Human Physical Activities Recognition (HPAR) using Health Shimmer Wearable Accelerometer Sensor Data Sets

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Abstract*: *Activity recognition is one of the important attributes for well being of human health and activity recognition field. Wearable sensor data sets are effectively for recognition of postural acclimation and human body motion in the realistic environment. A physical signal with respect to time-based directed toward recognizes human activity events is projected, in the view of this work usage wearable accelerometer sensing devices were implanted taking place the human body location on the upper body Chest Sensor (CS), Left Ankle Sensor (LAS) and Right Lower Arms Sensor (RLAs). Accelerometer feature extracted based acceleration signals with respect to time, physical appearance of the accelerometer x, y, and z dimension values reported/recorded using shimmer2 wearable sensor device is recommended at the categorization of the 10 different users was performed 12 different types human activities, including vigorous and moderate activities. User ages between 24 to 29 years and human body weight (HBW) are 53 to 83 Kg=m2. Results were on view a large validity performance precision and recall were getting 95 for each human activities. The whole classifiers accuracy results for all combination of the feature set of all sensors is 99:07%. The considered work could be used to observe the human body motion on different body location of users. That can be helpful for in good physical shape, physical _t health authority and also to measure the activities of healthy and unhealthy people

Index Terms*: *Activity Recognition, Wearable Sensor, Physical Activity

I. INTRODUCTION

Human Daily Physical Activity (HDPA) and ascertaining human body orientation/motion is useful in appropriate ways; the advantages of Physical action reach out a long ways past weight administration. Research shows that reliable physical development can help reduce your uncertainty for a couple of contaminations and prosperity conditions and upgrade your general individual fulfillment. Steady physical development can help shield you from the going with medicinal issues including the change of individual weight control outlines and the recuperation of patients in free-living circumstances. Physical activity includes standing still, sitting and relaxing, laying down, walking, climbing stairs, waist bend forward, front elevation of arms, knee bending, cycling, jogging, running and jump front and back, etc. Accordingly, the creators urge the group to add to this inventive stage by supporting the utilization of the most recent sensors, consolidating new behavioral calculations or basically making utilization of it for the improvement of versatile wellbeing mobile applications [1]. In a brilliant world (the physical condition where different sensors embedded in our day by day schedules to observed unmistakable parts of our living), the proficient condition of people can be checked by minimal effort remote sensors. Acceleration based movement checking is effectively connected to an assortment of people, including solid identity and patients inconvenience from different infections. Obesity is a sickness condition that is turning into the genuine medical issue in the total populace because of physical latency [2].

II. RELATED WORK

Human Physical Activity Recognition (HPAR) utilizing wearable sensors is an exceptionally far-reaching research subject. Using mobile phone motion accelerometer sensor data to perform Human Activity Recognition (HAR), an undertaking which includes distinguishing the physical movement a client is performing. To actualize this framework creator gathered named accelerometer sensor data information from twenty-nine subject as they accomplished everyday activities such as walking, jogging, climbing stairs, sitting, and standing, and then aggregated this time series data into examples that encapsulate the user activity over 10-second time-out in each activity. Creators at that point utilized the subsequent preparing information to instigate a prescient model for movement acknowledgment. Earlier work by Kwapisz J R et al [3]. The outcomes demonstrate that these classification assignments can be appreciated well by utilizing accelerometers and additionally gyroscopes at any of the given classification and in addition given position. The grouping rates were most breathtaking for sensors situated at the lower back and chest in every one of the trials, yet at the same time extremely high when the sensor is connected to the wrist or lower leg. The whole process for activity recognition beings with gathering the raw data, Specifically, motion data. The inertial sensor is an adequate solution to detect motion of the subject. This inertial sensor replies to stimulants by generating signals that can be analyzed and understood. Monitoring physical activity by using wearable sensors reviews of various classification methods used to recognize Daily Human Activities (DHA). Three inertial sensor units were used in the healthy subject at key points of the chest, right thigh and left ankle [4]. An absence of sufficient physical movement is a huge issue in our general public in light of the fact that physical inertia drastically expands the wellbeing dangers for some, maladies, including cardiovascular sickness.

