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A Robust Physical Exercise Recognition System Using Machine Learning Approach

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Abstract: Modern life is becoming more linked to our devices, and work is being done in a more regulated way. As life became more complicated, it is becoming challenging to keep track of human health and fitness, leading to unexpected illnesses and diseases. Moreover, a lack of activity monitoring and corresponding reminders is preventing the adoption of a healthier lifestyle. This research provides a practical approach for identifying Human Activity by using accelerometer data obtained from wearable devices. The model automatically finds patterns among 33 different physical exercises such as running, rowing, cycling, jogging, etc. and correctly identifies them. The principal component analysis algorithm was used on the statistical features to make the system more robust. Classification of the physical exercise was performed on the reduced features using WEKA. The overall accuracy of 85.51% was obtained using the 10-Fold Cross-Validation method and K nearest Neighbor Algorithm while 84% accuracy for Random Forest. The accuracy obtained was better than previous models and could improve recognition systems in monitoring user activity more precisely.

1. INTRODUCTION

Nowadays, people live and interact in ways that have lacked good physical activity, and these have brought adverse changes in their health. Not only it prevented a better lifestyle, but it has become the leading cause of many common chronic diseases such as obesity, heart failure and even premature death [1]. Besides, less severe conditions are contributing to the loss of muscle strength and immense fatigue [2]. To mitigate this issue, the United States Department of Health [3] advises people to do aerobic exercise regularly for 3-5 hours. Furthermore, with the rapid rise in the number of smart sensing devices, such as smartphones and smart watches, various high detailed applications linked to the monitoring of personal healthcare, management of obesity, interactive and experiential gaming, etc., have continually been made better to meet human standards [4]. But, in general, both are in short of meeting this standard regularly and have various significant causes.

One of the apparent causes is the failure to monitor where and how many times activity occurs, and time spent on each activity. Instead of keeping count in one's mind, technology has accomplished this task using small sensors inside IoT devices like smart watches and smartphones. If smart watches can employ a faster and efficient recognition system, then it will reduce both data consumed and time is taken. The recognition system in our devices performs activity in different ways. When Human acts, they require a combination of several basic movements repeatedly. Running of a child is very different from those of walking. In practice, each activity takes only a few seconds to complete and record. Each basic movement could be involved over any given duration. So, the study of HAR is very crucial to make advancements in academics.

The goal of this study is to find a better way through feature extraction and feature reduction procedure to produces accurate classification across a wide range of physical exercises. The context that was explored is in a gym setting where people performed 33 different physical exercises such as walking, running, cycling, etc. Through using adaptive time series, segmentation features were extracted, followed by reduction into the lower dimension using PCA. Instead of using a regular fixed sized window, the adaptive segment was used, which ensures more likely to detect activity in those respective segments. The reduction Algorithm makes the system computational efficient and robust in many scenarios.

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Finally, two classifiers, one of them is Lazy Algorithm, while the other Ensemble Tree was used to evaluate performance. This research can be pointed down into six sections. Section 2 reviews the previous research related works. Section 3 introduces our proposed model and discusses the practical steps that were involved. Section 4 portrays the findings of our study. Lastly, Section 5 gives the conclusion of the research and addresses future works.

2. LITERATURE REVIEW

In order to track and count human activity, there are two approaches: The wearable sensor approach and the other one is the smartphone-based. Vu Ngoc in [5] collected five activities data from the smartphone and was recognized where they obtained an accuracy of 74% for KNN and 75.3% for ANN, respectively. Activity and sensors were limited, and there was some ambiguity in the data collected. In [6], Rui proposed a modified full CNN based algorithm that predicted human activity sequences on the self-collected opportunist and hospital dataset. In [7], CNN was applied directly on 16 lower limb activities using five sensors, and it showed comparison to using one single sensor. The Researchers in [8] used a tenfold random partitioning cross-validation evaluation to evaluate the system performance, and the number of features was only limited to 3. For capturing repeated periods in activities, Banos et al. [8] used a time window to segment the discrete signal. The model failed to demonstrate reliable accuracy for accelerometer data when many activities were involved. The obtained accuracy was a little more than 80%. Tuan Le in [9] extracted related features from raw data of 30 volunteers performing six activities and finally used the IB3 method to improve accuracy by reducing dimension. 15% improved accuracy was obtained through Naïve Bayes (91.85%) and Decision Tree (96%). In [10] Yu-Liang Hsu used NWFE algorithm on two sensor data located at two places: the wrist and ankle.

