An Experimental Investigation Comparing Age-Specific and Mixed-Age Models for Wearable Assisted Activity Recognition in Women

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Abstract: In this paper, we investigate the impact of age diversity on accuracy for activity recognition among women with wrist-worn wearables. Using a sample of 10 elder women and 10 younger women, and by monitoring five activities related to cardiac care (Running, Brisk Walking, Walking, Standing and Sitting), we show that while personalized models are best, activities classification based on age specific models are definitely superior in terms of accuracy compared to classification using mixed age models. We do so by a) extracting 11 features from inertial sensing data; b) reducing dimensionality using Linear Discriminant Analysis methods; c) quantifying variance among features using Principal Component Analysis; d) clustering activities; and finally e) comparing classification accuracies of all activities for personalized, age-specific and mixed-age models. We believe that our study is unique, and potentially important for superior healthcare for women, a demographic that is largely underserved today across the world.

1 INTRODUCTION

Consistent physical activity is important for human health across all ages. To cater to this need, billions of dollars and significant human resources have been invested by industry and academia to advance the field of wearable assisted activity recognition. Chief among these are wrist-worn wearables like the FitBit band, Apple Watch, Samsung Gear etc., that are very popular today. The global demand of wearable technologies is estimated to be around 200 million devices in 2021 (Beaver, 2016).

1.1 State of the Art in Wearable Tech w.r.t. Elders and Identified Gap

As of today, the wearable tech market is dominated by sensory devices worn on the wrist for recognizing basic physical activities like walking, running, sitting, standing and sleeping. These wearables typically come with pre-trained models, but do suffer from accuracy problems to a certain degree. This lack of accuracy is unavoidable, since each person performs the same activity a little differently, and it is virtually impossible for an algorithm in a wearable to correctly identify all possible modes of diversity across all humans. However, when it comes to elders, both patients and physicians have very high accuracy expectations, since physical activities are extremely important, but can simultaneously be strenuous for elders, and so there is an expectation that every "step" be counted, and counted correctly. However, despite studies showing that aging causes diversities in the way humans perform and perceive physical activities (Borg, 1998), (Bar-Or, 1977), (Levy and Myers, 2004) there is no careful study yet on impact of age diversities on accuracy in wearable assisted activity recognition.

1.2 Our Contributions

In this paper, we investigate the importance of considering age diversities in wearable assisted activity classification for women, and identify critical observations. Each physical activity we investigate in this paper is vital for health, and specifically cardiac care. We specifically focus on women subjects in this paper since they are an underserved population in cardiac care (Valencia et al., 2011), (Benz Scott et al., 2002), and we can retain problem scope.

Our specific contributions are as follows. We conduct an experiment with 20 women subjects, where 10 subjects were younger in the age group of $21-26$, and the other 10 subjects were older in the age group of $65-75$. Each subject was asked to wear a wrist wearable, and they performed a series of five activities: Brisk Walking, Running, Sitting, Standing and Walking. During this time, the accelerometer and gyroscope readings were collected from the wearable device and later exported to high end server for further processing.

Subsequently, a) we extract 11 contextually relevant features each from the three axes of accelerometer and gyroscope sensory data, and analyze them extensively; b) perform dimensionality reduction using Principal Component Analysis; c) perform cluster analysis via Linear Discriminant Analysis; and d) implement several machine learning algorithms for classification. We make several interesting findings. We find that among principal components, only very few components contain large portions of variance in datasets for the younger cohort, compared to the elder cohort. The conclusion here is higher similarities in activities when performed by younger women, compared to elder women. The distribution of variances in the mixed-age cohort was the worst, hence making a case for age-specific models. After clustering, we find that the activity clusters on the younger cohort are highly separable with minimal overlap, while the elder only cohort had more than reasonable overlaps among activities classified, and the mixed-age model again performed the worst with significant confusion. Finally, we find that classification accuracies for the age-specific models outperform mixed-age models by an average of 20%. Models personalized for each individual are much more accurate.