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III. PROPOSED MODEL

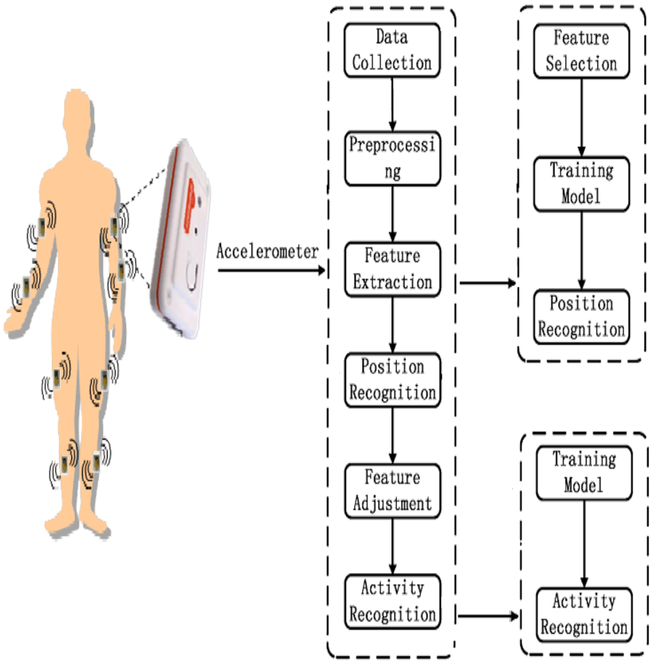

Fig. 1. Typical Human Activity Recognition

A. Data Set Description

The primarily mHealth informational datasets created by Banos, et.al [1] is used as secondary data sets in this research. The accelerometer shimmer2 sensor data sets contains 12, 15,749 (in Lacks) instances. All identifying modalities are recorded at a looking at rate of 50 Hz, which is viewed as adequate for catching human movement. Which were located at different positions of each person, from all ten persons, the descriptions of various types of activities being performed and their duration are described in the table 1.

B. Activity Set

According to mHealth accelerometer wearable sensor dataset we can calculate time for one instance = 1/50 = 0.02/ms. The user was taken 1/min time for each activities, except Waist bend forward, Front elevation of arms, Knee bending and Jump front and back for those activity user was taken 20/sec only. We can calculate time taken for each activity using the below formula [5].

$$T = T_A \frac{E_t * I_t}{t}$$

T_A = Total time taken for each activity
E_t = Time take for each instance
I_t = total number of instance in an individual activity
T = Time in second

C. Data Transformation

As said, to insert images in Standard organization computations can't be particularly associated with rough time-course of action accelerometer data. Rather, we initially should change the crude time arrangement information into examples. To accomplish this we isolated the intelligence into 5-second sections and afterward produced highlights that depended on the 256 readings contained inside every 5-second fragment. We assign to the interval of each segment as the illustration term Example Duration(ED).We picked a 5-second ED, since we felt that it gave commensurate time to catch a few repetitions of the movements associated with an allocation of the twelve different types of daily activities [3].

Table1. Activity Set

Sl.No	Human Physical Activity(HPA)	Actual time in second	Time
1	Standing still	61.44	1 min
2	Sitting and relaxing	61.44	1 min
3	Lying down	61.44	1 min
4	Walking	61.44	1 min
5	Climbing stairs	61.44	1 min
6	Waist bends forward	20	20 sec
7	Front elevation of arms	20	20 sec
8	Knees bending	20	20 sec
9	Cycling	61.44	1 min
10	Jogging	61.44	1 min
11	Running	61.44	1 min
12	Jump front & back	20	20 sec

