TrainingPal: An Algorithm for Recognition and Counting Popular Exercises Using Smartphone Sensors

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Abstract—**Nowadays, most of the smartphones come with 3D-accelerometer, magnetometer, and gyroscope. There is a growing interest in utilizing these sensors for monitoring and tracking exercises. In this paper, we proposed a framework, called TrainingPal, for recognizing five types of cardio exercises (i.e. walking, running, using elliptical machine, rowing, and jumping jack) and five types of resistance exercises (i.e. squat, lunge, sit-up, push-up, and bench dip). The TrainingPal is also capable of counting number of repetition of each exercise. To train and test the TrainingPal, data was collected by utilizing the built-in accelerometer, magnetometer and gyroscope of Samsung Galaxy S7 edge. Using an armband, the smartphone was attached to the outer side of arm approximately 10 to 12 cm below the shoulder. Leave-one-subject-out cross validation was used to avoid overfitting of the TrainingPal to the study participants. For recognition of different types of exercises, an overall accuracy of 91.71% was achieved. The accuracy was the highest for the recognition of push-ups (100%) and the lowest for the recognition of bench dips (60.33%). For counting the repetitions of the exercises, the TrainingPal achieved an accuracy above 90% for all types of exercises. In conclusion, the proposed framework can be used for tracking and recognizing the popular exercises included in this study. The framework could be potentially extended to other types of exercises and the data collected using other wearable devices.**

Keywords- Action recognition, Exercise tracking, Inertial motion units, Smartphone Wearable sensors.

I. Introduction

In recent years, smartphone sensors have emerged as a technology that holds tremendous potentials for solving health problems through monitoring physical exercises and determining how active an individual is. Previous studies revealed that physical inactivity and not doing exercises leads to an elevated risk of different chronic diseases such as cardiovascular diseases and type 2 diabetes [1-3]. Chronic diseases, which are mostly associated to common and preventable risk factors, are the leading cause of death worldwide, in both developed and developing countries [4]. These diseases are also the major cause of limitations in the adults' daily life [5]. Currently in Iran, cardiovascular diseases are the leading cause of deaths, accounting for more than 50% of all deaths each year [6]. The percentage is expected to rise continuously as a result of aging population [6]. In terms of health system costs, they are also the most expensive disease group [7]. Therefore, there is a growing interest in utilizing the wearable sensors to monitor the physical exercises and activities, as they play a vital role in prevention of cardiovascular and other chronic diseases [8]. Monitoring the exercises also provides information that determines whether a specific training program is effective and improves the athletic performance. Especially the importance of monitoring the performance in the high-intensity interval training, where a series of low to high-intensity trainings are done, has been highlighted in many previous studies [9-12].

Nowadays, with recent advances in MEMS technology combined with the miniaturization of electronics, manufacturing low-cost Inertial Motion Units (IMU) sensors, which require less power and a smaller chip area, becomes feasible [13]. Previous studies indicated IMUs have wide range of application in healthcare and medicine such as monitoring daily physical activities [14, 15] or managing patients affected by some motor control disorders such as Parkinson's disease [16, 17].

Currently IMU with 3D-accelerometer, magnetometer and gyroscope is the standard feature of most of the smartphones. An IMU records the angular velocity of the smartphone through its gyroscope and the external specific force acting on the smartphone using its accelerometer. Magnetometers measure the direction and strength of the magnetic field and is usually utilized for estimating the orientation of the smartphone [18]. The smartphones' built-in IMUs are utilized in a variety of mobile applications ranged from those dedicated to the automotive navigation [19] to different mobile games [20].

The smartphones' IMUs have been previously used for monitoring their users' physical activities. For example, Shoaib et al. [21] used accelerometer and gyroscope data to distinguish walking, smoking, drinking coffee, eating, typing, writing, talking, jogging, walking upstairs, biking, walking downstairs, sitting, and standing from each other. Guiry et al. [22] proposed

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TABLE I. THE DISCRIPTION OF THE COLLECTED DATA

	Total duration (s)	*No. of sets*	*No. of repetitions*	*No. of sessions*
Walking*	2880	48	2659	8
Running*	2400	40	3586	8
Elliptical**	6000	10	7967	10
Rowing***	3600	24	3731	12
Jumping jack	810	27	988	27
Squat	720	8	301	8
Lunge	720	8	782	8
Sit-up	720	12	167	12
Push-up	480	8	155	8
Dip	600	10	276	10

