Towards a Digital Personal Trainer for Health Clubs
Sport Exercise Recognition Using Personalized Models and Deep Learning

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Abstract: Human activity recognition has emerged as an active research area in recent years. With the advancement in mobile and wearable devices, various sensors are ubiquitous and widely available gathering data a broad spectrum of peoples' daily life activities. Research studies thoroughly assessed lifestyle activities and are increasingly concentrated on a variety of sport exercises. In this paper, we examine nine sport and fitness exercises commonly conducted with sport equipments in gym, such as abdominal exercise and lat pull. We collected sensor data of 23 participants for these activities, for which smartphones and smartwatches were used. Traditional machine learning and deep learning algorithms were applied in these experiments in order to assess their performance on our dataset. Linear SVM and Naive Bayes with Gaussian kernel performs best with an accuracy of 80 %, whereas deep learning models outperform these machine learning techniques with an accuracy of 92 %.

1 Introduction

It is commonly known that sport activities and regular exercises are the key for preserving people's physical and mental health. In 2010, the British Association of Sport and Exercise Sciences published a consensus statement pointing out the correlation between no regular physical activity and an increased risk of cardiovascular disease or type 2 diabetes (O'Donovan et al., 2010). Consequently, people regardless of their age seek to take part in exercise programs or join gyms to improve their fitness and strengthen their muscles. It is also recommended to regularly perform sport as this training lower blood pressure, improve glucose metabolism, and reduce cardiovascular disease risk (O'Donovan et al., 2010).
However, many athletes suffer from the right motivation to constantly practice over a long period of time. According to the study of Scott Robert, this is one of the people's main reason for hiring a personal training: The wish to have someone motivating themselves (Roberts, 1996).
Issues arouse from a practical perspective. Hiring a personal trainer is expensive; especially when exercising with a professional trainer. It does not make a difference whether a personal trainer is hired privately or provided by gyms. Professional health clubs usually offer personal trainer as a supplementary service promise. Even in this case, however, sportsmen are not constantly guided and supervised during their exercises in a way, which is really beneficial. Personal trainers are still a large cost factor and thus, there cannot normally be assigned a personal trainer per athletes over their entire training session.
Those problems can be avoided with a system that functions as a personal trainer, which accompany each and every sportsmen in their training. A digital personal trainer that is able to supervise athletes in their training has great potential to support both professional and amateur athletes. A system integrated into sport equipment can guide exercises through their training not only helping to motivate people. It can also supervise athletes performing sport activities, which increases the safety and efficiency of their training.
While many research studies focused on movement activities (i.e. walking or jogging (Parkka et al., 2006)) or daily life actions (vacuum cleaning or brushing teeth (Kao et al., 2009)), only little work has evaluated sport activities beyond endurance. Consequently, the problem being examined in this paper is how to perform activity recognition with sport equipment of modern gyms. Therefore, the focus lies on common devices (such as chest press) which are well

known among athletes and a common practice performed by many people in health clubs.
As to the best knowledge of the authors, no sport equipment is currently available, which is automatically sensing their users in gyms. This work utilized the athlete's smartphone and smartwatch, which are widely available nowadays. Recent studies showed the possibility to integrate such a human activity recognition system in wearable devices (Ravi et al., 2005; Shoaib et al., 2013). Sensor data of 23 participants were collected performing nine common exercises with sport equipment in gyms. We evaluated common state of the art machine learning algorithms as well as latest deep learning models to assess their classification accuracy. In order to enable and support further research with our collected dataset, we made our dataset publicly available.
In particular, this paper made following contributions:

- A novel and publicly available dataset containing smartphone and smartwatch sensor data of 23 male as well as female participants for nine common sport equipments of gyms. For each participants, we collected two sets of each exercise with ten till fifteen repetition in each set. The dataset can be downloaded from `http://www.dfki.uni-kl.de/~baumbach/digital_personal_trainer`.
- An detailed comparison of traditional machine learning algorithms and state of the art deep learning techniques, i.e. LSTM. Experiments showed that decision tree, linear SVM and Naive Bayes with Gaussian kernel performed best with accuracy of 80 %. However, deep learning model outperformed these machine learning models with accuracy of 92 %
- Our results showed a significant increase of 26 percentage points in the performance of all machine learning algorithms when personalized models were used.

