Physical Activity Classification with Smartphone based Accelerometer, Gyroscope and Device Motion for Personal Diabetes Healthcare Management

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***Abstract*—Physical inactivity has a substantial negative influence on one's health, lowers quality of life, and frequently causes cardiovascular disease, diabetes, and mobility problems. Both diabetes and the patient's lifestyle have a significant impact on each other. Although we shouldn't overburden most diabetes patients with technology since they can manage their condition without it, lifestyle-monitoring technology can nevertheless be helpful for both patients and their doctors. As a result, we created a method of lifestyle monitoring that makes use of smartphones, which the majority of patients already have. In this study, we demonstrate our smartphone-based system that uses the accelerometer, gyroscope and GPS incorporated into smartphones as sensors to identify, categorise, and rate running, walking, laying and standing activities. On two publicly accessible data sets, namely the UCI HAR data set and the motion sense data set for a physical activity sensor, several classification analysis approaches are explored. In comparison to previous efforts, our classification model technique significantly improves the classification of various activities. The proposed gated recurrent unit (GRU) architecture have an average accuracy of 94.91% in classifying activities.**

***Index Terms*—Diabetes, Smartphones sensors, Accelerometer sensors,Gyroscope sensors, Physical Activity Recognition,Classification, gated recurrent unit.**

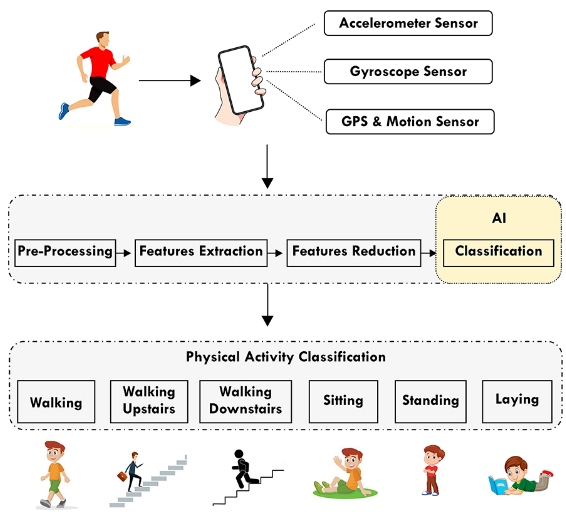

Fig. 1. This figure shows overall concept how we can extract the physical activity data from the smartphone with inbuilt sensor accelerometer, gyroscope and motion of the device and based on that how machine learning algorithm can able to classify the exact activity

I. Introduction

Diabetes affects almost 5.6% of the world's population, and the number that is rising as per the data available to International Diabetes Federation [1]. Patients with diabetes either do not generate enough insulin from their pancreas to adequately absorb glucose from their blood, or their body cells do not respond to the insulin in a healthy way [1]. Since diabetes cannot be cured, it must be controlled with medication and a healthy lifestyle, frequently necessitating insulin injections. Eating and exercising are important activities for diabetics since they increase blood glucose levels in the former and decrease it in the later [1]. They must thus carefully supervise and oversee these actions to maintain blood sugar levels between (70-180 mg/dL), as desired, and to avoid hyperglycemia (>180 mg/dL or more) or hypoglycemia (<70 mg/dL) [2].

The process of doing physical activity recognition, a crucial requirement in many healthcare applications, involves gathering contextual data when a person engages in various activities [3]. Excessive sitting and insufficient physical exercise are associated with obesity, diabetes, cardiovascular disease, poor metabolic health, and depression [2]. The study of a user's everyday activities may be done continuously using physical activity recognition. Such an analysis helps to understand the behaviour, which enables the provision of automated recommendations for lowering the risk factor for a variety of non-communicable illnesses [2].