* collected using treadmill
** collected using elliptical machine
*** collected using rowing machine

an algorithm based on larger set of sensors including accelerometer, magnetometer, gyroscope, GPS, light, and pressure to recognize walking, standing, running, cycling, sitting, stair ascents, stair descents, elevator ascents, and elevator descents. Among different types of exercises, most of the previous studies focused on detection of running and tracking steps while only a few ones included other types of exercises. Mortazavi et al. [23] used data collected by a wrist-worn device (Samsung Galaxy Gear) to classify movements as crunches, shoulder lateral raises, bicep curls, push-ups, and jumping jacks. In this study, we proposed an algorithm, called TrainingPal, for recognizing and tracking (counting number of repetitions) ten types of popular exercises based on the data collected from a smartphone.

II. MATERIALS AND METHOD

A. Dataset

As the study involved negligible risks for the participants, it was exempted from the institutional ethics committee approval. The built-in 3D-accelerometer, magnetometer and gyroscope of Samsung Galaxy S7 edge were utilized for data collection. Using an armband, the smartphone was attached to the outer side of arm approximately 10 to 12 cm below the shoulder. Data was collected from two female subjects aged 29 and 35 and two male subjects aged 31 and 25. All subjects attended the gym at least twice per week.

Each participant was asked to perform five types of cardio exercises (i.e. Walking (speed varied from 4.8-7.7 km/h), Running (speed varied from 9.7-14.5 km/h), Elliptical, Rowing, and Jumping jack) and five different strength exercises (i.e. Squat, Lunge, Sit-up, Push-up, and Bench dip). Subjects performed the exercises in multiple days (sessions). In addition, a single session was divided into multiple sets of