The rest of this paper is organized as follows. *Chapter 2* summarizes and assesses the state-of-the-art in sport activity recognition for both machine learning algorithms and deep learning techniques. *Section 3* presents the utilized activity recognition process including the preprocessing steps on the data as well as the applied classification algorithms. *Section 4* depicts the experimental setup where data for 23 participants were collected in a gym. *Section 6* presents our finding where deep learning outperformed traditional machine learning algorithms by twelve percentage points. Finally, the results are summarized and discussed in *Section 8*.

2 Related Work

Human Activity recognition is a vast area. Research work have studied different kind of activities, ranging from basic (such as walking, running, sleeping, or climbing stairs) to complex (including eating, vacuum cleaning, or swimming) activities. Especially sport activities (e.g., basketball (Perše et al., 2009)), health monitoring system (like sleep tracking (de Zambotti et al., 2015) and patient care (Chen et al., 2014)) recently gained attention in the research community. Promising results for deep learning also stimulated further research in the field of human activity recognition. Studies already conducted using deep neural network outperformed traditional machine learning approaches.

2.1 Recognition of Sports Activities

Although research work in the field of human activity recognition traces back to the 90s (Polana and Nelson, 1994) and assessed many fitness and sport exercises, only little work about sport equipment of gyms were published so far. Numerous studies focused the domain "ambulation" (such as walking or jogging), daily life (like reading or stretching), or upper body activities (e.g., chewing or speaking) (Lara and Labrador, 2013). Interested readers are pointed to the extensive survey on human activity recognition published by Lara et al. (Lara and Labrador, 2013).
Prior work focused on placing multiple acceleration sensors on several parts of the participant's body (Parkka et al., 2006; Subramanya et al., 2012). This setup were capable of identifying a wide range of activities, such as running, walking, or climbing stairs. However, they require users to wear multiple proprietary sensors distributed across his body. To come around these limitations, other studies conducted experiments where only a single accelerometer measures the activities (Lee, 2009; Long et al., 2009). With the constantly growing availability of mobile and wearable devices over the last years, "ubiquitous sensing" (Lara and Labrador, 2013) comes into focus. Consequently, several investigations assessed the use of these widely available mobile devices for HAR. (Ravi et al., 2005; Lester et al., 2006).
Tapia et al. (Tapia et al., 2007) presented a real-time algorithm for automatic recognition of physical activities and partly their intensities. They utilized five triaxial accelerometers and a heart rate monitor to differentiate 30 physical gymnasium activities from 21 participants. For recognizing activity types with their intensity, the authors obtained a recognition accuracy of 94.6 % using subject-dependent and 56.3 % using

subject-independent training.
Velloso et al. (Velloso et al., 2013) dealt in their work with the qualitative activity recognition of weight lifting exercises. Their goal was the recognition of correct and false execution as well as providing feedback to the user. For a 10-fold cross validation, their approach scored a precision of 98.03%. For leave-one-subject-out cross validation it scored 78.2%.

2.2 Machine Learning vs. Deep Learning

Deep learning is by no means a new technology, the recent progress in GPU based data processing gave new possibilities to apply deep learning to a wide variety of problems. This section provides an overview over the recent research results and classification accuracy in deep activity recognition.
Yang et al. (Yang et al., 2015) proposed a convolutional neural network (CNN) with 17 layer and rectified linear units (ReLU) as activation function. Alsheikh et al. (Alsheikh et al., 2016) applied the deep learning paradigm to triaxial accelerometers and presented a hybrid approach of deep belief network (DBN) and hidden Markov models (called DL-HMM) for sequential activity recognition. The authors showed that deep models outperform shallow ones, more layers will enhance the recognition accuracy, and overcomplete representations are advantageous. Ordóñez et al. (Ordóñez and Roggen, 2016) proposed an 8 layer deep architecture based on the combination of convolutional and long short-term memory (LSTM) recurrent layers, called DeepConvLSTM. Once trained in a full-supervised manner, DeepConvLSTM directly works on raw data with only minimal pre-processing required. Wang (Wang, 2016) proposed a continuous autoencoder (CAE) as a novel stochastic neural network as well as a new fast stochastic gradient descent (FSGD) algorithm to update the gradients of the CAE. The FSGD is capable of achieving a 0.3 % error rate after just 180 epochs of training. Wang then applies time and frequency domain feature extract (TFFE) to extract feature vectors, followed by PCA to end up with a 42 dimensional feature vector. This feature vector is then fed into a DBN composed of stacked CAEs. The DBN consist of 6 layers (2 CAEs and a BP layer) and is trained in a semi-supervised manner. Ronaoo and Cho (Ronaoo and Cho, 2015) proposed to utilize CNNs to classify activities. Their experiments showed that increasing the number of convolutional layers increased performance, but the complexity of the derived features decreased with every additional layer. Zeng et al. (Zeng et al., 2014) proposed a method based on Convolutional Neural Networks (CNN), which can capture local dependency and scale invariance of a signal. They use a 6-layer deep CNN (input - convolution - max-pooling - fully connected - fully connected - softmax).

