Measuring the Performance of Push-ups
Qualitative Sport Activity Recognition

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Abstract: The trend of mobile activity monitoring using widely available technology is one of the most blooming concepts in the recent years. It supports many novel applications, such as fitness games or health monitoring. In these scenarios, activity recognition tries to distinguish between different types of activities. However, only little work has focused on qualitative recognition so far: How exactly is the activity carried out? In this paper, an approach for supervising activities, i.e. qualitative recognition, is proposed. The focus lied on push-ups as a proof of concept, for which sensor data of smartphones and smartwatches were collected. A user-dependent dataset with 4 participants and a user-independent dataset with 16 participants were created. The performance of Naive Bayes classifier was tested against normal, kernel and multivariate multinomial probability distributions. An accuracy of 90.5% was achieved on the user-dependent model, whereas the user-independent model scored with an accuracy of 80.3%.

1 INTRODUCTION

Physical activity is commonly known to be essential for keeping a healthy physical and mental state. Many people from almost all age groups seek to join exercise programs for that specific reason. McClaran examined the impact of professional trainers on exercisers' motivation to perform sport activities. According to this study, 73% of the participants showed significant improvement in their willingness for exercising while 1% showed decrease in their willingness. For his investigation, 129 clients joined a 10-week training program with a pre-evaluation and a post-evaluation of motivational willingness for exercise adoption with the assistance of a senior university personal trainer. The study confirms a positive relation between one-to-one personal training and the willingness for training (McClaran, 2001).

Issues arouse when it comes to a personal trainer. On the one hand, hiring a personal trainer is expensive especially when hiring a professional trainer. On the other hand, meeting with the trainer on a regular basis could be inefficient from the time point of view since one would have to adjust his or her schedule according to the trainer. Those problems can be avoided with a system that functions as a personal trainer. A system that is able to detect incorrect exercise performances has great potential to support both professional and amateur athletes in increasing the safety and efficiency of their routines.

The applications focus in this study lies on push-ups which are well known among athletes and a common practice performed by many people. The personal trainer was embedded in the exerciser's smartphone and smartwatch which are widely available nowadays. With recent advances and progress in the wearable technologies, it is possible to integrate such a human activity recognition system in wearable devices (Ravi et al., 2005; Shoaib et al., 2013; Yang, 2009). However, the system has to recognize a much narrower range of physical activity spectrum where all activities mainly fall under the same activity type, e.g. *too fast* or *too slow* instead of walking or *role-jumping*. This leads to the research question, how accurate are activity recognition systems when it comes to a very narrow spectrum of activities?

In this paper, an approach for qualitative recognition of push-ups is proposed that determines different common error types while performing push-ups (Section 3). Therefore, two experiments were done to collect data from 20 participants using a smartphone placed in pant pocket and a smartwatch worn on the wrist. (Section 4). A Naive Bayes classifier with different probability distributions was evaluated in order

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to find the best recognition accuracy (Section 5). Finally, the results show that this approach is able to supervise push-ups in principle. In the future, the proposed approach can be transferred to other sport activities (Section 6).

2 RELATED WORK

While human activity supervision is a relatively new research field that gets mainly attention from researchers in the medical rehabilitation domain, human activity recognition has been researched for years and many approaches were tried in this area. To the author's best knowledge, no previous research had focused on a classifier recognizing different types of push-up so as to distinguish incorrect ones from correct ones.