Solutions of advanced healthcare assistive technology provide cost savings since they allow older persons with chronic conditions, in particular, to live freely. These innovative technologies, which often function both indoors and outdoors, allow for the detection of significant replaces in a patient's health [4]. Due to the built-in sensors in a smart phone and the ability to create useful apps employing these sensors, smart smartphones play a significant role in healthcare management systems (such as GPS,camera, accelerometer and gyroscope sensors) [5]. The Smartphones may be employed in cutting-edge healthcare systems because of their many benefits [1]. Nowadays, everyone owns a smartphone, which enables the

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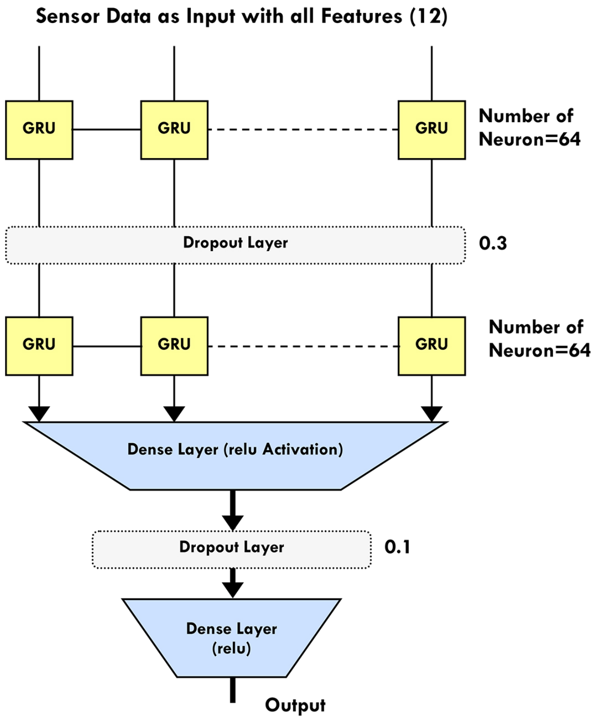

Fig. 2. This figure shows details internal architecture of our proposed deep neural network used for classification of physical activity from mobile based sensor only with out any external sensors

system to function outside, even in remote areas. Communications also rely on the already-existing cellular networks. Hence, the smartphone is a used as a very useful platform for systems that recognise physical activity. In this research, we describe two approaches for tracking and categorising patients' different physical activities (including walking, jogging,laying and standing) for evaluation of the patients' levels of physical activity using a smart mobile phone platform. The main benefit of these strategy is that no new technology is needed for the data collecting, which may be carried out covertly. Therefore, ongoing study of a user's everyday actions is ideally suited for this method to activity classification.

Therefore, ongoing study of a user's everyday actions is ideally suited for this method to activity classification. Bieber et al. [4] uses the device's accelerometer to track daily physical activity using a mobile device only. Using the accelerometer data which is gathered from a smartphone, Kwapisz et al. [5] achieved activity recognition in his work. The participants kept their phones in their front pants pockets while going about their everyday business, including walking,climbing, running and descending on stairs, standing and sitting activity. Dernbach et al. [6] expressed in his work based on the value of gyroscope and accelerometer sensor signals for classifying both basic and complex activities. Shoaib et al. [7] in his research, he carried out leg and hand movement data acquired from the wrist and pocket locations using smartphone-based detection and identification. The authors took routine physical activity as well as other behaviours like eating, smoking, and typing into consideration.

The rest of this article is divided into the following sections. In Section II, the machine-learning strategy for categorising physical activity is described after the conventional method for activity recognition, which includes a description of the dataset with pre-processing and feature extraction. In Section III, the experimental evaluation and its results are discussed. Section IV offers a conclusion to the article.

II. Methodology

A. Overview

Fig. 1 displays the basic block diagram of the suggested approach to activity classification. The input data is gathered using the inbuilt smartphone's internal gyroscope and accelerometer sensors only. The information collected from the accelerometer and gyroscope sensors, respectively, furnishes angular velocity and tri-axial linear acceleration information. The different input signals are also used to produce a collection of signals. The proposed descriptors are used to finish the feature extraction, and the feature sets that result are then combined at the feature level. The user's behaviour for the test set is then determined by feeding the classifier the composite feature vector.

