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Hybrid deep learning framework for human activity recognition

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Abstract

The aim of the recognition in the human activity is to recognize the actions of the individuals using a set of observations and their environmental conditions. Since last two decades, the research on this Human Activity Recognition (HAR) has captured the attention of several computer science communities because of the strength to provide support to different applications and the connection to different fields of study such as, human-computer interaction, healthcare, monitoring, entertainment and education. There are many existing methods like deep learning which have been used to develop to recognize the different activities of the human, but couldn't identify the sudden change of the activities in the human. This paper presents a method using the deep learning methods which can recognize the specific identities and identify a change from one activity to another for the applications of the healthcare. In this method, a deep convolutional neural network is built using which the features are extracted for the collection of the data from the sensors. After which the Gated Recurrent Unit (GRU) captures the long-tern dependency between the different actions which helps to improve the identification rate of the HAR. From the CNN and GRU, a model of wearable sensor can be proposed which can identify the changes of the activities and can accurately recognize these activities. Experiment have been conducted using open-source University of California (UCI) HAR dataset which composed of six different activity such as lying, standing, sitting, walking downstairs, walking upstairs and walking. The CNN-based model achieves a detection accuracy of 95.99% whereas the CNN-GRU model achieves a detection accuracy of 96.79% which is better than most existing HAR methods.

Keywords: Deep learning; Convolutional neural networks; Activity recognition; Gated recurrent unit

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1. Introduction

The Human Behavior Recognition (HAR) detects, interprets and recognizes the behaviors of the human which can be used in the field of the smart healthcare to help the doctors or the patients according to their different requirements. The HAR is used in many fields using different kind of applications such as the monitoring system in home automation, different kind of sensors in sports to detect the movement of the players, and using the gyro sensors to identify the various movements of the body. HAR has a huge impact in the research field [17] and helps to make the day-to-day life easier, safer and convenient.

Presently, in the real world the data of the human data can be extracted using two ways. The first way is to rely on the field of computer vision and the second way is to get the data using the different sensors [16]. The study of recognition of the human behavior in computer vision field has been since a long time and each study has different approach to their own model. Though, using the computer vision methods there are many restrictions faced during the modelling of the model. The studies on the sensors which help to recognize the human behavior has been in process and helps us to use the sensor technologies to detect the behavior of the human body. There are different sensors used for different purposes such as gyroscopes which detect the angular velocity, accelerometers which measure the acceleration, magnetometers which helps to calculate the magnetic field intensity and the barometer sensor which detects the atmosphere pressure. All of these sensors can be used in the mobile phone, smart watches and even the clothes. The wearable sensors have resolved the problem of the electromagnetic shielding, like in [**?**], which evaluates the velocity and acceleration accurately of the motion sensors in the actual time even in the existence of the electromagnetic shielding. The wearable sensors have small size, high sensitivity, and has an ability to reduce the electronic interference during the radio transmissions, so that it can be used efficiently in day- to-day life without any harm to the environment. Furthermore, the recognition of the human behavior using the sensor technology is currently being used everywhere which help to detect the human activities more efficiently. Hence, the study on the different applications regarding the HAR using the sensors has more importance and significance.

There are mainly two types of actions in the HAR: the different actions and the changes in the actions. As the changes of the human activities are unpredictable, there are very few research in the changes of the movement of the human activities such as suddenly changing from the standing position to the sitting position, or from walking position to the standing position. The research in the changes of the movement of the human activities is a very significant aspect in the HAR. The evaluation of the changes in the movement can help to improve the accuracy rate in the human activity recognition. The changes in the action can be identified using the basic actions. The recognition rate can be increased by dividing the changes in the actions in the streaming data to some limit so it gives us an improved accuracy. There are some limitations because the features of the behaviour are extracted manually from the traditional methods. The different type of applications and the development in the field of deep learning, the deep learning-based model has a benefit in the HAR.