3 Methodology of the Sport Activity Recognition Process

The exercises sensed in our experiment consists of rotation, magnetic field and acceleration of different body part. The accelerometer sensor data from phone and watch needs to be preprocessed before the data can be classified by machine learning approaches. Furthermore, sensor data is noisy and passing the raw data to the learning algorithms negatively effect the accuracy of the recognition.

3.1 Preprocessing

The orientation of devices affects the accelerometer sensor data (Thiemjarus, 2010). To standardize the sensor data regarding the underlying coordinate system, a rotation matrix was calculated using gyroscope and magnetometer sensor data. This rotation matrix was then used to transform the acceleration values from device coordinate to fixed word's coordinate system.
The sensor data from phone and watch contains noise and outliers. The reason are the sensors' inaccuracy and noise in the sensors' signals as well as some unexpected behavior of the users during the exercise. Removing these noise element from sensor data proved to produce better recognition results for human activities (Wang et al., 2011). A median filter of order three was applied to the sensor data to remove impulse noise (Thiemjarus, 2010).

3.2 Feature Extraction

Data was collected with sample rate of 30 Hz for all sensors. From this data, a specific set of features is extracted from each segment using a sliding window approach without inter-window gaps for segmentation. Four different window sizes, 1.5, 2, 2.5 and 3 seconds were used here.
A features vector were calculated on each sensor data segment in two domain, namely the time and frequency domain. Mean, Minimum, Maximum, Range, Standard Deviation, and Root-Mean-Square were calculated for time domain features. To calculate features in the frequency domain first we transformed the signal to frequency domain using Fast Fourier Transform (Cooley et al., 1969). The dominant and the

second dominant frequencies were extracted from the transformed signal.
For each feature 4 values are calculated, one for each axis A_x, A_y, A_z and the fourth component as magnitude component calculated by $\sqrt{x^2+y^2+z^2}$. These features were extracted for each sensor and for each device. Thus, we used a feature vector of 192 values to define the feature space of exercises (2 device types $\times$ 4 components $\times$ 8 features $\times$ 3 sensors). Each window size in the sliding window corresponds to a feature vector which describes one repetition of the exercise. For deep learning, data from the segmented windows were passed as input without any feature extraction.

4 Experimental Setup

The conducted experiments focused on collecting data of activities from sport equipment of Unifit gym located at the Technical University Kaiserslautern. The data was used to build two datasets for evaluation the performance of the system: an impersonal (user-independent) and a hybrid personalized model.

4.1 Devices

We used Samsung Galaxy phone along with the Samsung Gear Live smart watch to collect sensor data from participants. A standalone Android application was developed for the wear and a mobile Android application was developed for the phone. The data was collected with the constant frequency of 30Hz. The smartphone was placed on a west band and attached to the participant's west aligned to the right side. The smartwatch was worn on the left hand. This arrangement facilitates the data with information of hand movements and the lower body movements. Sensors in the devices record different aspects of the movement like acceleration, magnetic field, rate of turn and orientation of sensor frame with respect to earth.

4.2 Participants

The data was collected from 23 participants. 20 male and three female participants took part in the experiment. The dataset consists of data from participants with novice, intermediate and expert level of exercise. Each exercise has been performed in two till three sets with 10 till 15 repetitions in each set. Table 1 shows the demographics of exercise participation.