B. Dataset

The following two datasets were used in our research.

1) MotionSense Data Set [14].
2) Smartphones Data Set or Human Activity Recognition Using or (HAR) [15].

In the initial dataset, 24 people were recorded using accelerometer, gyroscope, and device motion sensors at a sampling rate of 100 Hz while they were walking, walking up and down stairs, sitting, standing, and running. With the help of the mobile sensing framework Sensing Kit, the raw sensor data from an iPhone 6S is provided in this dataset.

The latter dataset contains sensor recordings (accelerometer and gyroscope at 50Hz sampling rate) from 30 persons engaged in walking, walking up-down stairs, sitting position, standing position, and lying action. Be aware that noise filters were used to pre-process the dataset, and that a number of characteristics were extracted in sliding windows with a set of 50 % overlap and a 2.56 second duration (128 readings/window).

C. Data processing

After importing the dataset we have to examine the first dataset as per our work. Since the data were acquired using 3-axis sensors, we can observe that the dataframe includes three measurements (x, y, and z) after adding the data, for each of the following traits:

- Attitude
- User Acceleration Rate
- Rotation Rate
- Gravity

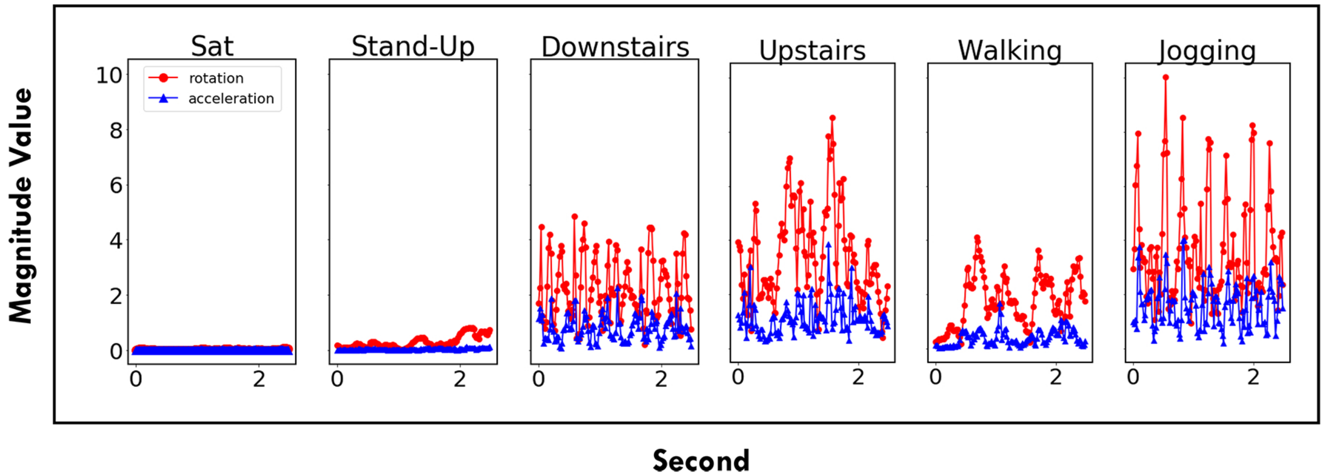

Fig. 3. This figure shows the different physical activity of the person with the magnitude value with respect to time after doing the pre-processing steps

In our situation, a classifier that reliably discerns motion activity in any physical alignment where the user has put the phone in his or her pocket is what we are looking for. Individual axis readings do not provide useful information since each user places the smartphone in the different physical alignment, so that calculating the magnitude or (resultant vector) of each sensor is very important. This formula can be used to determine the magnitude-

$$mag = \sqrt{x^2 + y^2 + z^2} \tag{1}$$

We have just pay attention to the user acceleration and rotation rate characteristics. Then we have select the features and label the data. Thus we have able to load the dataset with different variables.Then the pre process data is visualized in Fig 3 for different physical activity with different magnitude. We have used 70% data as for our training and remaining parts are using for testing purpose.