IV. FEATURE GENERATION

Next, we produced enlightening highlights in light of the 256 crude accelerometer readings, where each analysis contained an x, y, and z esteem relating to the three measurements. We brought about a twenty one features in each position like at the position Chest Sensor (CS), Left ankle Sensor (LAS) and Right Lower Arm Sensor (RLAS), in spite of the fact that these are altogether variations of only seven essential basic features. Human activity recognition from shimmer2 sensor data sets is normally gone before by a highlights extraction step. Signal qualities, for example, time-area and recurrence space highlights are broadly utilized for feature calculation. In this proposed work the author have used time domain features. Time-domain features include Mean Absolute Value (MAV), Harmonic Mean (HM), Variance (VR), Root Mean Square (RMS), Skewness (SK), Kurtosis (KT) and Simple Squared Integral (SSI) [6]. After we have selected the mHealth data sets for Activity Recognition (AR) we can setup new Human Activity Recognition (HAR) system which can divide 70% of train data and 30% of test data for classification. To get mHealth data then divide data into 5/sec segment then generate time domain based feature that we are based 256 readings of acceleration sensor data readings, each reading have x, y and co-ordinates equivalent to the three-dimension values.

A. Mean Absolute Values (MAV)

The mean total value is the summations inter quartile go which depicts the inconstancy of a lot of information. Another approach to portray the mean outright esteem is inconstancy of a lot of information is to utilize its mean total deviation of preeminent estimations of the significant number of Information motivations behind the sign in the window, divided by the window measure N.

$$MAV = \frac{1}{n}\sum_{i=1}^{n} x_i$$

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Table2. Feature from the frequency and time domain

Features	Sensor	axis	Total
Mean Absolute Value	A	XYZ	3
Harmonic Mean	A	XYZ	3
Variance	A	XYZ	3
Root Mean Square	A	XYZ	3
Skewness	A	XYZ	3
Kurtosis	A	XYZ	3
Simple Squared Integral	A	XYZ	3

B. Harmonic Mean (HM)

The mean The Harmonic mean is described as in number juggling; the symphonious mean (every so often brought in reality mean) is one of a couple of sorts of ordinary, and Specifically one of the Pythagorean methods. The symphonious mean can be imparted as the equivalent of the number juggling mean of the reciprocals of the given course of action of observations.

$$HM = \frac{n}{\sum_{i=1}^{1} \frac{1}{x_i}}$$

C. Variance (VR)

That variance may be an estimation of the spread the middle of numbers in an informational list. The progress measures how far every amount in the situated is from the mean. A change will be assumed by taking those contrasts between every amount in the situated and the mean, squaring the distinctions (to make them positive) and secluding the entirety of the squares by the number about qualities in the set.

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

D. Root Mean Square (RMS)

In data and its presentation, the root infers square is portrayed as the square establishment of the mean square (the math mean of the squares of a course of action of instructive accumulations). The RMS is similarly called as the symmetrical mean and is a specific case of the broad mean with safeguard; root infers square can in like manner be indisputable for a sometimes strange limit in wording and conditions of an imperative of the squares of the unconstrained regards all through a cycle.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=}^{N} x_i{}^2}$$

E. Skewness (SK)

In estimation and probability theory, skewness is a proportion of the irregularity of the probability scattering of a certified data subjective variable about its mean. Atmosphere skewness regard can make sure or negative, or even ill defined. The construed impression of the slant is astounding

$$SK = \frac{E(X_i - \mu)^3}{\sigma^3}$$

F. Kurtosis (KT)

In estimation and probability theory, kurtosis is a proportion of the limitless of the probability transport of a certifiable regarded unpredictable variable. It resembles skewness. The descriptor of the condition of the flow of the data reasons for the accelerating data and is described as

$$SK = \frac{E(X_i - \mu)^4}{\sigma^4}$$

G. Simple Squared Integral (SSI)

The basic squared fundamental computes the efficiencies of signs

$$SSH = \sum_{i=1}^{n} x_i^2$$

The feature was extracted descending window wt of 5/sec time duration. Shimmer2 wearable data in three dimensions of the three important body position and the time domain features are derived from every 256 instances in each physical activity to recognize the movement as being one of twelve conceivable alternatives. The sampler frequency was recorded the accelerometer data at 50Hz capacity. time domain features are intended on the duration of 5/sec and four features sets (TDFS1, TDFS2, TDFS3 and TDF4) of 11120 instances are obtained in each activity from each placed of accelerometer sensors, placed on the Chest, Right Lower Arms (RLA) and Left Ankle(LA), respectively. Table 3 shows the dispersion of instances of the different daily physical activities in the feature sets. The aggregate removed list of capabilities is haphazardly disconnected into two sets.