To the best of our knowledge, our study is the first to comprehensively investigate impact of age disparities on accuracies in terms of wearable assisted activities classification, and present a formal need for age-specific, or even better, personalized models. The exclusive focus on women is a further salience of our contributions.

2 RELATED WORK

In this section, we elaborate on important related work in two broad topics: technology assisted activity recognition in general, and works that specifically consider impact of diversities on wearable assisted physical activities recognition.

2.1 Physical Activity Recognition using Computing Technologies

Human Activity Recognition is a very well studied topic, with some good surveys in (Avci et al., 2010), (Sánchez et al., 2008). There are broadly three classes of work in this realm. The first one is to use sensors emplaced in the ambient infrastructure for activity recognition. Typically, the sensors are video cameras, WiFi receivers, PIR sensors, etc. Such systems have been used to detect activities like walking, sitting, standing, running in (Bao and Intille, 2004), gait study in (Lee and Grimson, 2002), activities performed by healthcare professionals in clinical settings in (Sánchez et al., 2008) and more. The second class of work detects activities using only wearables emplaced in different body positions like wrists, fingers, neck, feet and more. Among these, there are works like (Bharti et al., 2018a) that recognizes basic activities like walking, sitting, standing, running etc., and complex ones like cooking, cleaning etc. There are also works that detect more fine grained activities like self-harming activities (Bharti et al., 2018b); walking upstairs, walking downstairs, taking elevator up/ down, lying down (Jiang and Yin, 2015); lie-to-sit, stand-to-lie, lie-to-stand, cycling, ironing clothes etc. (Reyes-Ortiz et al., 2016). Finally, there are works that use a combination of wearable sensors and infrastructure sensors for recognizing activities like cooking, cleaning utensils and many more (De et al., 2015). From reading extensive related work in this space, we observed that the elder demographic is largely under-represented in existing studies today in wearable assisted activity recognition, as summarized in Table 1.

2.2 Impact of Diversities in Wearable Assisted Activity Recognition

We find that most works that look at wearable assisted activity recognition for elder subjects are specific for Fall Detection only (de la Concepción et al., 2017), (Kaur and Kaur, 2017), (Wang et al., 2017). From the perspective of detecting basic physical activities using wearables, there are very limited works that consider elder subjects. For instance, one very recent work in (Alinia et al., 2017), evaluate three different types of Fitbit activity trackers and concluded that these devices are accurate when subject walks/ runs on treadmill, but the accuracy goes down when the subject is walking with an assisted device, or walks very slowly, which are representative with elders.

In fact, we are aware of only one work (Del Rosario et al., 2014), where there was an at-

Table 1: Related work in space of human activity recognition using wearables.

Publications	Sensors	Age group (in years.)
(de la Concepción et al., 2017)	3-axis Accelerometer	19-48
(Jiang and Yin, 2015)	3-axis Accelerometer and Gyroscope	19-49
(Bharti et al., 2018a)	3-axis Accelerometer, 3-axis Gyroscope, Barometer pressure sensor, Temperature, Humidity, iBeacon, GPS	20-25
(Bharti et al., 2018b)	3-axis Accelerometer, 3-axis Gyroscope	25-30
(Reyes-Ortiz et al., 2016)	3-axis Accelerometer, 3-axis Gyroscope	19-48
(Alinia et al., 2017)	FitBit wearables	21-31
(Wang et al., 2017)	Wi-Fi signal	NA

tempt to study the efficacy of an age-specific model and a mixed-age model for activity recognition using smartphone sensors. The authors showed that accuracy is significantly higher when a model is trained and tested on age-specific datasets, compared to a mixed-age datasets. Our work in this paper is related to (Del Rosario et al., 2014), but there are compelling differences. In our paper here, we employ a wrist-worn device, which is more realistic and practical, when compared to smart-phones for activity recognition. Secondly, the work in (Del Rosario et al., 2014) does not look at statistical properties of features extracted (which will give more context to the results), and does not not consider activities like brisk walking and running, which we do in our paper, hence making our contributions significant and relevant.