D. Feature Extraction

In traditional machine learning, the raw data must be transformed into understandable characteristics using a feature extraction procedure. This labor-intensive and inventive approach is also known as feature engineering. The HAR is using only based on the data set for cellphones with fixed-width sliding windows and 2.56 seconds of pre-computed features and the overlap is 50% (so we got 128 readings/window), will be used to bypass this step.

E. Classification Algorithm

Different supervised machine learning algorithms are used to categorise the various forms of physical activity using the normalised inputs and the accompanying numerically labelled physical activity data that is captured and utilised as an output. The different ML algorithms which is used include- Random Forest, Decision Tree, Extra Trees, Logistic Regression, support vector machines (SVM), XGBoost and k-nearest neighbors(KNN). Further more we have proposed another deep learning architecture base on Recurrent Neural Network(RNN).

F. Proposed GRU Architecture

We have designed a novel GRU architecture which internal structure is shown in Fig 2 which have consist of GRU layers with 64 neurons, then one drop out layer is used. Then the input is passed through another GRU layers with 64 neurons. After that output is passed through dense layer with relu activation function. Finally out put is passed through a dense layer network after passing through another drop out layer. Thus we have created the deep learning based novel classification architecture for physical activity classification.

III. Results

Performance studies have been conducted using the physical activity sensor data and the UCI HAR dataset, two publicly available datasets. Here we have described the activity recognition performance in this section in terms of Precision, Recall, and F1-Score. These can be represented as follows: TP for true positive, FP for false positive, TN for true negative, and FN for false negative -

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F_1 Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

We have used all the above classification algorithm for generating the classification report and it is showed in the table I to VII. From the Table I it is showing that the classification matrices including precision, recall and F_1 score of different

TABLE I
CLASSIFICATION METRICS OF DIFFERENT PHYSICAL ACTIVITY DATA FROM MOBILE SENSOR USING RANDOM FOREST ALGORITHM

Physical Activity	Precision	Recall	F1-Score
Wlking Upstairs	0.90	0.89	0.89
Walking	0.87	0.97	0.92
Sitting	0.91	0.88	0.89
Walking Downstairs	0.97	0.85	0.90
Laying	0.92	0.92	0.92
Standing	0.89	0.92	0.91
Average	**0.92**	**0.92**	**0.92**

TABLE II
CLASSIFICATION METRICS OF DIFFERENT PHYSICAL ACTIVITY DATA FROM MOBILE SENSOR USING DECISION TREE CLASSIFIER ALGORITHM

Physical Activity	Precision	Recall	F1-Score
Wlking Upstairs	0.84	0.78	0.81
Walking	0.82	0.90	0.86
Sitting	0.83	0.76	0.79
Walking Downstairs	0.87	0.84	0.85
Laying	1.00	1.00	1.00
Standing	0.79	0.86	0.83
Average	**0.86**	**0.86**	**0.86**

TABLE III
CLASSIFICATION METRICS OF DIFFERENT PHYSICAL ACTIVITY DATA FROM MOBILE SENSOR USING EXTRA TREES CLASSIFIER ALGORITHM

Physical Activity	Precision	Recall	F1-Score
Wlking Upstairs	0.87	0.86	0.86
Walking	0.84	0.95	0.89
Sitting	0.90	0.89	0.90
Walking Downstairs	0.96	0.81	0.88
Laying	1.00	1.00	1.00
Standing	0.90	0.91	0.91
Average	**0.91**	**0.90**	**0.90**

TABLE IV
CLASSIFICATION METRICS OF DIFFERENT PHYSICAL ACTIVITY DATA FROM MOBILE SENSOR USING SUPPORT VECTOR MACHINES CLASSIFIER ALGORITHM