Attribute	Novice	Intermediate	Expert
Age (years)	23-28	22-29	26-30
Height (cm)	168-184	166-199	166-175
Weight (kg)	67-83	62-95	65-69

Table 1: Demographies of participants in experiment

4.3 Activities

According to the fitness trainers working in the *unifit gym*, the most common gym exercises were chosen for this research work. Table 2 shows the details of performed exercises, number of participants for each exercise and total number of sets. These exercises include movement of different combinations of body parts. These exercises were performed with the sport equipment located in unifit gym.

Exercises	Participants	Total sets
Abdominal Exercise	19	38
Back Extension	18	38
Chest Press	19	38
Fly	20	44
Lat Pull	16	30
Overhead Press	19	41
Pull Down	13	25
Rear Delt	18	38
Rotary Torso	17	36

Table 2: Experiment participation

5 Dataset

The conducted experiments results in a dataset containing sensor readings of 23 participants with nine common gym exercises. The total recording of 211.57 minutes contains 328 exercise set, each with 10 to 15 reputation. The data was collected in the form of CSV files which contains values in x, y and z axis for each sensor along with the timestamps. For each activity the data was recorded in six CSV files, one for each sensor and three for each device. Each CSV file contains additional information about the participant such as height, weight, age and gender. This personal information about the participant is useful to build a hybrid personalized models. CSV file name is in 'RandomID_ExeciseName_DateTime_Device_Sensor' formate and gives information about device and sensor type.

6 Evaluation

To evaluate the classification performance of different machine learning algorithms for our dataset, three different evaluation approaches were used: Participant separation and K-fold cross validation for impersonal models as well as a hybrid personalized models. The classification performance was evaluated for four most common traditional machine learning algorithms. k-nearest neighbor with k=2 and k=5, Support Vector Machine with linear and polynomial kernels, Naive Bayes algorithm with Gaussian and Bernoulli probabilities and decision tree.

6.1 Participant separation

For the evaluation of the impersonal model, data of 19 participant for training and data of four participant were used as test data. Table 3 shows the classification results as f-measure score for different machine learning algorithms. Linear SVM, Naive Bayes with Gaussian probability and decision tree algorithms performed best with window size 2.0 and 2.5 seconds. The maximum recognition score of 80% was achieved by decision tree and Naive Bayes classifier. Table 4 shows the confusion matrix for decision tree for window size 2.5 seconds.

Models	W=1.5 s	W=2.0 s	W=2.5 s	W=3.0 s
KNN (K=2)	61	62	63	63
KNN (K=5)	61	62	63	63
Linear SVM	77	77	79	76
SVM Polynomial	69	68	67	67
Naive Bayes Gaussian	77	79	80	80
Naive Bayes Bernoulli	33	34	36	37
Decision tree	75	80	78	80

Table 3: F-measure for different window sizes

Activity	*Abdominal Exercise*	*Back Extension*	*Chest Press*	*Fly*	*Lat Pull*	*Overhead Press*	*Pull Down*	*Rear Delt*	*Rotary Torso*	*Recall*
Abdominal Exercise	10291	447	294	4	53	35	0	9	228	0.97
Back Extension	111	17404	22	40	194	17	1	15	905	0.95
Chest Press	98	73	10037	127	118	285	126	150	553	0.89
Fly	11	0	0	8630	0	223	0	68	2251	0.89
Lat Pull	3	1	528	51	2631	1255	959	31	240	0.31
Overhead Press	1	0	269	45	1162	8540	574	12	99	0.70
Pull Down	15	82	68	37	4146	1758	3831	12	166	0.67
Rear Delt	0	0	43	552	58	4	249	14206	0	0.98
Rotary Torso	110	345	0	196	8	1	14	67	16981	0.79
Precision	0.91	0.93	0.87	0.77	0.46	0.80	0.38	0.94	0.96	

Table 4: Decision tree with window size 2.5 seconds (Participant separation).