3 EXPERIMENTAL SETTING

We now present our experimental set-up. We collected a dataset for five ADL (Activities of Daily Living) activities, namely Brisk Walking, Walking, Running, Standing and Sitting. Each one of these activities is vital for health across ages, and more so for cardiac care. Ten younger (age range: 21-26) and ten elder female participants (age range: 65-75) took part in our experiments. All the younger subjects did all of the activities, as did four elder subjects. Six elder subjects (in the higher age group) did not run (for obvious reasons), but did all the four other activities. Each activity was performed for 4 minutes by every individual. Thus, around 20 minutes of data were collected from each participant. A wearable device called Shimmer (Burns et al., 2010) equipped with tri-axial accelerometer and tri-axial gyroscope sensor was worn by each subject on their right wrist. Data was sampled from the accelerometer and gyroscope sensor at a frequency of 50Hz (samples per second). Data from both sensors were directly streamed and stored to server for processing and analysis.

Note that the Shimmer device is widely used in research today for its miniature size and powerful sensing/ computing/ wireless transmission abilities. The central element of the platform is the low-power MSP430F5437A microprocessor with 24MHz clock rate which controls the operation of the device. The CPU has an integrated 16-channel 12-bit analog-to-digital converter (ADC) which is used to constantly sample and capture triaxial acceleration signals from an in-built accelerometer in the unit. These accelerometers have a range of $\pm 16g$ (where g is gravitational acceleration) and were sampled at 50Hz. Note that the frequency of most human activities lie within range of 15Hz (San-Segundo et al., 2016). As such, this sensor sampling rate is ideal for our problem, since according to the Nyquist rule for lossless reconstruction of a signal, it needs to be sampled at a rate that is at-least twice its highest frequency (Landau, 1967). Figure 1 shows one subject in our experiments actually wearing the Shimmer wearable.

4 DATA PRE-PROCESSING, FEATURE EXTRACTION AND DIMENSIONALITY REDUCTION

We now present details on how we pre-processed the sensory data, followed by feature extraction, and reduction of data dimensionality for tractability.

4.1 Data Pre-processing

The first step after data collection is the pre-processing of raw accelerometer and gyroscope data collected from the Shimmer wearable. Depending on the orientation of device, gravity can influence the readings on one or more of the components of accelerometer data. To avoid this issue, Shimmer API provides methods to sample linear acceleration directly and hence eliminating the influence of gravity. Once the linear acceleration data is extracted, we further pre-process both the accelerometer and gyroscope data using an adaptive median filter (Hwang and Haddad, 1995) to remove noise, and we further feed the signal to a low pass filter using a 15Hz cut-off 4^{th} order Butterworth filter to limit the bandwidth of the signal to the frequencies common in human motion, hence removing high frequency noise.

After noise removal, the next step is to determine a sliding window size for the signals to attempt classification. A window size, $W = 150$ samples (approximately 3 seconds) with 50% overlap was used to create a new database that was used as the training/testing data for activity classification, also suggested by prior related work on human activity recognition (Banos et al., 2014) it is found that 2-5 seconds window works best for human activity recognition using accelerometer data. Hence, we conducted our experiment with window length from 2 to 5 seconds having 0.5 second intervals and found that window length of 3 seconds is working best for our problem. Subsequently, the segmented window is forwarded to next steps for feature extraction and selection.