2.1 Human Activity Recognition

Past work focused on the use of multiple accelerometers placed on several parts of the user's body, for example (Bao and Intille, 2004; Bao and Intille, 2004; Krishnan et al., 2008; Parkka et al., 2006; Subramanya et al., 2012). These systems using multiple accelerometers and other sensors were capable of identifying a wide range of activities. Other studies focused on the use of a single accelerometer for activity recognition (Lee, 2009; Long et al., 2009). All of these studies used devices specifically made for research purposes. Several investigations have considered the use of widely available mobile devices. (Lester et al., 2006; Ravi et al., 2005). However, the data was generated using distinct accelerometer-based devices worn by the user and then sent to the phone for storage. Various studies took advantage of the sensors incorporated into the phones themselves in order to distinguish between diverse activities (Brezmes et al., 2009; Rasekh et al., 2014; Sefen et al., 2016; Shoaib et al., 2013; Yang, 2009). Saponas et al. have developed a platform called iLearn that uses the Apple iPhone's three-axial accelerometer along with the Nike+iPod fitness tracker embedded in the user's training shoe for human activity recognition (Saponas et al., 2008; Witten and Frank, 2005). The system scored with an accuracy of 99.48% for user-dependent models[1] and 97.4% for user-independent models[2].

[1]The training samples and test samples belonged to the same person.

[2]The training data is different from the test data.

2.2 Human Activity Supervision

Michahelles et al. have used accelerometers, gyroscopes and force-sensing resistors to help skiers and their trainers share the impressions and observations during exercise (Michahelles and Schiele, 2005). Kuntze et al. used foot contact data collected from a pressure sensor embedded in sprinters' spikes in order to aid the coaches with required data such as velocity, step frequency and limb asymmetries (Kuntze et al., 2009). Chang et al. embedded a tri-axial accelerometer in the exerciser's glove in order to obtain data about weightlifting activities and help the exerciser count his repetitions (Chang et al., 2007). In addition, novel research has been done on energy consumption estimation during workouts for proper measurement of exercise capacity and intensity (Albinali et al., 2010; Campbell and Choudhury, 2012).

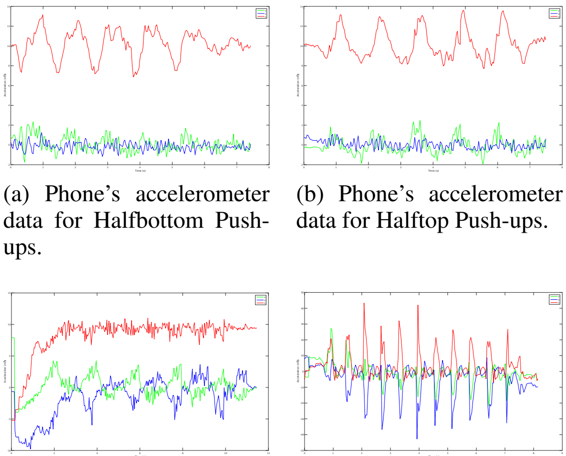
Moeller et al. have produced an automated personal trainer for the balance board exercises (Möller et al., 2012). Gymskill is an Android phone application that uses the phone's sensing capabilities in order to assess the exerciser's performance on the balance board. Before the exercise, the smartphone needs to be calibrated for the specific type of exercising board since all balance boards are different.

3 METHODOLOGY

The approach used in this paper is based on the work of Sefen et al., but some modifications were required in order to enable their recognition system for activity supervision (Sefen et al., 2016). This section mainly focuses on the proposed enhancements and only briefly introduces the overall architecture.

3.1 Supervision: Qualitative Activity Recognition

The activity recognition system was developed for and tested against recognizing activities (such as walking, jogging, and idle) as well as sports activities (such as push-ups, rope jumping, crunches and squats). The spectrum of activities recognized by this system is wider than the one subjected in this study where all activities are push-up activities. Figure 1 shows the comparison between sensor values from the phone's accelerometer. The similarities between two different push-up activities (half-bottom push-ups in Fig. 1a and half-top push-ups in Fig. 1b) make discrimination among them a harder task than distinction between Crunches (Fig. 1c) and Rope-jumping (Fig. 1d).



(a) Phone's accelerometer data for Halfbottom Push-ups.

(b) Phone's accelerometer data for Halftop Push-ups.

(c) Phone's accelerometer data for crunches activity.

(d) Phone's accelerometer data for Rope-jumping activity.