Table3. Number of instances per activity

Physical Activity	Number of Instances
A1: Standing still	1120
A2: Sitting and relaxing	1120
A3: Lying down	1120
A4: Walking	1120
A5: Climbing stairs	1120
A6: Waist bends forward	1120
A7: Front elevation of arms	1120
A8: Knees bending	1120
A9: Cycling	1120
A10: Jogging	1120
A11: Running	1120
A12: Jump front & back	1120

The main preparing dataset contains 70% of the information cases from the time area highlights set and this 70% dataset utilized for preparing the classifiers, though the rest of the informational indexes considered as a testing set of the information occurrences from the time-space include set and are utilized for testing the characterization precision introduction of the classifiers. The information exactness consequences of every one of the twelve of the physical exercises utilizing tri quickening agent wearable sensors and a blend of each of the four sensors body area are expressed in the following allotments.

V. ANALYSIS OF RESULTS

Human Physical Activity Recognition (HPAR) the machine learning algorithms using accelerometer sensor data can be balanced in human physical activity recognition in different human body aspects and activities based on Precision, Recall, and F-measure. The accuracy or positive prescient esteem is differentiated as the degree of events that has a place with a class by the total events, including TP and FP requested by the classifier as being legitimate to this component class.

$$Precision = \frac{TreuPositive}{TruePositive + FalsePositive}$$

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The review or affectivity is described by the quantity of cases requested in one class by the total events affirmation to that class. The total number of cases of a class fuses authentic positive and false negative.

$$Recall = \frac{TreuPositive}{TruePositive + FalseNegative}$$

F-measure is retrieval data evidence. It contemplates both exactness and review and as a rule joins them into a weighted consonant mean. It ponders both exactness and review and as a rule joins them into a weighted consonant mean, where it achieves its best an incentive at 1 and the most exceedingly terrible incentive at 0. As a general measure of precision, F1 has been broadly utilized as a part of prior works for the appraisal of investigation execution. We utilize F-measures to enable us to appraise how exact and quickly we can make a proposition for the proper articles. The F-measure is defined as

$$F1\ score = \frac{2 * Precision * Recall}{Precision + Recall}$$

VI. RESULTS AND DISCUSSION

A. Acceleration Sensor Device Located on Different Body Position

The accuracy of machine learning algorithms the classification results of all twelve different types Human Daily Physical Activities (HDPA) applying the three dimensional accelerometer sensor device implanted on the Right Lower Arm Sensor (RLAS), Chest Sensor (CS) and Left Ankle Sensor (LAS) all types of sensors are reported. With respectively the time domain features set TDFS1, TDFS2, TDFS3, and TDFS4 are contained within of 21 extracted features from the three dimensional acceleration sensor data in all the three dimensions. The accuracy results of classifiers, the Support Vector Mission (SVM), Naive Bayes (NB) and J48 algorithms. Using time domain feature testing feature set to the obtained classification accuracy of three Classifiers results in Table 4. Precision, recall, and F-measure are stated for all four different sensor positions. The overall results of Precision, Recall and F1 measures for support vector machine (SVM) are 0.933, 0.943 and 0.935. Naive Bayes (NB) is 0.945, 0. 963 and 0.938 and finally, J48 algorithms are getting more values 0.99, 0.99 and 0.99 Specifically. The SVM was carried out very poor in comparability the activities of sitting and relaxing and standing still. In spite of the fact that the exactness of every one of these exercises are very low and furthermore poor review created low F-measure esteems. In this manner, clearly the proportion of the genuine positive is low and furthermore, there are a substantial number of false negatives, in this manner bringing about low estimations of sensitivity. Naive Bayes (NB) method is comparatively better than SVM classifier. In Naive Bayes (NB) Classifiers, were got 0.927 of precision and recall rate except activities of sitting and relaxing and standing still. The J48 algorithm was comparatively getting more precision, recall and f-measure values for all physical activities is almost greater than are equal to 0.99. The best precision, recall and f-measure results are fulfilled by the J48 algorithm. The activities of climbing stairs and walking are getting same precision, recall and values 0.972, 0.972, and 0.972 respectively.