6.2 Cross Validation

To further evaluate the performance of the impersonal model, leave-one-out cross validation is applied. The value was chosen according to the number of participant and average number of sets for exercises (Baumbach and Dengel, 2017). As the dataset contains data from 23 participants and average sets performed for each exercises are two, we used 46-fold cross validation here. Table 5 shows the performance measure for different machine learning algorithms for cross validation. Same as for participant separation, linear SVM and decision tree performed best with maximum f-measure score of 80%. Table 6 shows the final confusion matrix for linear SVM as the average of the classification results from 26 iterations.

Models	W=1.5 s	W=2.0 s	W=2.5 s	W=3.0 s
KNN (K=2)	60	68	60	68
KNN (K=5)	60	68	60	68
Linear SVM	80	80	79	79
SVM Polynomial	68	74	68	75
Naive Bayes Gaussian	75	72	74	74
Naive Bayes Bernoulli	35	30	35	32
Decision tree	78	79	77	79

Table 5: F-measure for different window sizes for 46 fold cross validation

Activity	*Abdominal Exercise*	*Back Extension*	*Chest Press*	*Fly*	*Lat Pull*	*Overhead Press*	*Pull Down*	*Rear Delt*	*Rotary Torso*	*Recall*
Abdominal Exercise	727	17	17	5	1	2	1	0	34	0.94
Back Extension	3	835	2	25	4	5	10	1	8	0.94
Chest Press	6	2	701	7	6	41	8	3	15	0.83
Fly	11	18	18	554	34	12	0	129	60	0.64
Lat Pull	6	7	1	17	407	21	65	40	9	0.67
Overhead Press	3	4	42	11	22	574	39	0	7	0.84
Pull Down	1	0	34	12	112	25	307	0	6	0.70
Rear Delt	0	1	12	149	14	1	1	638	3	0.78
Rotary Torso	14	5	14	88	9	5	8	12	1489	0.91
Precision	0.9	0.94	0.89	0.66	0.71	0.82	0.62	0.78	0.91	

Table 6: Linear SVM with window size 2.0 seconds (46-Fold cross validation).

6.3 Personalized Models

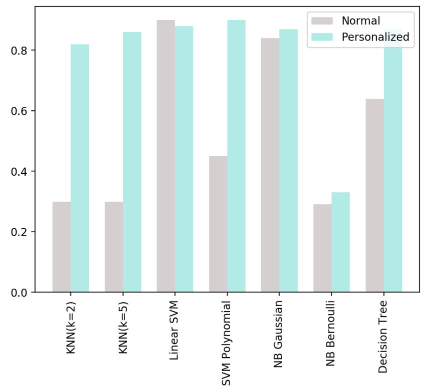
In the work of Baumbach and Dengel (Baumbach and Dengel, 2017), the qualitative analysis of pushup exercise showed that personalized models improves the classification accuracy. To assess the performance of a personalized models, we utilize a hybrid personal model with a two phase process. In the first phase, the learning models (M) were trained on data from 22 participants and tested for one test participant (T). In the second phase, a subset of data of the test participant is used to train the models again. The data of the test participant (T), was divided into two sets T1 and T2. The learning models (M) were again trained using T1 and these newly trained models were tested on data set T2. Table 7 shows the result of normal and personalized models for window size 2.0 and 2.5 seconds. Results shows a significant increase in the performance of all machine learning algorithms when personalized models were used. Figure 1 shows the comparison between normal and personalized model in the form of bar charts.

Models	Normal		Personalized	
	w=2.0s	w=2.5s	w=2.0s	w=2.5s
KNN (K=2)	30	30	82	81
KNN (K=5)	30	30	86	81
Linear SVM	90	62	88	85
SVM Polynomial	45	49	90	88
Naive Bayes Gaussian	84	86	87	88
Naive Bayes Bernoulli	29	26	33	33
Decision tree	64	66	87	91

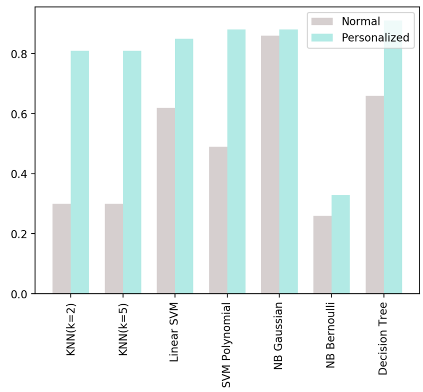
Table 7: F-measure for different window sizes for hybrid personalized model