Figure 1: Comparison between the phone's accelerometer data from two push-up activities and other sports activities.

3.2 Preprocessing

The original system measures only linear acceleration in the three major directions (X,Y and Z). All the examined push-up activities contain slight rotational movements, where the foot of the exerciser is the pivot and the movement is performed around it. Accordingly, two new sensors were incorporated: gyroscopes and orientation sensors. The gyroscope measured the rate of rotation around the three major axes (X, Y and Z) in $^{rad}/_{s}$. The orientation sensor measures the angle in degrees around the three major axes. As suggested in the original approach, the sensors were sampled with a constant frequency of 10 Hz and segmented with a window size of 5 seconds.
Because of the sensors' inaccuracy and noise in the sensors' signals as well as some unexpected behavior of the users during the exercise, noisy values in the accelerometer data were observed. Thus, a median filter of order 3 was again used to move the noise, since median filters perform well on such impulse noises (Wang et al., 2011).

3.3 Feature Extraction

A specific set of features is extracted from each segment for the magnitude component as well as for each of the three signals A_x, A_y, A_z. Hence, each feature type is extracted eight times, i.e. each type (acceleration, orientation, and gyroscope) for each device (phone and watch).
In the time domain, the following statistical features are computed: Mean, Minimum, Maximum, Range, Standard Deviation, and Root-Mean-Square. For the frequency domain, the dominant and the second dominant frequencies were extracted by performing a fast Fourier transform (FFT) (Sharma et al., 2008).
To sum up, eight different types of features are computed, six from the time domain and two from the frequency domain. Since each feature type is extracted from four components, 32 features will be used to describe each sensor type, i.e. acceleration, orientation, and gyroscope. Finally, the features computed from both the phone's and the watch's sensors will be combined, producing a 192 value feature vector.

3.4 Naive Bayes Classifier

The Naive Bayes Classifier is one of the most simple and low-cost classifiers, at the same time, providing similar results in comparison to complex classifiers (Langley et al., 1992). The original system suggests using Naive Bayes, but have not configured the Naive Bayes classifier with the appropriate probability distribution. Adjusting the probability distribution is crucial for better classification accuracy, since the classified data is continuous (John and Langley, 1995; Juan and Ney, 2002). Therefore, normal, kernel, and multivariate, multinomial probability distributions were evaluated in this study according to their recognition accuracy.

4 EXPERIMENTAL SETUP

The conducted experiments focused on collecting data of correct and incorrect push-up activities from participants.

4.1 Devices

The Samsung Galaxy phone along with the Samsung Gear Live were the used devices for this study. A standalone Android application was developed for the wear and a mobile Android application was developed for the phone. To make the system as realistic as possible, the norm positions of the used devices were chosen. The phone is placed in the exerciser's right front pocket and the watch is worn on the exerciser's left wrist.

4.2 Activities

According to the fitness experts at the fitness center at Technical University in Kaiserslautern, Germany, those are the common mistakes exercisers commonly do. Figure 4.3 shows an illustration of all the activities examined in this study.

(a) Normal, Fast and Slow Push-ups (b) Half-top Push-ups (c) Half-bottom Push-ups

(d) Lower-body Push-ups (e) Upper-body Push-ups

Figure 2: Illustrations of the different push-up types performed by the participants.