Table4. Results of three classifiers with different sensor position

Sensor Position	J48			NB			SVM		
	P	R	F1	P	R	F1	P	R	F1
RLAS	0.95	0.94	0.96	0.94	0.96	0.93	0.93	0.94	0.93
CHEST	0.96	0.95	0.99	0.94	0.96	0.93	0.78	0.78	0.78
LAS	0.98	0.95	0.95	0.94	0.96	0.93	0.93	0.94	0.93
ALL	0.99	0.99	0.99	0.94	0.96	0.93	0.93	0.94	0.93

Table5. Final classification accuracy of all activities

Activity	RLAS/TDFS1			CHEST/ TDFS2			LAS/ TDFS3			ALL/ TDFS4		
	J48	NB	SVM	J48	NB	SVM	J48	NB	SVM	J48	NB	SVM
A1	97.22	100	100	97.22	100	88.88	97.22	100	100	97.22	100	100
A2	97.22	100	100	98.09	100	80.55	100	100	100	100	100	100
A3	97.22	100	83.33	100	100	83.33	100	100	83.33	100	100	97.22
A4	97.22	97.22	100	100	97.22	94.44	100	97.22	100	100	97.02	100
A5	100	100	100	98.02	100	91.66	100	100	100	100	97.02	97.22
A6	98.02	100	100	97.22	100	83.33	100	100	100	100	97.02	100
A7	100	100	100	97.22	100	100	100	100	100	100	100	100
A8	97.22	100	100	97.22	100	100	97.22	100	100	97.22	100	97.22
A9	97.22	100	88.88	97.22	100	88.88	97.22	100	88.88	97.22	98.02	97.22
A10	98.02	61.11	52.77	100	61.11	63.88	100	38.88	44.44	100	98.02	97.22
A11	98.02	100	100	100	100	100	100	100	100	100	100	100
A12	97.22	97.22	100	97.22	97.22	44.44	97.22	97.22	100	97.22	97.22	100
Total	**97.88**	**96.29**	**93.74**	**98.28**	**96.29**	**84.94**	**99.07**	**94.44**	**93.05**	**99.07**	**98.69**	**98.84**

Use Human Physical Activities (HPA) comprises the body movement of various body areas, contingent upon the sort of physical movement. For instance, the exercises of stopping and running elaborate more movement of the entire body. Hence, different human physical activities classify accurately by synthesis of the frequency and time area appearance derived from the different human body location. In the earlier segments, physical activities had low accuracy values for the sitting and relaxing and standing still in different positions of accelerometer data. Further-more, sometimes cycling and walking are below par classified by the shimmer2 accelerometer data positioned on the Right Lower Arms (RLA) and Chest. sit- ting and relaxing and standing still activities have deep accuracy values, when a shimmer2 accelerometer device was located at the position of the Left Ankle Sensor (LAS). Therefore, in this portion, time domain features isolated from three important locations of human body and all three important classifiers are functional to differentiate the set of human different body motion. Time domain features set for all three important position [TDFS4 = TDFS1 TDFS2 TDFS3]. The combined all RLMS, CHEST, LAS all three sensors classification and accuracy results are summarized in Table 5. The J48 and SVM

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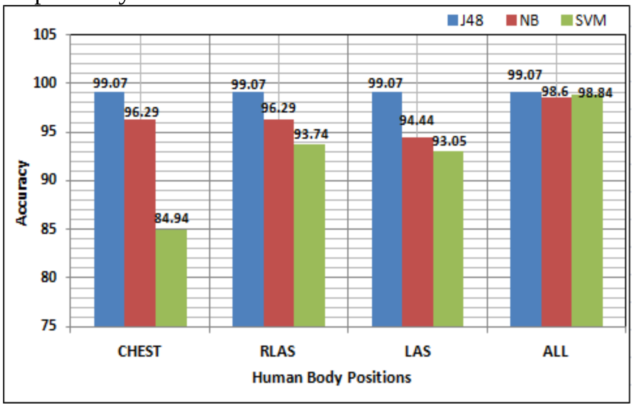
classifiers are slightly better than naive Bayes classifiers. The overall classification accuracy of all three sensors position combined is observed to be 96:29% with overall Precision, Recall and F-measure values are 0.944, 0.963 and 0.938 respectively.