4.2 Feature Extraction

We extracted 11 features (Table 2) for each window along three axes of tri-axial accelerometer and tri-axial gyroscope sensor. Each of the features we extract is contextually relevant, and extensively used in the literature for classifying physical activities (Gupta and Dallas, 2014), (De et al., 2015), (Sousa et al., 2017). For example, variance, entropy and mean crossing rate features have very good discriminating power to classify activities like running, walking and standing. The energy feature is very useful for discriminating more intense activities like brisk walking and running. Features like variance, entropy and mean crossing rate also can give vital information about activities of interest to this paper. Maximum frequency, skewness, percentile, min and max feature values captures information from signals that differentiate the activities of interest to this paper from other physical activities that humans perform. As such, a total 66 features were computed for our problem, which comes from 11 features in Table 2 for accelerometer and gyroscope across all the axes.

4.3 Dimensionality Reduction with PCA and LDA

Processing high dimensional data sets (66 features for our problem) can be noisy, harder to visualize and computationally demanding. To ensure accuracy and tractability, dimensionality reduction is a popular approach, for which we use two techniques in this paper[1]. The first is Principal Component Analysis (PCA), where the overall goal is to identify 'principal components', each of which quantify a notion variance among features, while also being orthogonal to other components (Mika et al., 1999) The second technique is Linear discriminant analysis (LDA), where the overall goal is to find a linear combination of features that characterizes or separates two or more classes of objects or events. The resulting com-

[1]Both techniques we use in this paper are well established, and so we don't present details.

Table 2: Feature set.

$$Norm = \sum_{i=1}^{N} \sqrt{(a_{xi})^2 + (a_{yi})^2 + (a_{zi})^2}$$

$$Variance = \frac{1}{N}\sum_{i=1}^{N}(a_i - \mu)^2$$

$$Max = \underset{i \in \{1,2..N\}}{\text{argmax}}\ (a_i)$$

$$Min = \underset{i \in \{1,2..N\}}{\text{argmin}}\ (a_i)$$

$$Entropy = -\sum_{i=1}^{N} p_i(\log p_i)$$

$$Max\ reduced\ Mean = (\underset{i \in \{1,2..N\}}{\text{argmax}}\ a_i) - \bar{a}$$

$$Mean\ crossing\ rate = Count\ of\ signal\ crossing\ mean\ in\ each\ window$$

$$Spectral\ energy = \sum_{f=0}^{fs/2} |a[f]|^2$$

$$Maximum\ Frequency = \underset{i \in \{1,2..N\}}{\text{argmax}}\ FFT(a_x, a_y, a_z)$$

$$Mean\ absolute\ Deviation = \frac{\sum_{i=1}^{N} |a_i - \mu|}{N}$$

$$IQR = 3rd\ Quartile_{median} - 1st\ Quartile_{median}$$

Figure 1: Shimmer wireless sensor device worn on a participant's wrist.

bination may then be used as a linear classifier (Wold et al., 1987).

5 DATA ANALYSIS OF ELDER VS YOUNGER ACTIVITY RECOGNITION

In this section, we show the impact of age-specific, mixed-age and personalized model development for classifying physical activities. We do so by a) demonstrating that variance of features are concentrated among fewer PCA components only for younger specific model compared to elder specific model, both of which are better than mixed-age models; b) results from clustering activities that demonstrate superior performance for younger group, followed by the elder group and the mixed age group; c) classification results from many machine learning algorithms that validate the above results; and d) finally demonstrating that models personalized for each user have much higher accuracies compared to any model that mixes data from subjects.

5.1 Difference in Variance in Each Category

For all the 66 (2 sensors$\times$3 axes$\times$11 features) features listed in Table 2 for our problem, we applied PCA to transform the feature set into orthogonal PCA components. Recall that PCA components have variances of features in decreasing order. If the data is too noisy or have many orthogonal features, then PCA components have variances distributed across more components. When data is more consistent, then most of the variances are present in very few PCA components only. In Figure 2, we immediately see that a significant portion (i.e., 90%) of the variances are present in only one principal component in the left most figure (i.e., the younger cohort), compared to the other two cohorts, which are 76.2% and 72.4% respectively. To quantify further, for the case of the younger cohort, only 7% of variance are distributed among other components other than the principal component. But for the elder and mixed-age cohorts, we see 20% and 22% of variances are distributed among components other than the principal component. This validates our intuition that features of the younger only cohort have the least amount of noise. The features among the elder only cohort is more noisy, but it is worse than the mixed-age cohort.