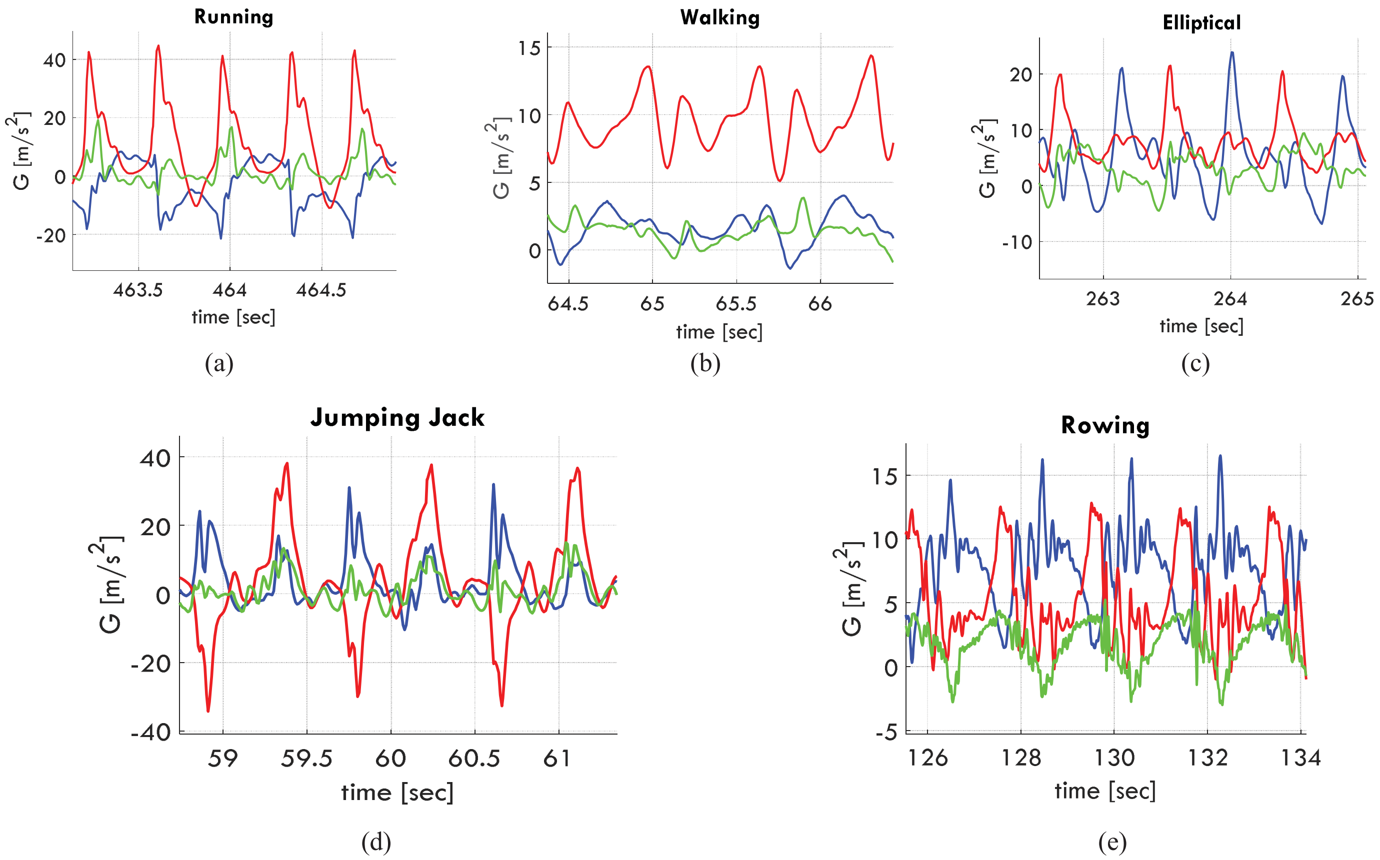

Figure 1. Sample data collected from the accelerometer data collected during the cardio training. Blue, red, and green lines show the acceleration on the X (width), Y (length), and Z (depth) axis, respectively.