This model uses both the accelerometer sensor and gyro sensor data using a CNN-GRU model to identify the changes in the action. The Convolution Neural Network (CNN) is a neural network which is used for the extraction of the features from the data taken using the sensors. The changes are categorized using the local requirement, so it can have best performance during the extraction of the features. The movement of the human body composes of complex actions and movements which change along with the time. Due to the complex action and movement, the CNN method does not extract the features properly in a given time. Hence the Gated Recurrent Unit (GRU) is used to extract the data in a time dependent sequence problem. Thus, the CNN-GRU combined can identify the actions and change in the actions accurately in a time-series data. The proposed model of the CNN-GRU can be summarized as follows:

- The model consists of the Convolution Neural Network (CNN) and the Gated Recurrent Unit (GRU), which learns the different actions and identifies the change in the action using the features and models the time-dependence for the features in a noisy environment.
- The CNN-GRU based model can be used to solve both classification and as well as regression problem. However, here the model is tested for solving classification problems.
- The impact of the important parameters in a deep learning-based model is discussed and the best parameter for our CNN-GRU model is determined.
- The results were evaluated and compared using different models that have used the same dataset. The evaluation of the results shows that the CNN-GRU model is more efficient when compared to the existing models.

The paper is arranged is the following way: The Section 2 explains the literature survey done on the various models of the HAR. The Section 3 gives the HAR model which explains the recordings of the motion signals in the human behavior, normalization of the signal, measurement of the data, format, and finally the CNN-GRU proposed model. In the Section 4 the results have been compared with the existing systems and in the last section i.e. Section 5 the conclusion along with the future work is given.

2. Literature Survey

As there is fast development in the field of the computer vision and the embedded systems, the HAR using the wearable device having the sensors has become an essential in the day-to-day life and is currently being used in various fields such as action recognition, health management, remote control, medical monitoring and rehabilitation activities [5, 23, 3, 12, 14, 18, 10, 27, 2, 25]. Various wearable devices embedded with sensor are in the development for the usage in the day-to-day life and in sport activities. The benefit of these sensors is that they provide the monitoring of the motion and recognition without the use of any external sensor like camera, radar or infrared sensors [29, 9, 28]. As the sensors are small in size, have light weight, can be bought at low cost and consume very less power these can be used in sport activities for the recognition of the motion of the players. The KEH can help to resolve the issue of the power consumption of the battery in the wearable devices. Using the KEH, the power consumption of the battery in the wearable devices in HAR can be reduced to 79% [14]. The data of the common activities were recorded using the professional equipment's which are expensive and inconvenient [17]. Nowadays, the mobile devices have made a huge impact on the people's day-to-day life. Many mobile devices offer different functionalities other than the basic functions such as basic telephone and different sensors are used for other functionalities. Many efforts have been made to use the mobile devices for the HAR [21, 6]. Hence a lot of studies have been conducted mainly on the mobile phone sensors to get the data regarding the human activities. The dataset of the human activities was classified using the mobile devices [20]. A method has been proposed using the histogram gradients and Fourier form for the extraction of the human behaviour, and then used this method on the UCI human activity recognition database. This method was build using the supervised machine learning algorithm i.e., SVM and KNN algorithm for the classification [11]. The performance of the model gives higher accuracy throughout the extraction of the feature. A model has been proposed for the military wearable devices using the multi-layer perceptron to classify the different activities of the individual. The design of the model consumed less time and power during the execution. The model used the UCI HAR dataset for the development and verification [7]. A recognition model has been proposed using the accelerometer and the gyro sensor to recognize the activities. In this model, a three-layer LSTM has been proposed where the accuracy reached at 93.7% using the UCI HAR dataset and with additional dataset it got an accuracy of 97.4% [26]. For the recognition of the activity, a method has been proposed using the accelerometer in the mobile phones. In this model, the data was extracted using the accelerometer from the original input signal. The model uses the PCA to minimize the features and mainly extract the required features of the different activities of the human in a given time and frequency for the categorization of the six activities. This method used 70% of the data for training having 6.11% accuracy and 30% of the data for the testing having 92.10% accuracy [24]. During the pre-processing, the extraction of the features required special method to retrieve the data from different database, and small changes in the deep learning method, the features can be retrieved, but there will be a reduction in the accuracy. A method in which the UCI human interaction recognition database was used for the verification of their proposed model and for the classification of the dataset using their model. There are currently many studies being done in the field of deep learning in HAR. As the machine learning algorithms require manual extraction of the features from the dataset, the deep learning algorithms can automatically extract the features from the dataset. Hence, the data were extracted using the sensors, the outcomes were evaluated and an efficient model of HAR was developed. A system using LSTM model was developed to detect and identify different activities from the dataset. The number of dimensions were reduced using the PCA method and achieved an accuracy of 97.64% [1]. A method using the three-axis acceleration sensors in the mobile devices were collected and using the 1D CNN method the model was proposed. The three-axis accelerometer data was used as an input for the neural network and achieved an accuracy rate of 92.7% [15]. Another method using the values of the gyro sensor and accelerometer taken as an input for the extraction of the features automatically through the CNN was proposed. The model was compared using the SVM model and multi-layer perceptron method. The CNN model achieved a higher accuracy and computational complexity [31]. A method that extracted the data using the 3D raw accelerometer using the CNN algorithm without the pre-processing of data was proposed. The model achieved an accuracy of 91.91% and a 9% increase to the traditional SVM model of HAR [34]. A method using the CNN model and the dataset of HAR has been used through which the data has been extracted and evaluated and an accuracy of 95.4% has been achieved [33]. Another model of deep CNN has been used for the classification of the basic human activities for an extensive time. The model uses the raw data of the gyroscope and accelerometer from the wearable device as an input and this model achieved an accuracy of 96.4% [30]. A model of deep neural network along with the convolutional layer and LSTM was developed. This model extracted the features automatically and classified the extracted features of the three datasets (OPPORTUNITY, UCI and WISDM) and achieved an accuracy of 92.63%, 95.78% and 95.85% respectively [13]. A model was developed using a dataset of seven individuals who performed the daily activities like walking, sitting and standing which achieved an accuracy rate of 82% [4]. After going through different studies, we can conclude that using the deep learning algorithms, the neural networks extract the features automatically. As the neural networks extract the features automatically, the CNN-GRU method is proposed as the CNN helps to extract the features easily and it can be done automatically. The GRU method helps to identify/detect the changes of the different activities from one activity to another activity.