5.2 Clustering Activities

Now that we understand the impact of age-specific models on noise, we leverage Linear Discriminant Analysis (LDA) to create compact clusters for each activity, while keeping center of each cluster as separated as possible. The LDA approach outputs a list of transformed components for our problem scope. Out of these, the first two components, namely LDA1 and LDA2 are used to draw the clusters for each activity for younger, elder and mixed-age dataset. Using just two components helps in better visualization, without losing the generality of our results. Clusters are plotted in Figure 3. As we can see in the figure, for younger dataset, each activity cluster is well separated except brisk-walking and walking. Even these two activities have less than 10% of samples overlapping. The reason we believe is very minimal difference in these two activities which are hard to distinguish by using just 2 sensors. On the other hand, the activities in the elder dataset can be seen as more spread apart from the center of each cluster, indicating more noise. Furthermore, there are more overlapping points. Especially brisk-walking with walking, and sitting with standing have more than 70% samples overlapped. Running cluster is also not as well separated in elder dataset as it is compared to the younger dataset. The mixed-age dataset performs the worst overall.

5.3 Cross-validation Classification Accuracy

Finally, to delve deeper towards understanding the impact of age of activities classification, we leverage state-of-the-art classification techniques to classify the activities within younger, elder, and mixed-age cohort. Unlike in the previous clustering scenario, here we use 4 LDA components to classify activities. Classification results using the cross-validation approach for each algorithm for younger, elder and mixed cohorts are shown in Figure 4. The machine learning algorithms used are Linear Support Vector Machines (Suykens and Vandewalle, 1999) , Support Vector Machine with Radial Basis Function Kernel (Scholkopf et al., 1997), K-nearest Neighbors (Larose, 2005), Decision Trees (Safavian and Landgrebe, 1991) and Random Forests (Breiman, 2001).

Note that the metrics we use, Precision, Recall and F1-score are standard metrics in evaluating performance of machine learning algorithms for classification. The precision is the ratio of correctly classified positive instances to the total number of instances classified as positive. Recall is the ratio of correctly classified positive instances to the total number of

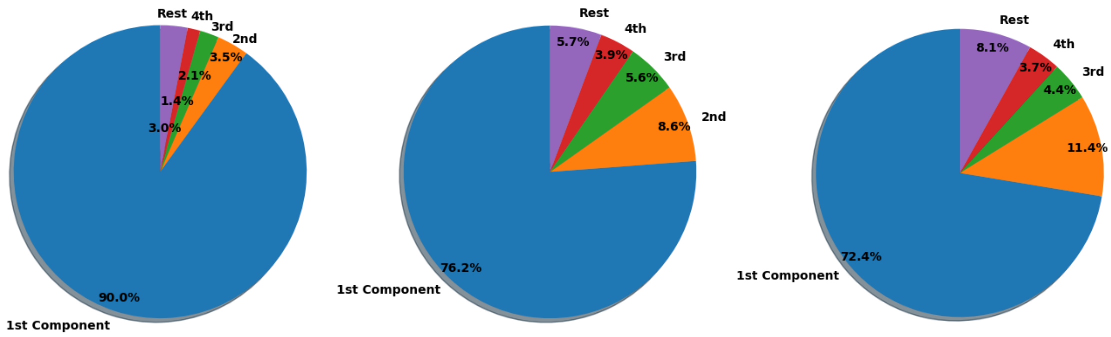

Figure 2: Variance distribution in PCA components for Younger (on left), Elder (on middle) and Mixed (on right) age group dataset.