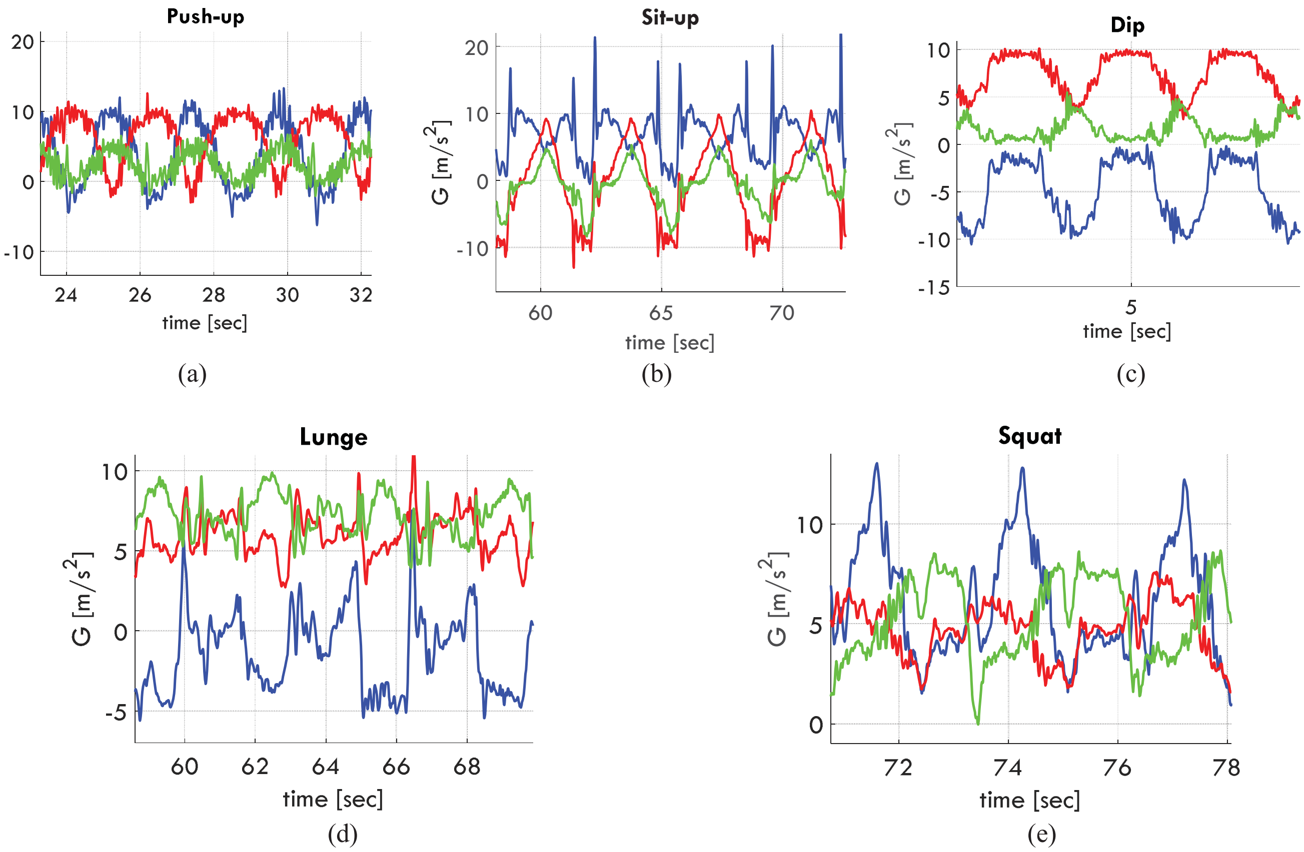

Figure 2. Sample data collected from the accelerometer data collected during the strength training. Blue, red, and green lines show the acceleration on the X (width), Y (length), and Z (depth) axis, respectively.

doing a specific exercise. Before each set, the armband was taken off and then worn again so that we can assure the algorithm was robust enough to slight differences in the way the armband was attached to the subject. To count the repetitions, a video camera was used for recording the subjects' movements. We separated the signal corresponding to each type of exercise from the rest signal manually based on the time as recorded by the camera. Table I shows the description of the data collected from all four subjects pooled together. Figure 1 and 2 indicate sample accelerometer data on three axes collected during the cardio and resistance training, respectively. The plotted data is corresponding to the first female subject.

B. *TrainingPal*

The TrainingPal algorithm composed of two modules, the first module, called exercise recognition module, is dedicated to categorizing the input signal recorded into ten different classes, corresponding to ten types of exercise included in this study while the second module is responsible for counting the repetition of each movement.

Figure 3 illustrates the block diagram of the proposed method. As shown, a 12-dimensional feature vector, including the accelerometer data on three axes, gyroscope data on three axes, and two sets of Euler angles, was generated for each timestamp and fed into a classifier. The performances of four different, namely support vector machine (SVM), bag of decision trees, K-nearest neighbor, discriminant analysis, were investigated to find the best classifier. In order to extract the Euler angles, the TRIAD algorithm as suggested in [24] was used.

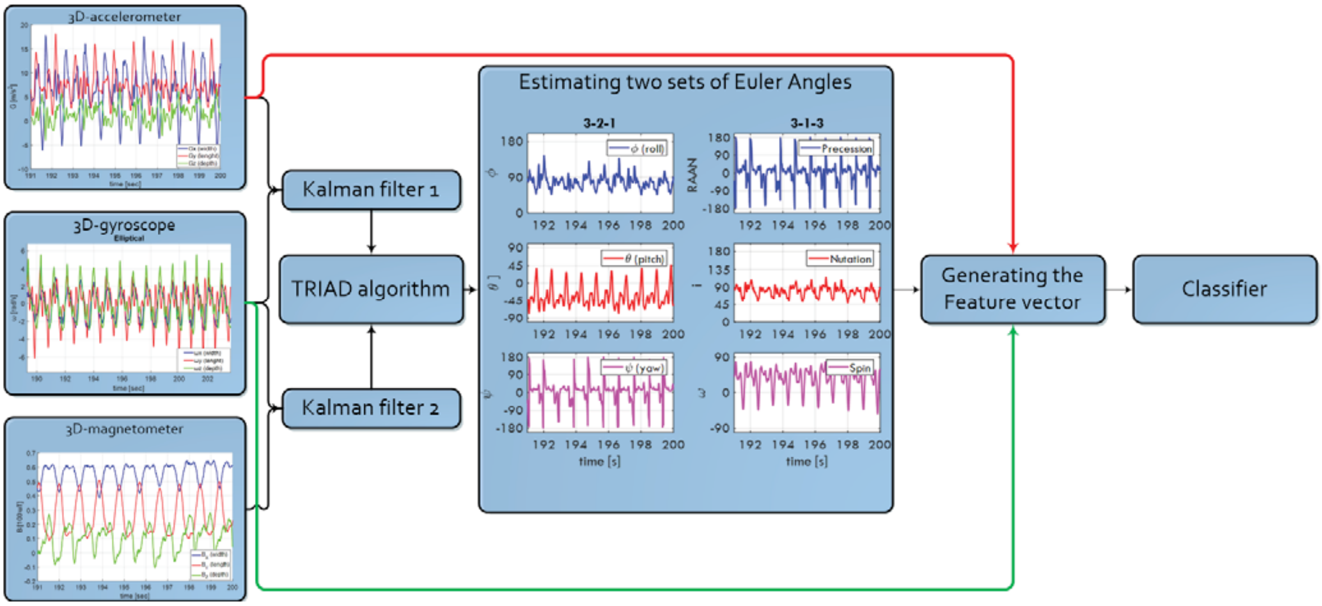

Figure 3. Steps of the exercise recognition module.