Physical Activity	Precision	Recall	F1-Score
Wlking Upstairs	0.94	0.96	0.95
Walking	0.94	0.99	0.97
Sitting	0.91	0.86	0.88
Walking Downstairs	0.98	0.90	0.94
Laying	1.00	1.00	1.00
Standing	0.88	0.92	0.90
Average	**0.94**	**0.94**	**0.94**

TABLE V
CLASSIFICATION METRICS OF DIFFERENT PHYSICAL ACTIVITY DATA FROM MOBILE SENSOR USING XGBOOST CLASSIFIER ALGORITHM

Physical Activity	Precision	Recall	F1-Score
Wlking Upstairs	0.89	0.84	0.86
Walking	0.84	0.94	0.89
Sitting	0.84	0.82	0.83
Walking Downstairs	0.90	0.85	0.87
Laying	1.00	1.00	1.00
Standing	0.84	0.84	0.84
Average	**0.88**	**0.88**	**0.88**

TABLE VI
CLASSIFICATION METRICS OF DIFFERENT PHYSICAL ACTIVITY DATA FROM MOBILE SENSOR USING K-NEAREST NEIGHBOR CLASSIFIER ALGORITHM

Physical Activity	Precision	Recall	F1-Score
Wlking Upstairs	0.91	0.92	0.91
Walking	0.85	0.98	0.91
Sitting	0.89	0.83	0.86
Walking Downstairs	0.96	0.78	0.86
Laying	1.00	1.00	1.00
Standing	0.86	0.91	0.88
Average	**0.91**	**0.91**	**0.91**

physical activity which we have got average value as 92% in all three evaluation factors using random forest algorithm. In table II we used the decision tree classifier algorithm to get the average value for each of the three assessment parameters which was 86%. In the table III we have used extra tree classifier algorithm and the average value for precision is 91% and recall and F_1 score is 90%. Table IV shows the accuracy rate for SVM classification algorithm which is 94%. For XGBoost classification algorithm accuracy is 88% and it is showed in table V. And lastly KNN algorithm also gives 91% which is showed in table VI and finally proposed model in performance showed in table VI.

IV. DISCUSSION & ANALYSIS

In the table VIII we have showed the comparison between our classification model with different existing literature, where we have got higher accuracy for physical activity classification in both the proposed model architecture.

TABLE VII
CLASSIFICATION METRICS OF DIFFERENT PHYSICAL ACTIVITY DATA FROM MOBILE SENSOR USING PROPOSED GRU ARCHITECTURE

Physical Activity	Precision	Recall	F1-Score
Wlking Upstairs	0.94	-	-
Walking	0.96	-	-
Sitting	0.92	-	-
Walking Downstairs	0.94	-	-
Laying	1.00	-	-
Standing	0.93	-	-
Average	**0.94**	**-**	**-**

TABLE VIII
COMPARISON TABLE OF PHYSICAL ACTIVITY CLASSIFICATION ACCURACY DATA FROM MOBILE SENSOR WITH VARIOUS EXISTING WORK WITH DIFFERENT CLASSIFICATION METHODS

SL No	Related Literature	Model Used	Precision (%)	Recall (%)	F1-Score (%)
1	Mauner et al. [8]	Decision tree	80	-	-
2	Sun et al. [9]	SVM	94	-	-
3	Kwapisz et al. [10]	MLP	91.7	-	-
4	Difrancesco et al. [11]	K-Means	-	78	95
5	Zheng et al [12]	CenceMe	-	76	76
6	Karantonis D M et al. [13]	Decission Tree	90.8	-	-
7	D. van Kuppevelt et al. [16]	CNN	91.67	-	92
8	N. T. H. Thu et al. [17]	BiLSTM	93.91	-	94
9	**This Work**	**Proposed GRU Network**	**94.91**	**-**	**-**