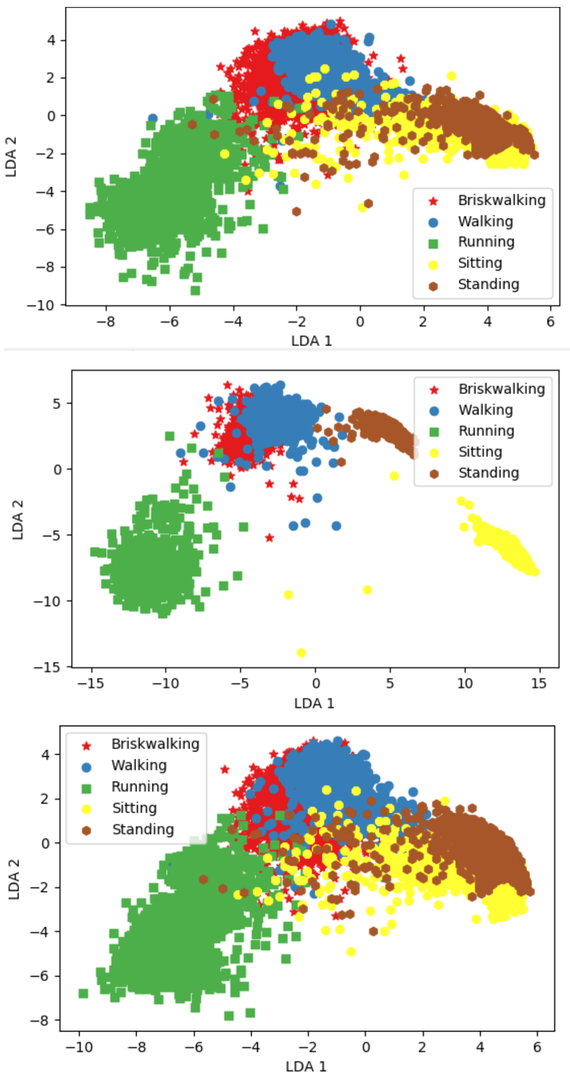

Figure 3: Activity cluster for elder (on top), younger (on middle) and mixed (on bottom) dataset.

positive instances. The F1-score balances precision as recall, and is given by $2 \times \frac{Precision \times Recall}{Precision + Recall}$.

We see from Figure 4 that while the algorithms do yield similar classification performance (Recall), we can see that the Younger only model performs much better, compared to the Elder only model, while the Mixed-age model performs the worst overall in all cases. Most confusion happens between walking and brisk-walking, which is understandable.

5.4 Personalized Classification Model for Elder People

With the diversities in activities as performed by elders compromising classification accuracy (when data from all elders was used for modeling) as presented above, we now attempt to investigate if personalized models can help improve classification accuracy for the elder cohort. In Figure 5, we present classification accuracy results based on the Random Forest learning algorithm (which performed the best). As we can see, the accuracy of all activities is much higher when a model is trained for each elder subject exclusively - with an average improvement of 30% in activities classification.

6 DISCUSSIONS AND CONCLUSIONS

In this paper, we investigate the impact of age-specific and personalized algorithms on accuracy for classifying physical activities among women using a wrist worn wearable device. Using only accelerometer and gyroscope sensory data, and leveraging state of the art data mining, and classification algorithmic techniques, we demonstrate that models focusing on a younger cohort (21-26 age group) were superior in terms of activities classification compared to an elder