7 DER - Deep Exercise Recognizer

(Hammerla et al., 2016) showed a significant improvement of the classification accuracy for activity recognition when deep learning algorithms were applied. This research work evaluated different deep learning approaches such as Deep feed-forward networks, Convolutional networks and Recurrent networks using LSTM on three different datasets (Reiss and Stricker, 2012; Chavarriaga et al., 2013; Bulling et al., 2014). Neural networks with LSTM and CNN outperformed in most of the cases. Our dataset contains data in the form of time series, where the body movement recorded at previous time stamps effects the next time series value and thus, contributes to the overall recognition accuracy. Using LSTM, the network can exploit these temporal dependencies. With these circumstances in mind, we developed a deep neural network architecture using LSTM cells. The deep neural network for our exercise recognition (DER) consists of three hidden layers. Each hidden layer consists of 150 LSTM cells. Dropout regularization was used after each layer to prevent overfitting. This deep neural architecture was again evaluated using participant separation, k-fold cross validation and personalized models. Table 8 shows the result of the



(a) w = 2.0 Seconds.



(b) w = 2.5 Seconds.

Figure 1: Comparison of Normal and Personalized Models.

classification for our proposed approach. The maximum score for f-measure achieved by traditional machine learning algorithm was 80% while the deep network increases the classification performance by 12% with maximum accuracy of 92%. Figure 9 shows the confusion matrix for window size 2.5 Seconds.

Evaluation Method	W=2.0 s	W=2.5 s
Participant Separation	91	92
46-Fold Cross Validation	91	91
Personalized Models	81	82

Table 8: Results for deep neural network for classification

8 Conclusion & Future Work

In this paper, activity recognition for sport equipment in modern gyms are assessed by applying different machine learning algorithms and deep learning models. The results showed that learning approaches

Activity	*Abdominal Exercise*	*Back Extension*	*Chest Press*	*Fly*	*Lat Pull*	*Overhead Press*	*Pull Down*	*Rear Delt*	*Rotary Torso*	*Recall*
Abdominal Exercise	10935	45	85	700	4	70	312	439	0	0.91
Back Extension	293	12716	48	118	103	19	51	298	22	0.95
Chest Press	61	49	12121	14	9	41	2	128	2	0.96
Fly	135	43	0	11802	59	26	50	881	0	0.78
Lat Pull	0	46	5	116	7780	253	66	82	651	0.89
Overhead Press	7	9	178	13	56	10379	0	2	19	0.94
Pull Down	325	303	31	601	37	0	10893	220	0	0.96
Rear Delt	310	116	71	1683	21	40	26	24867	32	0.92
Rotary Torso	0	24	51	96	636	176	0	62	6416	0.90
Precision	0.87	0.93	0.98	0.91	0.86	0.97	0.88	0.92	0.86	

Table 9: Deep Exercise Recognizer with LSTM (window size = 2.5 seconds).

can recognize different exercise types like pull down or chest press. Among machine learning models, decision tree, linear SVM and Naive bayes with Gaussian kernel performs best with a maximum accuracy of 80 percent. Furthermore, we proposed a deep neural network for our exercise recognition (DER) consisting of three hidden layers with each hidden layer having of 150 LSTM cells. DER outperformed traditional machine learning techniques with a maximum accuracy of 92 percent. Additionally, we made the collected dataset for our evaluation publicly available in order to support and encourage further research.

The main drawback is the confusion between exercises for the same body part, i.e., fly and rear delt as well as lat pull, overhead press, and pull down. Since mainly exercises for the same body part are affected, other sensors producing more information could help the recognition system differentiating between these exercises.

Most important is conducting of larger experiments in order to perform more robust evaluation. This includes experiments with not only more people, but also more women and different levels of athletic (professional and non-professional participants). This work could be further extended by incorporating more sensors (e.g. heart rate sensor) or by examining the effects of changes to the location of sensors on the exerciser's body. In the same way, participant specific attributes, such as height, weight, age, or gender, can be fit into the models in order to assess if these kind of physical information per participant leads to an higher recognition accuracy.

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