VII. COMPARISON OF WEARABLE SENSOR PLACEMENT

Here some of the published literature review papers have mentioned that relates to the framework in this paper on different data sets and body position. The comparison of physical activity recognition results mentioned in Table 6 is not same data and same position [7]. Used time area based features to classify seven physical activities were got 94% accuracy [8].Human activity recognition of sensor data, the sensor were located on a various location of the human body. Wearable sensor data developed from a wearable sensor data was placed on the different human physical activities gives little bit knowledge about different physical body motion such as sitting and Relaxing, walking, lying down in various positions, standing, running, stairs and Climb. The proposed work was two accelerometer sensor realized overall 90% accuracy were got for various body orientation recognition Hristijan et al[9], an approach to fall detection using accelerometer sensor data here the author was considered nine different activity and four different body locations. In this scenario can difficult to identify whether person fall or non-fall using two accelerometer sensor devices.

Table6. Similarities of occurrence with the different body location

References	Location of sensor	Activity	Classification Accuracy
[10]	Waist	12	90.60 %
[7]	Chest, Wrist Ankle	9	86%
[7]	Waist	5	98.90%
[11]	Wrist	8	95%
[12]	Thigh, Necklace, Wrist	6	91.50%
[13]	Thigh, Waist, Chest, Ankle	8	91%
[14]	Chest, Thigh, Ankle	6	90.30%
[15]	Chest, Thigh, Ankle	16	89.08%
[16]	Waist	7	98%
[17]	Thigh, Trunk	4	90%
[18]	Chest, Wrist, Ankle	12	98%
Proposed	**Chest, Wrist Ankle, All**	**12**	**99.07%**

In our proposed work, we have familiar to various types of Human Physical Activities (HPA) and also 21 features was extracted in each activity based on the time area based and realized an comprehensive accuracy of 99:07% by using the time area based features of shimmer2 acceleration sensors device position. three classifiers of SVM, NB and J48 algorithms in all fours Feature set TDFS1, TDFS2, TDFS3 and TDFS4 is 95:36%, 95:52%, 93:43% and 99:07% respectively. The all acceleration sensor classification feature set (TDFS4) overall classification accuracy was very rich compared with three feature set. By using time area based feature set, we are capable to differentiate a few complex Physical Activity (PA) activities as well, such as sitting and relaxing and standing still activities were got very poor accuracy values in all four-time domain feature set of data. Finally, we were got very rich 99:07% in classification accuracy in all three advance classifiers methods corresponding with all three sensor position in all twelve different physical activities.

VIII. CONCLUSION

The shimmer2 wearable sensors devices are located on different human body locations namely Chest, Right Lower Arms Sensor (RLAS) and Left Ankle Sensor (LAS) respectively, to recognize 12 various types of Human Physical Activity (HPA). Features were isolated based on time domain from the shimmer2 acceleration data and the appearance of three different advanced machine learning classifiers are evaluated for every proposed position. The j48 algorithms are found to be the accuracy of the very good classifier between among the three advanced classifiers methods in all location. A normal classification exactness of 99:07% is achieved by J48 algorithms. Moreover, the collective all three acceleration Time Domain Feature Set (TDFS4) is found to be 93:74%, 92:29% and 99:07% for the SVM, naive bayes and J48 algorithms respectively. The proposed work classification results were evaluated with the reported literature in Table 6 and it is proof of our proposed work is quite better than published review papers in table 10. Our proposed methods are shimmer2 wearable accelerometer sensor data was useful for identifying the healthy lifestyle for people and also Survey the physical movement sound individual and the patient.

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