Normal Push-ups are defined in this study as the standard push-up technique, where the exerciser's feet-tips and hands are on the floor. The width of the arms is shoulder-wide. During the exercise, the exerciser should be bending his elbows till the chest is almost on the ground between the hands. The exerciser's body and core should be kept tight and not bent at any point of the movement (fig. 2a). The exercise should be one at the user's average pace.
Fast Push-ups look exactly like the normal push-up exercise if the type of movement is considered. However, they are performed at a much higher pace.
Slow Push-ups also look exactly like normal and fast push-ups regarding the type of movement. However, they are performed at a slow pace.
Half-top Push-ups is the first type of wrong push-ups the system is recognizing. In contrast to normal push-up, the movement differs in the fact that the body is not lowered completely till the body almost touches the ground. Instead, the exerciser slightly bends his/her elbows and raises his body again (fig. 2b).
Half-bottom Push-ups are wrong in the sense as half-top push-up because the exerciser is also doing just half of the correct movement. The exerciser does lower his/her body completely till almost touching the ground, however on the way up, the arms are not fully stretched (fig. 2c).
Lower-body Push-ups are wrong because the user is just using his lower-body while performing push-ups. Arms are kept stretched throughout the exercise. The exerciser lowers and lifts the lower-body only (fig. 2d).
Upper-body Push-ups are wrong in the same sense as lower-body push-ups because the exerciser is training only one half of the body, the upper-body only. The lower-body till the hips lies completely on the ground throughout the exercise. Only the upper-body is being lowered and lifted (fig. 2e).

4.3 Participants

Two different experiments were conducted in order to examine possible configuration of the system. Table 1 shows the demographics of the participants.

User-dependent configuration: In this experiment, the train data and the test data belong to the same participant. Four male participants were asked to perform in 10 sets of exercise where each set consisted of 5 repetitions of each of the seven push-up types. This resulted in a total of 350 repetitions for all the push-up types per user. Since four users participated in this experiment, a total of 1400 repetitions were collected for this experiment.
User-independent configuration: In this experiment, the train and test data belonged to different participants. 14 male and two female participants took part in this experiment. Each user performed three sets of the above mentioned sets resulting in 1680 repetition for this experiment.

Table 1: The details of the collected recordings for each activity type.

Attribute	*User-dependent*	*User-independent*
$Age(years)$	$21-22$ (21.75 ± 0.5)	$19-33$ (23.88 ± 3.59)
$Weight(kg)$	$74-82$ (77.5 ± 3.4)	$59-95$ (75.88 ± 10.87)
$Height(cm)$	$174-180$ (175.75 ± 2.87)	$158-195$ (177.63 ± 8.95)
$BMI(kg/m^2)$	$24.4-25.5$ (25.13 ± 0.52)	$20.4-29.7$ (24.01 ± 2.41)

4.4 Cross Validation

Testing a classification model on the same dataset it was trained on, leads to imprecise results (Babyak, 2004). Esterman et al. have found that LOPOCV solves the problems of training and test data being extracted from the same dataset for fMRI data analysis, where the tested subjects are unseen for the model (Esterman et al., 2010). The problem that Esterman et al. faced is similar to the one in this study, since the model should be trained for unseen exercisers. This is why LOPOCV was used. However, Baumann et al. showed in their study about cross validation that LOPOCV has an overfitting drawback (Baumann, 2003). As they suggest it is a best practice to combine LOPOCV with another type of cross validation. This is why a k-fold cross validation is used for this study, where k is the number of training sets mentioned in section 4.3. Hence, for the user-dependent experiment it is a 10-fold cross validation method and for the user-independent experiment it is a 48-fold cross validation method.

5 EVALUATION

Several evaluations were conducted in order to investigating the feasibility of creating an automated personal trainer embedded in the exerciser's smartphone and smartwatch. Thus, the focus of the evaluation lies on the recognition accuracy.

5.1 User-dependent Model

10-fold cross validation technique was used for each of the four users contained in this dataset and the performance is evaluated over the average of these four participants.

5.1.1 Normal Distribution (10-fold CV)

A Naive Bayes classifier with a Gaussian Probability Distribution performed with a high precision for the user-dependent dataset. Figure 2 shows the confusion matrix. All fast push-ups were recognized correctly. Lower- and upper-body push-ups were also recognized with a high accuracy reaching almost 96%. Half-top push-ups showed the lowest recognition precision with 78.9%. Overall, the Naive Bayes classifier with the Gaussian probability distribution for the user-dependent data set performed with a recognition accuracy of **90.5%**.