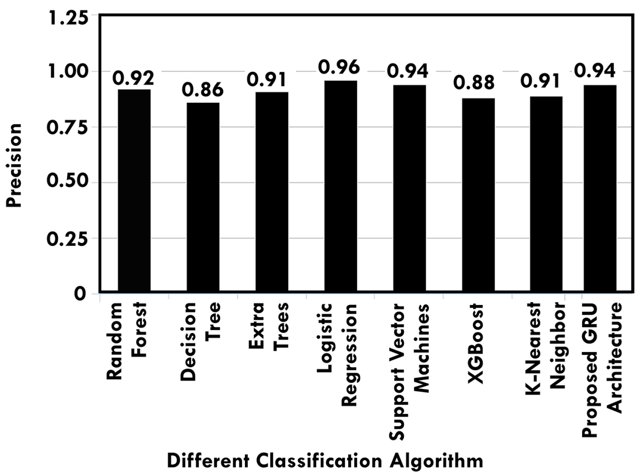

Fig. 4. This figure shows the precision value of different algorithm for physical activity classification

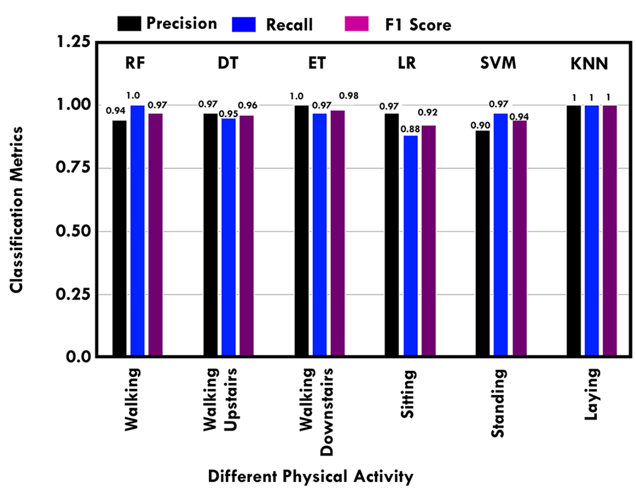

Fig. 5. This figure shows the different classification metrics including precision, recall and f1 score with respect to different pattern of physical activity

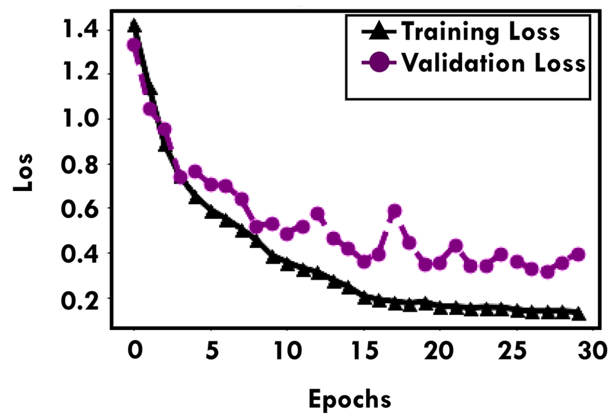

Fig. 6. This figure shows the training and validation loss for each epochs for proposed GRU deep learning framework to classify the physical activity

V. CONCLUSION

The level of physical activity is a significant factor for determining a patient's movement and, subsequently, their health condition. The overall amount of time a patient spends exercising gives a fast overview of their health. Using the GPS, accelerometer, and gyroscope sensors included into smartphones itself, In this work, we have provided our important approach for classifying and identifying physical activities (walking, jogging, walking to the downstairs, walking to the upstairs, lying, and standing) with great accuracy (96%) which is performed very well as compared to the existing art of work. Also our proposed GRU architecture performs well which has give 94% accuracy and it is also very good performance as compared to existing model. Our main goal was to offer a system of assistive technology that would enable caregivers to track and assess patients' physical activity. We wish to examine more edge cutting deep learning architecture for physical activity identification in the future in order to categorise higher-level physical activities (such eating lunch or drinking coffee or different activities).

VI. ACKNOWLEDGMENT

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