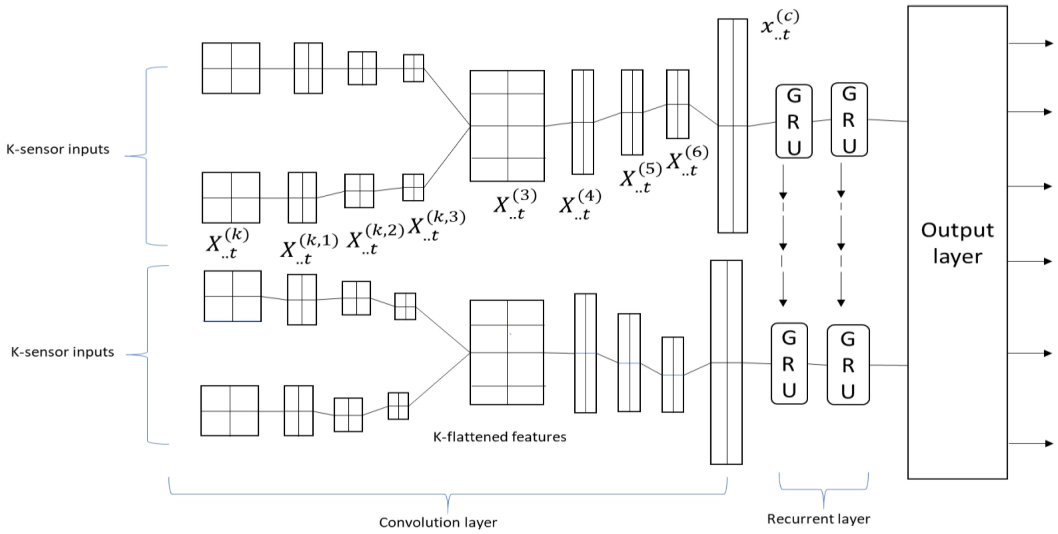

Figure 1: Architecture of Noisy Measurement Aware Human Activation Recognition model using Hybrid Deep Learning Framework.

3. Noise Measurement Aware Human Activity Recognition Model using Hybrid Framework

This section presents a hybrid framework for human activity recognition. First system model is discussed. The architecture of noise measurement aware human activity recognition model using hybrid deep learning framework is shown in Figure 1.