5.1.2 Kernel Distribution (10-fold CV)

Similar to the results for normal distribution, the Naive Bayes classifier with kernel probability distribution reached similar accuracy as shown in Figure 3. Furthermore, the results indicate similar behavior for fast, half-top and half-bottom activities, where all fast push-ups were recognized correctly and half-top as well as half-bottom have the lowest accuracy. The classifier performed with a total accuracy of **89.8%**, a slightly lower performance than the normal distribution.

Table 2: Naive Bayes with normal distribution (10-fold CV).

Activity	*Normal*	*Fast*	*Slow*	*Halftop*	*Halfbottom*	*Lowerbody*	*Upperbody*	*Recall*
Normal	177	0	9	14	0	0	0	88.5
Fast	0	200	0	0	0	0	0	100
Slow	6	0	179	9	6	0	0	89
Halftop	23	0	23	154	0	0	0	76.5
Halfbottom	0	0	4	18	178	0	0	88
Lowerbody	0	4	0	0	4	192	0	95
Upperbody	0	0	4	0	0	4	192	95.5
Precision	86	98	81.7	78.9	94.6	97.9	100	

Table 3: Naive Bayes with kernel distribution (10-fold CV).

Activity	*Normal*	*Fast*	*Slow*	*Halftop*	*Halfbottom*	*Lowerbody*	*Upperbody*	*Recall*
Normal	173	4	5	14	4	0	0	86.5
Fast	0	200	0	0	0	0	0	100
Slow	6	0	180	8	6	0	0	90
Halftop	18	0	14	164	4	0	0	82
Halfbottom	8	0	18	0	170	4	0	85
Lowerbody	0	4	0	0	9	187	0	93.5
Upperbody	4	0	4	0	0	0	191	95.5
Precision	82.8	96.2	81.4	88.2	88.1	97.9	100	

5.1.3 Multivariate Multinomial Distribution (10-fold CV)

In contrast to normal and kernel distributions, the classification performance of the Naive Bayes classifier with multivariate multinomial distribution is lower (Figure 4). Slow push-ups scored the highest recognition accuracy with 87.7% and half-bottom push-ups scored the lowest accuracy with 37.2%. The total recognition accuracy for all activities was **57.8%** which is significantly lower than the normal and kernel distributions. Another remark on this result is that around 11% of the activities were labeled falsely as slow push-ups. This observation is expected since a Naive Bayes classifier with multivariate multinomial distribution works best for discrete, categorical domains while the feature vectors in this case have numerically continuous variables.

5.2 User-independent Model

A 48-fold and LOPOCV technique were applied on the user-independent dataset.

5.2.1 Normal Distribution (LOPOCV)

The Naive Bayes classifier with Gaussian probability distribution for the user-independent data set did

Table 4: Naive Bayes with multi-variate multinomial distribution (10-fold CV).

Activity	*Normal*	*Fast*	*Slow*	*Halftop*	*Halfbottom*	*Lowerbody*	*Upperbody*	*Recall*
Normal	108	0	18	32	28	14	0	54
Fast	0	164	18	0	14	0	4	82
Slow	6	3	176	3	0	6	6	88
Halftop	33	10	14	83	32	28	0	41.5
Halfbottom	23	23	33	32	75	14	0	37.5
Lowerbody	28	5	37	28	9	93	0	46.5
Upperbody	26	4	49	22	4	9	86	43
Precision	48.2	78.5	51	41.5	46.3	56.7	89.6	

not perform as good as for the user-dependent dataset (Figure 5). The best recognition accuracy of 93.8% was recorded for fast push-ups, while half-top push-ups scored the lowest accuracy of 52.1%. Unlike the user-dependent dataset, however, the recognition accuracy of normal push-ups was only 56% and the rest was scattered over fast (12%), slow (18%) and half-top (14%) push-ups. The Naive Bayes classifier with normal distribution performed with **76.1%**.

Table 5: Naive Bayes with normal distribution (LOPOCV).