Moreover, the model ensured accuracy of 90.5% for ten daily activities. In [11], the task of inferring activities when travelling by metro was explored. It showed when two features could be selected based on feature selection method; the model can obtain good accuracy. Our model improves the existing system by using an adaptive sliding window on pre-processed accelerometer signals and then normalizing those features. After using PCA, the reduced features were classified using Machine Learning models.

3. RESEARCH METHODOLOGY

In order to extract the signals into useful parts, an adaptive time-series technique [12] was utilized that extracted the features from the accelerometer data from all the subjects. A segment length of 200 was used to obtain the data as a time series. Figure 1 shows architecture of the Proposed System.

3.1 Data Sets

To conduct our experiment, we have collected REALDISP Activity Recognition dataset [8] from the UCI Machine Learning Repository. The dataset consists of recordings from 17 subjects, ten males and seven females. The recordings include 13 inertial signals obtained from sensors located at the different parts of the body. A multivariate time series were obtained from the accelerometer sensors, which are sampled at regular intervals. The experiment consisted of subjects performing 33 physical Activities in 3 scenarios. The exercise lasted about 15-20 min. Figure 2 represents the overall repetition count of each activity performed by the users. Due to limited repetition, it is observed that exercises having short reps, such as Jump rope and arm related practices, are in the middle. After completion of each set, it is usual for the user to take a break or rest in between for each activity. Since rest-activity number out counts every activity combined, it is excluded in the figure.

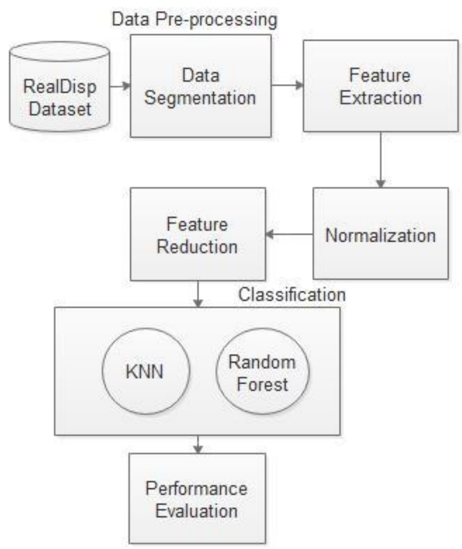

Figure 1. Proposed System Architecture of Physical Exercise Recognition System.

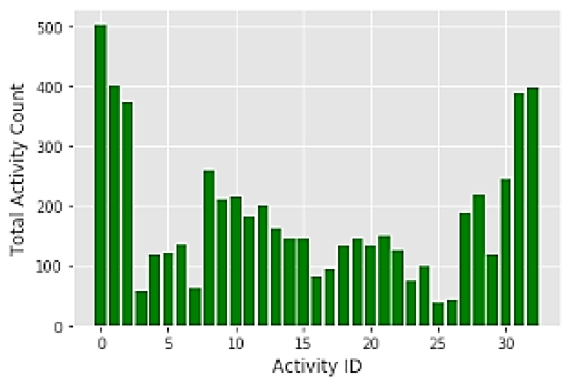

Figure 2. Total Activity Count performed by the users

3.2 Feature Extraction

The obtained initial signal generated from the accelerometer signals were grouped into segments of fixed length [12]. Then the feature vector was measured having the following features:

The mean is obtained by obtaining the average distance between each value and mean.

$$\bar{x} = \sqrt{\frac{1}{n}\sum_{i=1}^{N} x_i^2} \quad (1)$$

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Standard deviation is the calculation that provides us with information about how much the values are close to the mean or spread out.

$$s = \sqrt{\frac{\sum_{i=1}^{N}(xi-x)^2}{(N-1)}} \qquad (2)$$

The quantity of distribution for numerical data can be measured using a histogram.

$$h_i = \sum_{j=0}^{n} \frac{1}{n} r_i(x_i) \qquad (3)$$

An amplitude RMS can be expressed as

$$\text{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{N} x_i^2} \qquad (4)$$

To obtain how spread the values are in the dataset, we have calculated the average distance between each data value and their mean.

