activity, and the stability of standing, sitting, and lying down activities between the elderly and adults. To analyze these three factors, we calculated the mean length of the transitional activities while for walking and static activities, we calculated the variance of the magnitude of the three-axis acceleration within the window segmentation of all subjects in the local and UCI HAPT datasets. The findings of the analysis indicate that the mean length of stand-to-sit and sit-to-stand activity signals of the elderly are approximately 0.2 and 0.095 s longer than the mean length of stand-to-sit and sit-to-stand activity signals of the adult respectively. As a result, the fixed sliding window segmentation method failed to produce perfect segmentation due to the varying completion time of the activity. Table 16 shows the mean length of stand-to-sit and sit-to-stand activity signals. The analysis also shows that the walking activity of adults generates higher acceleration than the walking activity of the elderly. This is shown in Table 17 where the mean of the variance of walking activity of adults. The mean of the variance also shows that the static activities of adults are more statble than the static activities of the elderly as shown in Table 18.

Table 16 The mean length of transitional activity signals of elderly and adults

Category of subject	Stand-to-sit (s)	Sit-to-stand (s)
Elderly (Local dataset)	3.566	2.675
Adult (UCI HAPT)	3.408	2.580

Table 17 The mean of the variance of walking activity of elderly and adults

Category of subject	A_x	A_y	A_z
Elderly (Local dataset)	0.021	0.035	0.034
Adult (UCI HAPT)	0.043	0.035	0.041

Table 18 The mean of the variance of static activity of elderly and adults

Category of subject	A_x	A_y	A_z
Elderly (Local dataset)	0.284	0.244	0.072
Adult (UCI HAPT)	0.194	0.177	0.128

The difference in the intensity of the walking activity, and the presence of irregular, random and sparse spikes in the static activity signals of the elderly causes the classification models that were trained on UCI HAPT dataset failed to generalize to the local dataset.

6 Conclusions

In this paper, we investigated the effect of subject variability on the performance of activity recognition. In the experiments, two datasets with different age groups are used to train and test machine learning and deep learning models. The experiments are carried out in three stages: activity recognition using the public dataset only, activity recognition using the local dataset only, and activity recognition using the public dataset as training and the local dataset as testing. The results show that subject variability due to age differences among the subjects significantly drops the performance of the classification models. On average, the drop in recognition accuracy is 9.75 and 12% for machine learning and deep learning models respectively. The classification results showed that transitional activities such as stand-to-sit, sit-to-stand, sit-to-lie, and lie-to-sit have the worst performance decline compared to dynamic and static activities. This is due to the slower movement nature of elderly people compared to adults. This affects the window size as fixed sliding window segmentation technique cannot adaptively adjust the window size depending on the time to perform the activity to produce optimal window size. The experimental results confirm that subject variability is an important issue that requires immediate attention. The future work of this study is to propose a method for solving performance degradation caused by such kind of subject variability.

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Code Availability Not applicable.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest to report regarding the present study.

Ethics approval Written informed consent was obtained prior to data collection in accordance with the approval by the human research ethics committee of Universiti Sains Malaysia (USM/JEPeM/18040205).

Consent to participate Informed consent was obtained from all participants included in this study.

Consent for publication We give our consent for our paper to be published in the Journal of Ambient Intelligence and Humanized Computing.

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