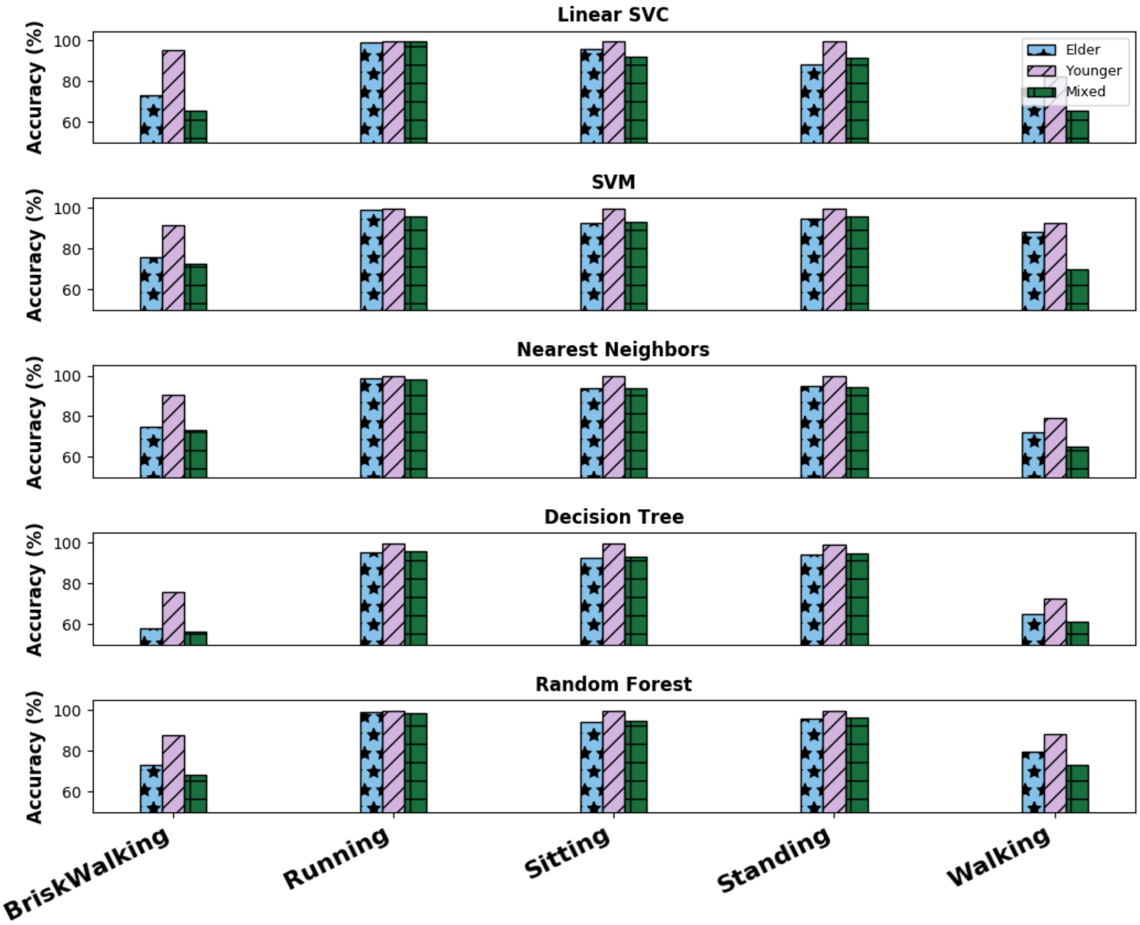

Figure 4: Comparison between accuracy (recall) of activities classification for elder, younger and mixed data using different classifiers.

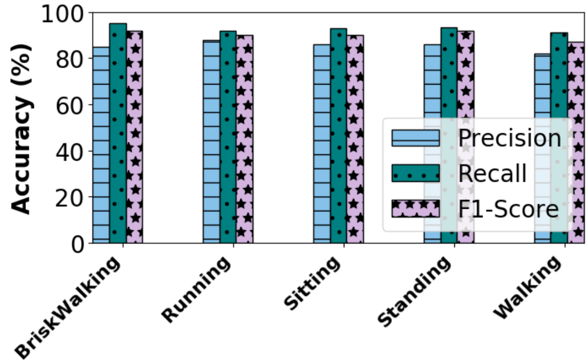

Figure 5: Personalized classification accuracy using Random Forest on elder data.

only cohort (65-75 age group), with the mixed age cohort performing the worst. We finally also showed that for the elder only cohort, a personalized model performed much better.

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