3.1. System Model

In CNN, the layers are divided as follows such as solitary cumulated convolution subnetwork (SCCSN) and distinct convolution subnetwork (DCSN). In the DCSN the network of all the incoming sensor tensor is given using the X^k, and in the SCCSN the output of the incoming sensor network is given using the distinct convolution subnetwork.
As the design of the DCSN for all the sensors is same, the main focus is on the DCSN having the input tensor X^k where the X^k is a $d^k * 2f * T$ tensor, where d^k is the measurement of the sensor attributes, f represent the attribute of the frequencies and T is the session period.
In each of the session period t, the model $X^k_{..t}$ will be used in the convolution neural network architecture which has three layers in this model. There are two sort of elements/associations inside the $X^k_{..t}$ which need to be extracted i.e., the association of the frequencies and the association of the measurement of the sensor attributes. The frequencies have a greater number of local patterns in some of the neighbouring areas of the frequencies. The interaction between the measurement of the sensor having all the attributes is done. Hence, the 2D filters having the shape $d^k, cov1$ to $X^k_{..t}$ is applied first to study the interaction between the measurement of the sensor attributes and the local patterns in the frequencies, having the output as $X^{(k,1)}_{..t}$. After this the 1D filters using shape $(1, cov2)$ and $(1, cov3)$ categorically is applied to study the high-level associations, $X^{(k,2)}_{..t}$ and $X^{(k,3)}_{..t}$. The matrix $X^{(k,3)}_{..t}$ is flattened into the given vector $x^{(k,3)}_{..t}$ and then the concatenation of all the K vector $\{x^{(k,3)}_{..t}\}$ into the K-tuple $X^3_{..t}$ is done, which is the data of the merged convolutional subnetwork. The framework of the merged convolution subnetwork is same to the DCSN. Here, the 2D filters with the shape $(K, cov4)$ is applied first to study the connections between al the K sensors, with the output $X^4_{..t}$. After this the 1D filters having the shape $(1, cov5)$ and $(1, cov6)$ categorically

is applied to study the high-level associations, $X^5_{..t}$ and $X^6_{..t}$.
In all of the CNN layer, our model CNN-GRU studies 64 filters, and then utilizes the ReLU method for activating the function. In this model, each layer uses the batch normalization method [20] to minimize the covariance shift. The residual network structure [28], is not used as we wanted to simplify the framework of the network for all the mobile applications. The final output $X^6_{..t}$ is flattened into the vector $x^{(f)}_{..t}$; concatenate $x^{(f)}_{..t}$ and session period width, $[\tau]$, together into $x^{(c)}_t$ as an input to the recurrent layer.

3.2. Recurrent Layers

RNN have a powerful framework which can be trained using the features for the given classifications that can estimate the function. In RNN, there are two models, the GRU model [8] and the LSTM model [22] which have been used in our model. The Gated Recurrent Unit model is used because it shows some similar properties and performances when compared with the Long-Short Term Memory model [8]. The GRU model has more short expressions, which minimizes the complexity of the network in the mobile application. The architecture of HAR uses a GRU model which has two layers. According to the bi-directional Gated Recurrent Units [32], it contains two session periods in which the time period starts and goes to the end and the same happens again from the end it comebacks to the start. This process runs continuously when there is a new session period which has more faster processing of the required stream data. Since the bi-directional Gated Recurrent Unit cannot be used until all the information of the session period is ready, which is unfeasible for the mobile applications. Inputs $\{x^{(c)}_t\}$ for $t = 1, ..., T$ from the earlier CNN layer is used as an input to the Gated Recurrent unit to get the output $x^{(r)}_t$ for $t = 1, ..., T$ as an input for the output of the final layer.

3.3. Output Layer

The yield of the RNN layer contains a sequence of vector $\{x^{(r)}_t\}$ for $t = 1, ..., T$.
In the task of regression-oriented, the value of all the required vector $x^{(r)}_t$ is in between $\pm 1, x^{(r)}_t$ which encode the output at the end of the session period t.
Suppose, in the output layer if we want to study the dictionary W_{out} using a prejudice term b_{out} to interpret $x^{(r)}_t$ into $\hat{y}t$, such that $\hat{y}t = W_{out}.\ x^{(r)}_t + b_{out}$, then the layer contains a fully linked layer in which the top of each session has sharing parameter W_{out} and b_{out}.
The classified task, $x^{(r)}_t$ is the vector at the session period t. The layer of the output first requires to comprise $x^{(r)}_t$ into a given length vector for the additional processing. The weights of the neural network are learnt by using the function r. The average features are used to generate a final feature, $x^{(r)} = \frac{\sum_{t=1}^{T} x^{(r)}_t}{T}$. Finally, the $x^{(r)}$ is taken as an input into the SoftMax layer for the prediction of the probability $\hat{y}$.