$$\text{Mean absolute deviation} = \frac{\sum|X-\mu|}{N} \qquad (5)$$

3.3 Z-score- Normalization

Following the arrangement of similar features by combining all the 17 subjects, the feature was normalized to create a normal distribution upon the entire set of features. It is done before the reduction phase to maximize the variance of the components. The equations are

$$z = \frac{x-\mu}{\sigma} \qquad (6)$$

Where,

$$\Sigma = \sqrt{\frac{1}{N}\sum_{i}^{N}(x_i - \mu)}^{2} \qquad (7)$$

$$M = \frac{1}{N}\sum(x_i) \qquad (8)$$

3.4 Principal Component Analysis

The principal component analysis (PCA) is a useful dimension reduction algorithm where the orthogonal transformation of the data converts correlated variables into linearly uncorrelated features called main components. Through the reduction of original data features, the amount of noise is reduced, and in addition, it diminishes the training data to let the model become computationally faster. If the number of observations made with p is n, then the number of separate main components is min (n 1, p). The resulting vector contains n observations having different variances [13]. The linear combination of the variables 1, 2, is the first principal components Y_1 represented by the equation

$$Y_1 = A_{11}Z_{11} + A_{12}Z_{12} + \dots + A_pZ_r \qquad (9)$$

The first principal component is calculated by choosing large values for weights a11, a12, alp once could make the variance of Y_1 as large as possible. In addition, it is the maximum variance. So, to limit the size of variance, weights are calculated with the sum of squares as 1.

$$A_{21}X_{21} + A_{21}X_{21} + A_{21}X_{21} = 1 \qquad (10)$$

Similarly, the second principal component is calculated. Collectively, all these original variables are transformed into the main components.

$$Y = XA \qquad (11)$$

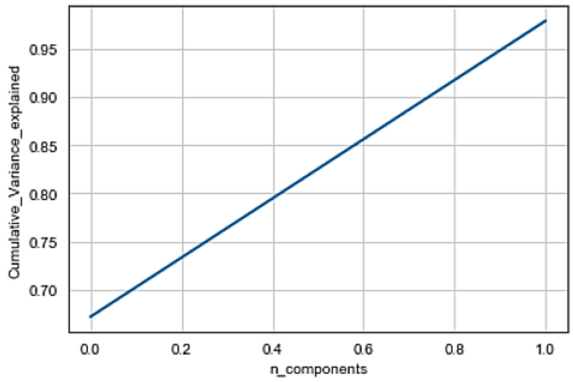

Figure 3. Variance Plot of PCA

In the graph of Figure 3 we can see that for the first component, we can cover almost 67% of the variance, and for the second component, 98% of the variance can be obtained.

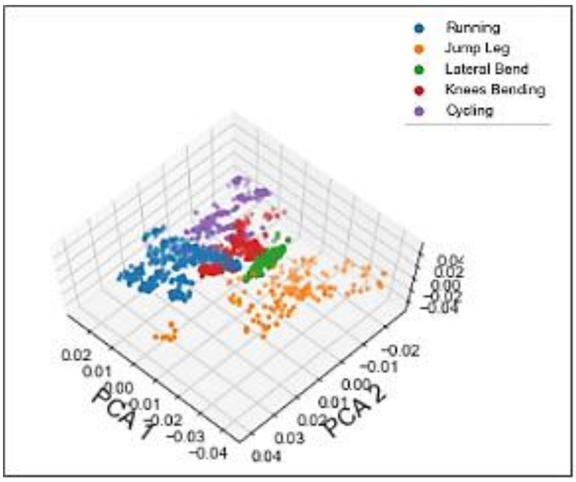

Figure 4. 2D Plot Scatterplot of PCA

Figure 4 represents the scatterplot of PCA 1 and PCA 2 scores. There is some degree of overlap between clusters represented by each activity. Cluster 2 is comprised entirely of points classified as jump Leg. Cluster 1 has some degree of overlap between cluster 4. Cluster 5 has a slight overlap with cluster 3. All these

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clusters individually represent an activity performed by the subject.

3.5 K Nearest Neighbor

K Nearest Neighbor (KNN) is a non-parametric supervised learning algorithm that is used in both classification and regression problems. It is also known as the lazy learning algorithm because it does not classify based on the training data points. The purpose of this algorithm is to classify a new sample based on its features and labelled training samples. Given a query point, k training points closest in the distance (Euclidean distance) to be found. Based on most of the neighbors found, the new query is classified into its cluster. Any ties in voting are broken at random. So, no specific training model is used for classification. KNN algorithm works based on nearest neighbor's classification and works best on the smaller dataset with fewer features. The Euclidean distance [13] of two n-dimensional vectors, x, and y, is defined as:

$$d(i,j) = \sqrt{(x_{i_1} - x_{j_1})^2 + (x_{i_2} - x_{j_2})^2 + \cdots + (x_{i_p} - x_{j_p})^2} \tag{12}$$

and Manhattan (or city block) distance [15] is defined as:

$$d(i,j) = \sqrt{|x_{i_1} - x_{j_1}| + |x_{i_2} - x_{j_2}| + \cdots + |x_{i_p} - x_{j_p}|} \tag{13}$$