The second module includes a Savitzky-Golay smoothing filter and a peak/valley detection unit followed by a peak/valley matching unit [25]. Briefly, the module eliminated the high frequency noise from the signal recorded by accelerometer, gyroscope, and magnetometers by using the Savitzky-Golay filter in the first step. Then the dominant axis for the magnetometer, where the difference between the minimum and maximum value of the signal is the most, was found and only the magnetometer data corresponding to the dominant axis was considered. For each specific exercise, among seven available signals (three from accelerometer, three from gyroscope, and one from magnetometer), three signals with the highest standard deviation were selected and local maxima and minima (peaks and valleys) were extracted from each signal. Finally, only local extrema that matched between at least two signals were included. Depending on the exercise type, each one or two local extrema could represent a single repetition of the exercise.

C. Evaluation

TrainingPal classifies data corresponding to each timestamp into one of ten exercises, included here. The sampling rate of the sensors utilized in the study was 0.01 second. However, this temporal resolution is very high for exercise recognition. Hence, for evaluating the TrainingPal, the labels assigned by the TrainingPal to 100 timestamps within each second was found. Then, using the majority voting, a single type of exercise was assigned to each second.

In order to evaluate the performance of the TrainingPal, it should be trained and tested on the separate data. Two different evaluation scenarios were taken into account. In the first scenario, called leave-one-set-out (LOSeO) cross validation, each time one set was left out and used as the test data while the rest of sets were used for training the TrainingPal. Therefore, data from the same subject was included in training set. In the second scenario, called leave-one-subject-out (LOSuO) cross validation, each time all data belonging to a single subject was left out and used as the test data whereas the data from the rest of subjects were used as the training set. The LoSuo cross validation assures that the TrainingPal is not over-fitted to the subject included in this study. The reason that we evaluated the first scenario as well, was that the TrainingPal could be ultimately used as a personalized smartphone

TABLE II. RECOGNITION RATE FOR DIFFERENT TYPES OF EXERCISES AND VARIOUS CLASSIFIERS

Type	SVM		Decision Tree Ensemble		K-nearest neighbor		Discriminant analysis	
	LOSeO	*LOSuO*	*LOSeO*	*LOSuO*	*LOSeO*	*LOSuO*	*LOSeO*	*LOSuO*
Treadmill -Running	79.72%	96.01%	89.13%	97.08%	89.86%	90.17%	39.86%	79.65%
Treadmill -Walking	96.38%	92.13%	94.92%	95.00%	94.92%	91.13%	78.00%	79.25%
Elliptical machine	99.32%	96.40%	100.00%	59.58%	100.00%	11.82%	99.32%	26.80%
Rowing machine	99.69%	99.69%	100.00%	98.75%	100.00%	98.75%	99.69%	44.06%
Jumping jack	98.52%	83.33%	100.00%	79.01%	100.00%	38.52%	87.53%	1.85%
Squat	67.36%	71.67%	100.00%	95.00%	100.00%	77.78%	62.50%	71.25%
Lunge	100.00%	63.19%	100.00%	37.50%	100.00%	67.22%	78.06%	73.19%
Sit-up	75.28%	72.78%	99.58%	100.00%	99.58%	100.00%	55.69%	56.53%
Push-up	100.00%	100.00%	100.00%	97.92%	97.92%	100.00%	30.42%	0.00%
Bench dip	93.50%	60.33%	98.00%	77.33%	98.33%	100.00%	78.17%	58.50%
Average	90.98%	83.55%	**98.16%**	**83.72%**	98.06%	77.54%	70.92%	49.11%
Weighted Average	93.73%	**91.71%**	97.62%	81.64%	**97.69%**	64.47%	80.85%	48.62%