3.4. General customization process

In this section, some parameters of the HAR model which are used for computing different task and for mobile sensing are customized. The process of the customization is given as follows:

1. Identification of the data from a number of sensors, K. Pre-processing of the data of the sensors and make a set of it using $X = \{X^k\}$ as an input data.
2. Identification of the given task and classify it into what kind of application it is (the application can be a classification oriented or it can be a regression application). Selection of the output layer according to the given task.

3. Designing a modified cost function or a default cost function.

Hence, for the HAR model configuration, the number of inputs is set using the K, then the pre-processing on the input measurement of the sensor is done and then finally the identification of what kind of task is being performed is evaluated.
Using the Fourier transform on each sensor, the frequencies can be stacked into the output as $(d^k k) \times 2f \times T$ tensor X^k, where d^k is the measurement of the sensor attribute, f is the frequency, and T is the session period. For the identification of the data from a number of sensors K, the K is set to a number of different sense modality. If there are more than two sensors which have the same sense modality, then it is considered as a multi-dimensional sensor whose value is set accordingly to the measurement dimension. For having the best cost function, we can generate our own function rather than having a default one. The Deep Learning Framework for HAR model is defined using the function $F(\cdot)$, using the training sample pairs as (X, y). The cost function can be given as follows:

$$L = l(F(X), y) + \sum_j \lambda_j P_j \tag{3.1}$$

Here the $(\cdot)$ represents the loss function, P_j is the regularization or consequence function, and λ_j hold the reputation of the regularization or the consequence function.

3.5. Human activity recognition

In this section, the cross validation of the HAR using the measurements of the accelerometer and gyro sensor is evaluated. In this manner, as indicated by the overall customization method, the human activity recognition is a classification-oriented issue with $K = 2$ (gyroscope and accelerometer). For the training objective the cross-entropy cost function is used which is given by

$$L = H(y, F(X)) \tag{3.2}$$

The H represents the entropy for the given two distribution. The method of HAR achieves more higher accuracy, which is given and proven is the simulation study.

4. Simulation study

Here experiment is conducted to validate the outcome achieved using hybrid deep learning model for human activity recognition with respect to existing CNN-based HAR model. The HAR model is implemented using Python framework.

4.1. UCI HAR Dataset Description

The dataset was extracted from the UCI Machine Learning Repository. In this dataset of HAR, there were 30 contributors from which the data was taken. There was a total entry of 10,299 in which the dataset was divided into two for the testing and training. The dataset was divided into 70% of the contributors having 7252 entries for the training and 20% of the contributors having 1470 entries were used to test the accuracy of the model. The 30% of the contributors which had entries of 2947 were used in testing the data. Several frames for all the contributors were used, the width of the frame was 256 signals, the sampling of the frame was done in a fixed-width sliding windows of 2.56s and an overlap of 50%. The accelerometer and the gyro sensor reading for the three axes were taken every 0.02s.