Activity	*Normal*	*Fast*	*Slow*	*Halftop*	*Halfbottom*	*Lowerbody*	*Upperbody*	*Recall*
Normal	135	29	43	33	0	0	0	56.3
Fast	15	225	0	0	0	0	0	93.8
Slow	15	3	207	9	0	0	6	86.3
Halftop	35	24	55	126	0	0	0	52.5
Halfbottom	0	20	30	5	185	0	0	77
Lowerbody	0	5	5	5	5	220	0	91.7
Upperbody	46	9	9	9	0	0	167	69.6
Precision	54.9	71.4	59.3	67.4	97.4	100	96.5	

5.2.2 Kernel Distribution (LOPOCV)

The same results and conclusions for normal distribution are also true for kernel distribution (Figure 6). Both classifiers show very similar results with the slightly lower recognition accuracy of the kernel distribution of **73.1%**. Normal push-ups showed similar behavior as normal distribution, 6.9% of the activities were classified falsely as normal push-ups and 38% of normal push-ups were classified as other activities.

5.2.3 Multivariate Multinomial Distribution (LOPOCV)

The multivariate multinomial distribution shares many results with normal and kernel distributions for the user-independent data set as well as with multivariate multinomial distribution for the user-dependent data set. On the one hand, it showed low

Table 6: Naive Bayes with kernel distribution (LOPOCV).

Activity	*Normal*	*Fast*	*Slow*	*Halftop*	*Halfbottom*	*Lowerbody*	*Upperbody*	*Recall*
Normal	150	14	33	43	0	0	0	62.5
Fast	5	220	0	10	0	0	5	91.7
Slow	15	3	201	9	3	3	6	83.8
Halftop	54	10	40	136	0	0	0	56.7
Halfbottom	20	15	20	5	160	20	0	66.7
Lowerbody	0	0	23	0	14	198	5	82.5
Upperbody	27	18	18	23	0	0	154	64.2
Precision	55.4	78.6	60	60.2	90.4	90.4	93.3	

recognition accuracy of 28% for normal push-ups and 13.3% of the activities was classified as normal push-ups. On the other hand, the overall recognition accuracy of this classifier is **45.2%**, as shown in Figure 7. Furthermore, 9.8% of the activities was classified falsely as slow push-ups.

Table 7: Naive Bayes with multi-variate multinomial distribution (LOPOCV).

Activity	*Normal*	*Fast*	*Slow*	*Halftop*	*Halfbottom*	*Lowerbody*	*Upperbody*	*Recall*
Normal	69	19	62	33	28	20	9	28.8
Fast	25	160	0	10	45	0	0	66.7
Slow	9	0	216	3	0	6	6	90
Halftop	55	30	30	70	35	10	10	29.2
Halfbottom	55	65	5	30	50	30	5	20.8
Lowerbody	37	9	37	18	28	97	14	40.4
Upperbody	55	4	41	0	4	41	95	39.6
Precision	22.6	55.7	55.2	42.7	26.3	47.5	68.3	

5.2.4 Normal Distribution (48-fold CV)

The Naive Bayes classifier with normal probability distribution performed with **79.8%**. The recall and accuracy problem for the normal Push-up class still remains because of the diverse execution of this activity by different users. Thus, normal push-ups are the activity with the most common similarities with other push-up types.

5.2.5 Kernel Distribution (48-fold CV)

Naive Bayes with kernel distribution reached a recognition accuracy of **80.3%** for the 48-fold cross validation. The confusion matrix is shown in Figure 9. The activity with the highest recognition accuracy of 97.9% is fast push-ups. Normal push-up was the activity with the lowest recognition accuracy of 62%. Because the dataset is user-independent, the variance in the exercise execution caused the low recognition accuracy as well as the low recall for normal and slow push-ups.

Table 8: Naive Bayes with normal distribution (48-fold CV).