3.6 Random Forest

Random forest is an ensemble algorithm that works well for models with low bias (high feature target relevant relationship) and high variance (spread of data). For classification, it joins more than one or similar kind of learning algorithms and predicts labels with much more accuracy. From randomly chosen training set decision trees are created. After totalling the votes produced, the final class of the dataset tested is decided [15]. Finally, computing the average of single tree prediction for each new object is made. It is the number of trees used for bagging then,

$$\hat{y} = \frac{1}{B}\sum_{i=1}^{B} pred(\mathrm{g_i}) \tag{14}$$

4. EXPERIMENTAL RESULT AND EVALUATION

We measured and evaluated our performance as follows:
Accuracy is a measure which determines the probability of how many results are correctly classified

$$\text{Accuracy} = \frac{\text{TN+TP}}{\text{TN+TP+FN+FP}} \tag{15}$$

The ratio between the true positive values and the sum of the true positive and false positive values is the precision

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{16}$$

The ratio between the true positive values and the sum of the true positive and false positive values

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{17}$$

F1 score helps to regulate the balance between precision and recall. It is the harmonic average of precision and recall. It is formulated as:

$$\text{F1 Score} = \frac{\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \tag{18}$$

The majority of the activity is where the user isn't performing any movement. First, our model was tested along with this activity as Null Activity. The results are shown in Table 1. Null class is sometimes ambiguous, with activities having similar patterns. Therefore, we also tested it, treating no activity as irrelevant to our calculations.

Table 1. Results with Null Class

Method	CA	F1	Precision	Recall
KNN	92.99%	94.55%	93.77%	91.45%
Random Forest	86.73%	87.04%	86.73%	86.11%

Considering a round robin strategy, nine subsets were used training, and one subset was used for testing. After averaging the accuracy obtained from these ten experiments, a final cross-validation result was obtained, as shown in Table 2. It is the same cross-validation method used in [8]. K-nearest algorithm gives an accuracy of 85.51%, while the Random Forest Algorithm gives an accuracy of 84.005%. The experiment was performed on WEKA [17]. It is observed the K nearest algorithm performs better to predict Activity recognition on the entire dataset for ideal placement scenarios. Figure 5 shows the accuracy of 3 different machine Learning Models based on our architecture that outperforms previous models.

Table 2. Cross-validation results

Method	CA	F1	Precision	Recall
KNN	85.51%	85.3%	85.7%	85.5%
Random Forest	84.00%	83.2%	84.3%	84.0%

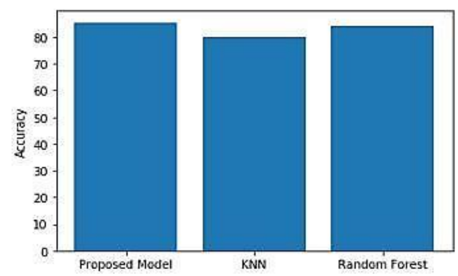

Figure 5. Bar chart of 3 Algorithms

The results obtained with a success rate of 85.51% are better compared with the paper [8] [5] in Table 3. Although this accuracy seems low, one of the causes is the inter-class variability as a similar user does similar activity differently.

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Another reason is the intra class variability is that some activity is closely related. In this study, the evaluated data includes 33 various exercises, which is mostly dynamic done by 15 different users. We believe this research would be useful in developing systems where a large number of people having different nature use the system to monitor and track their activity accurately in a data-efficient manner.

Table 3. Comparisons with other paper

Method	Method	Accuracy
Propose Model	KNN (reduced feature)	85.51%
Banos et al. [8]	KNN	80%
Vu Ngoc [5]	ANN	75.3%

5. CONCLUSION

While classifying Human activity, there are many uncertainties for the best algorithm. Different combination of signals vibrational features gives different activity detection rate. Moreover, the sheer amount of data created by these devices causes a significant amount of strain. Researchers still debate what features influence the recognition of Human Activity in Signals. In our research, a model for successful detection of Human Activity was proposed. About five features were used and normalized using PCA. The classification was done with two classifiers. KNN shows the best accuracy. Further experiments with a vast volume of irrelevant data where no activity was identified data show significant improvement in result. Possibly results may be improved using RFE to remove the weakest feature to reach a desired set of features. Moreover, combining smart watch features with those of a smartphone or any wearable sensor can provide much better recognition.

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