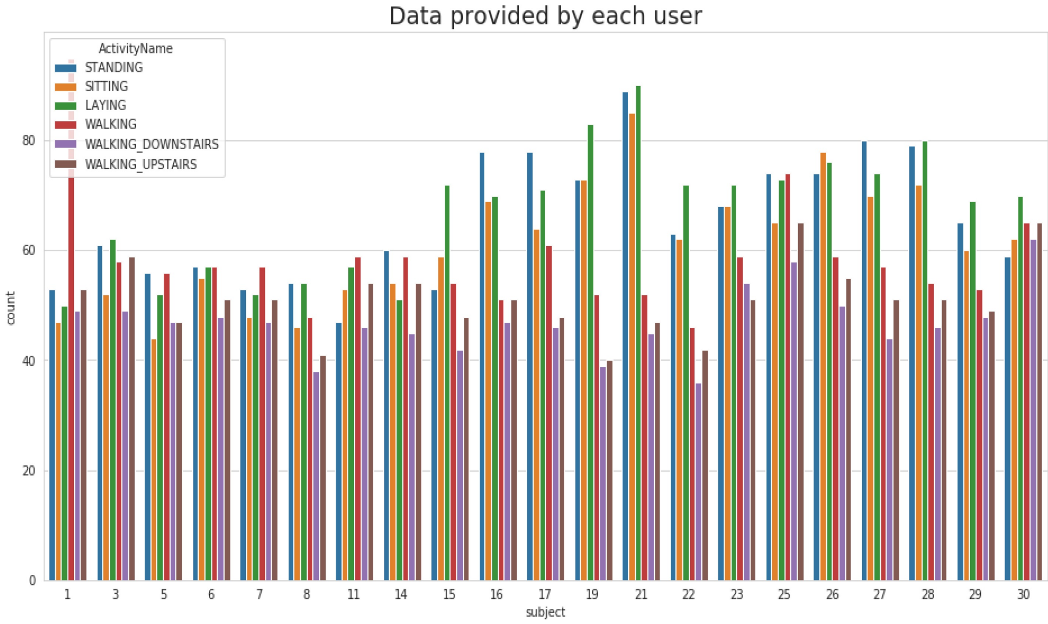

Figure 2: Graphical representation of Data provided by different user.

Table 1: Result achieved for open dataset.

	Accuracy	Precision	Recall	F1-Score
Yen, 2020 [15]	95.99	96.04	95.98	96.01
CNN-GRU	96.79	96.93	96.78	97.82

The Figure 2 describes the different activity recorded by each user which is collected by UCI HAR data. From data we can see that each users provide all kind of activity; thus, there is no issues of data imbalance. The Figure 3 describes the number of data points available for each activity. The Figure 4 shows the relationship between stationary and moving activity. From figure it can be seen for stationary activity the frequency are higher; however on motion the frequency tend to be very small. Similarly, Figure 5 shows the relationship between stationary (zoomed) and moving activity. The Figure 6 defines the acceleration magnitude information of different style and Figure 7 and 8 defines the angle X and angle Y gravity information, respectively. The Figure 9 shows the training and validation loss outcome achieved using CNN-GRU-HAR model. The Figure 10 shows the training and validation accuracies outcome achieved using CNN-GRU-HAR model. The confusion matrix outcome obtained for human activity recognition using CNN-GRU model is shown in Figure 11. The Table 1 show the outcome achived by proposed CNN-GRU based HAR model over existing CNN-based HAR model. From result achived it can be seen the CNN-GRU based HAR model achieves better precision, recall, F1-Score, and accuracies when compared with CNN-based HAR model.

5. Conclusion

Here experiment is conducted to validate the outcome achieved using hybrid framework for human activity recognition with respect to existing HAR model. This model proposes a classification method for activity using the CNN and GRU. This model comprises of a recognition algorithm for the various human activities. This algorithm takes the data from the sensors using the signals of the motion for

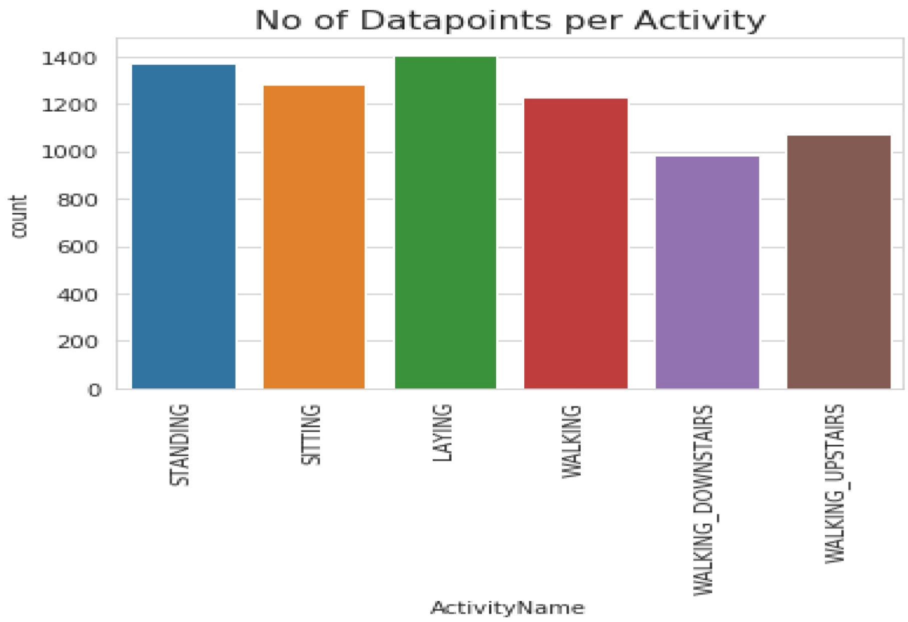

Figure 3: Graphical representation of Data provided for each activity.