TABLE III. CONFUSION MATRIX FOR LEAVE-ONE-SUBJECT-OUT SCENARIO AND SVM CLASSIFIER

	Treadmill - Running	Treadmill - Walking	Elliptical machine	Rowing machine	Jumping jack	Squat	Lunge	Sit-up	Push-up	Bench dip
Running	**96.01%**	4.92%	0.00%	0.31%	0.00%	0.00%	0.28%	0.00%	0.00%	0.00%
Walking	0.00%	**92.13%**	3.00%	0.00%	14.32%	0.00%	32.50%	0.00%	0.00%	0.00%
Elliptical	0.35%	2.96%	**96.40%**	0.00%	1.85%	0.69%	4.03%	0.42%	0.00%	5.83%
Rowing	0.00%	0.00%	0.00%	**99.69%**	0.00%	15.42%	0.00%	31.11%	0.00%	0.83%
Jumping jack	0.00%	0.00%	0.00%	0.00%	**83.33%**	0.00%	0.00%	0.83%	0.00%	0.00%
Squat	0.00%	0.00%	0.00%	0.00%	0.00%	**71.67%**	0.00%	0.00%	0.00%	1.00%
Lunge	0.00%	0.00%	0.00%	0.00%	0.49%	12.22%	**63.19%**	0.00%	0.00%	0.00%
Sit-up	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	**72.78%**	0.00%	13.00%
Push-up	3.65%	0.00%	0.60%	0.00%	0.00%	0.00%	0.00%	0.00%	**100.00%**	19.00%
Bench Dip	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	**60.33%**

application, which first learns the its owners' pattern of movements while doing different exercises and after the training phase, is being used for recognizing and tracking the exercises.

III. RESULTS

A. Accuarcy of recognition of different types of exercises

The accuracies of different classifiers for categorizing the collected data into different classes are shown in Table II. As explained in section II.C, two different evaluation scenarios were considered. The results of both scenarios are shown in Table II. As shown the recognition accuracy varied across different types of exercises. As shown, all four classifiers in both scenarios performed well in distinguishing running and walking from the rest of exercises. Also, as expected, in most of the cases, the error for LOSeO was lower than that of LOSuO cross-validation. Interestingly, K-nearest neighbor, which was the best classifier during LOSeO, was the second worst classifier in LOSuO cross-validation. This suggests that the classifier was over-fitted to the subjects. As shown, we calculated the average performance across ten exercises. The weighted average (based on number of repetitions) was also found.

The SVM achieved the best overall accuracy (91.71%) for the exercise recognition in the more difficult evaluation scenario (LOSuO). Table III shows the confusion matrix for this classifier. The diagonal elements of the matrix show the correctly classified data points. As shown, mis-recognized cardio exercises were mostly misclassified as other cardio exercises. Similarly, the mis-classified strength exercises often labeled as other types of strength exercises and not the cardio ones. As the cut-off of the low-pass filter used for cardio exercises differed from that of strength exercises in the second module of the TrainingPal, fortunately the error from the recognition module did not propagate to the next step.

TABLE IV. THE ACCURACY OF COUNTING ALGORITHM

	Overall accuracy	*STD over sets*	*Range**
Walking	0.979	0.012	(0.961-1.00)
Running	0.961	0.023	(0.913-1.00)
Elliptical	0.979	0.012	(0.957-1.00)
Rowing	0.971	0.012	(0.947-1.00)
Jumping jack	0.965	0.023	(0.906-1.00)
Squat	0.960	0.019	(0.923-0.976)
Lunge	0.958	0.027	(0.922-0.989)
Sit-up	0.916	0.056	(0.800-1.00)
Push-up	0.981	0.027	(0.941-1.00)
Dip	0.934	0.044	(0.875-1.00)

* (Minimum-Maximum)

B. Accuracy of counting

Table IV shows the accuracy of counting for different types of exercises. As shown, the TrainingPal achieved the highest accuracy for counting the repetitions of movements using the elliptical machine. The accuracy was the lowest, for counting the sit-up and bench dip. This could be due to the fact that continuing these exercises for 90 seconds was very difficult for the participants and they often rested for a few seconds between two repetitions of these exercises.

IV. CONCLUSIONS

In this paper, we proposed the TrainingPal for recognition and tracking of ten different types of popular exercises, namely walking, running, using elliptical machine, rowing, jumping jack, squat, lunge, sit-up, push-up, and bench dip. The performance of different classifier within TrainingPal framework was evaluated. The results showed that for the best classifier (SVM) the TrainingPal achieved an overall accuracy of 91.71% for recognizing different types of exercise done by a participant whose data was not included in the set used for training the classifier. The accuracy of TrainingPal in counting the repetitions of exercises varied for different types of exercises. However, the accuracy was above 90% for all movements. One potential avenue for the future work is extending the proposed framework to other types of exercises and also smartwatches (wrist-worn smart devices).

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