Activity	*Normal*	*Fast*	*Slow*	*Halftop*	*Halfbottom*	*Lowerbody*	*Upperbody*	*Recall*
Normal	158	14	43	20	5	0	0	65.8
Fast	10	230	0	0	0	0	0	95.8
Slow	21	6	204	9	0	0	6	85
Halftop	35	15	54	136	0	0	0	56.7
Halfbottom	15	15	25	0	185	0	0	77.1
Lowerbody	5	5	5	0	5	215	5	89.5
Upperbody	14	9	9	0	0	5	203	84.5
Precision	61.2	78.2	60	82.4	98.9	97.7	97.6	

Table 9: Naive Bayes with kernel distribution (48-fold CV).

Activity	*Normal*	*Fast*	*Slow*	*Halftop*	*Halfbottom*	*Lowerbody*	*Upperbody*	*Recall*
Normal	149	20	33	33	5	0	0	62.1
Fast	5	235	0	0	0	0	0	97.9
Slow	9	3	210	12	0	0	6	87.5
Halftop	35	15	40	150	0	0	0	62.5
Halfbottom	5	15	35	20	160	5	0	66.7
Lowerbody	0	0	14	0	9	217	0	90.4
Upperbody	5	0	0	18	0	0	217	90.4
Precision	71.6	81.6	63.3	64.4	92	97.7	97.3	

5.2.6 Multivariate Multinomial Distribution (48-fold CV)

Looking at the confusion matrix in Figure 10, it is clear that the Naive Bayes classifier with multivariate, multinomial distribution did not perform well for the 48-fold cross validation on the user-independent dataset. It achieved an overall accuracy of **45.5%**. Slow push-ups were recognized with the highest accuracy of 81% which is almost 20 percentage points higher than the second highest activity.

Table 10: Naive Bayes with multi-variate multinomial distribution (48-fold CV).

Activity	*Normal*	*Fast*	*Slow*	*Halftop*	*Halfbottom*	*Lowerbody*	*Upperbody*	*Recall*
Normal	59	5	48	29	33	33	33	24.6
Fast	0	158	5	5	48	24	0	65.8
Slow	3	3	195	6	3	18	12	81.3
Halftop	40	25	50	25	35	55	10	10.4
Halfbottom	25	45	20	30	85	35	0	35.4
Lowerbody	28	9	70	24	9	100	0	41.6
Upperbody	14	27	51	5	14	32	97	40.4
Precision	34.9	58.1	44.4	20.2	37.4	33.7	63.8	

6 CONCLUSION & DISCUSSION

A state-of-the-art activity recognition system was adjusted and enhanced in order to recognize different types of the same activities.
The average recognition accuracy of the above mentioned experiments is **81.7** % for Normal Distribution, **80.7** % for Kernel Distribution and **49.1** % Multivariate Multinomial Distribution. The fact that slow push-ups have more recordings than other activities and hence dominates the prior probability with $P(C_slow) = 1/5$ instead of $1/7$ for all the seven activities, is clearly affecting the recognition accuracy. This is why many activities were recognized falsely as slow push-ups. These results show it is not only feasible to recognize the type of an activity, but also its quality. In addition, it implies that activity supervision in practice should include a profiling technique where the classifier is calibrated to specific users.
The main drawback is the high false rate for classifying correct push-ups (12 % for personal models). The classification accuracy has to be improved before the system can be used in training since correctly performed push-up will occur with the most in practice.

7 FUTURE WORK

A system that is able to detect incorrect exercise performances has great potential to support both professional and amateur athletes in increasing the safety and efficiency of their routines.
Most important is conducting of larger experiments in order to perform more robust evaluation to clarify if human activity supervision is indeed feasible and weather user-dependent models are necessary. This includes experiments with not only more people, but also more women and different levels of athletic (professional and non-professional participants).
There is also a strong need for investigating other exercise types. Push-up activities were used as a proof of concept for this study. However, experiments with other sports activities that differ in their movements from push-ups can lead to different results. Possible activities for further studies are rope-jumping, squats or sit-up.

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