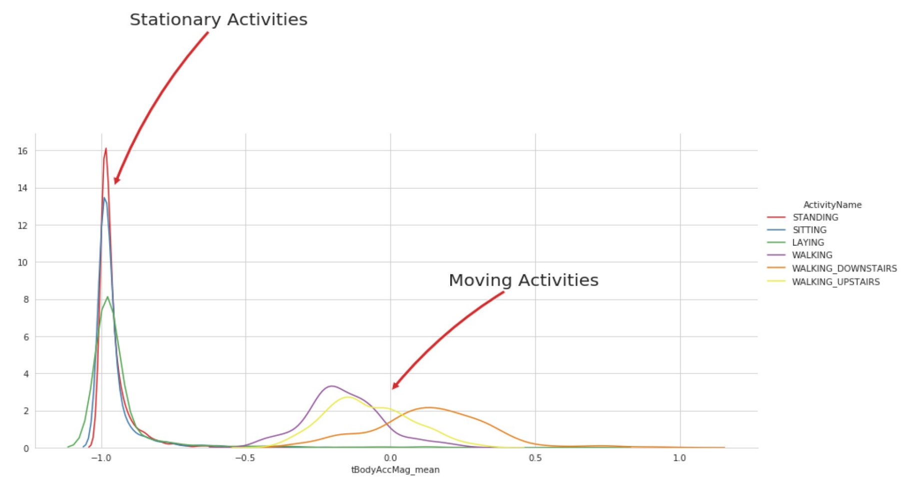

Figure 4: Graphical representation of relationship between stationary and moving activities.

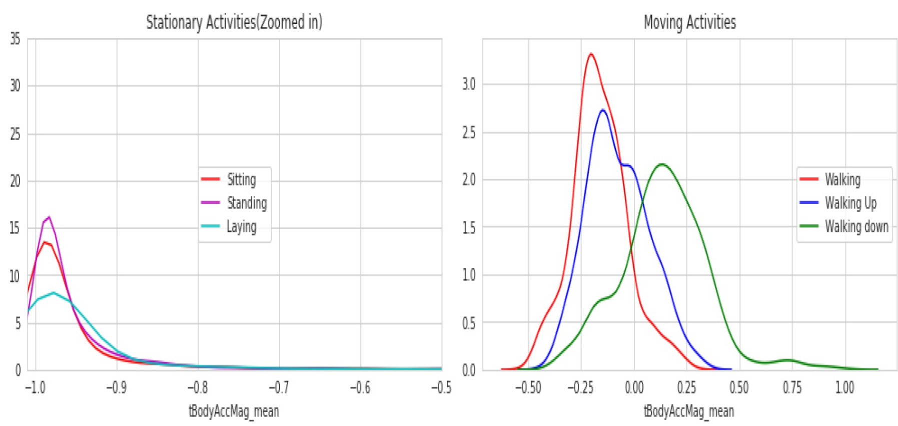

Figure 5: Graphical representation of relationship between stationary and moving activities.

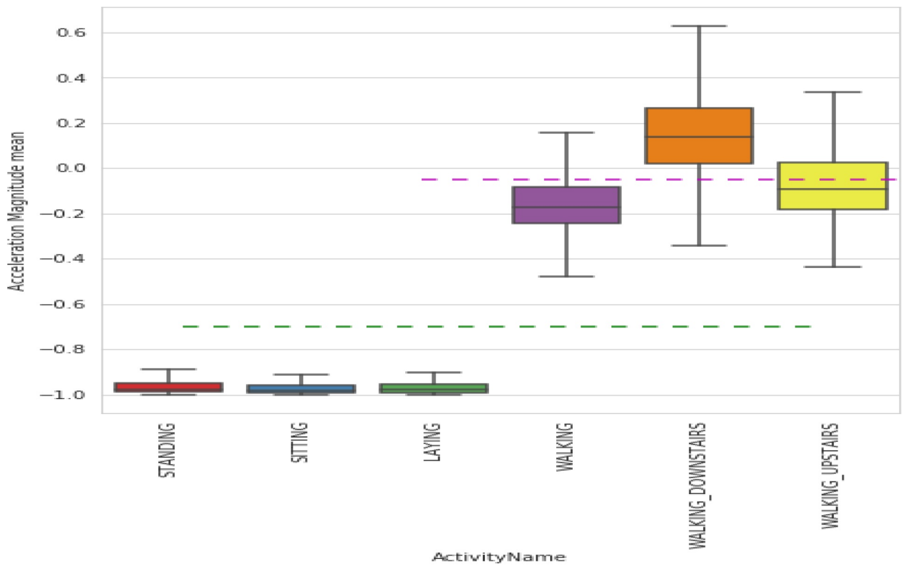

Figure 6: Graphical representation of acceleration magnitude of different activity.

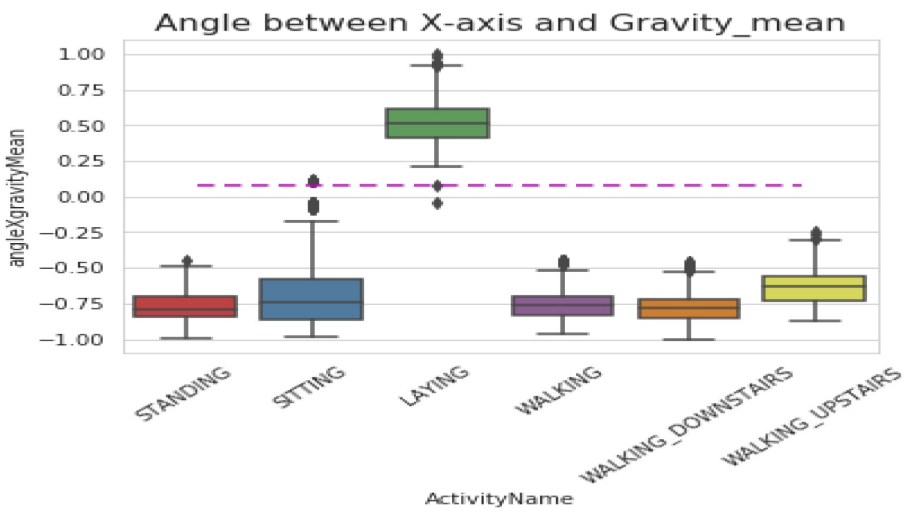

Figure 7: Graphical representation of angle X gravity of different activity.

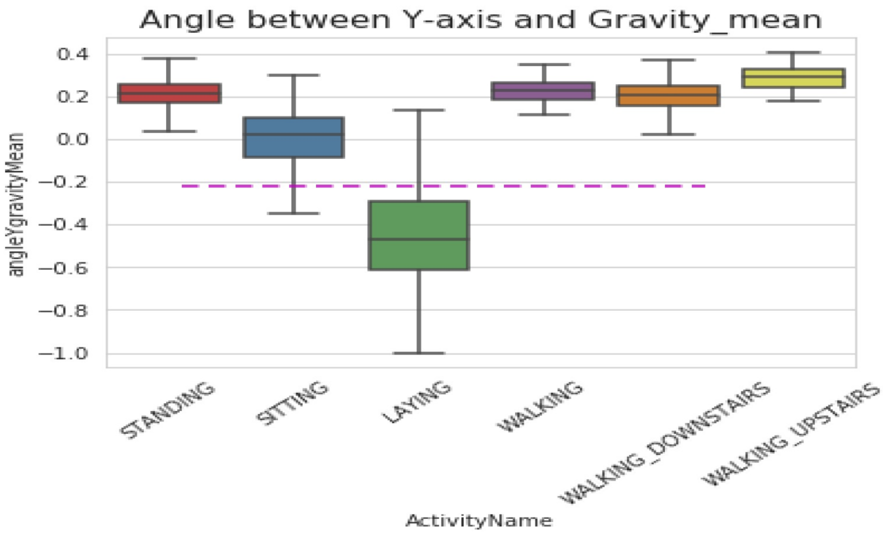

Figure 8: Graphical representation of angle Y gravity of different activity.

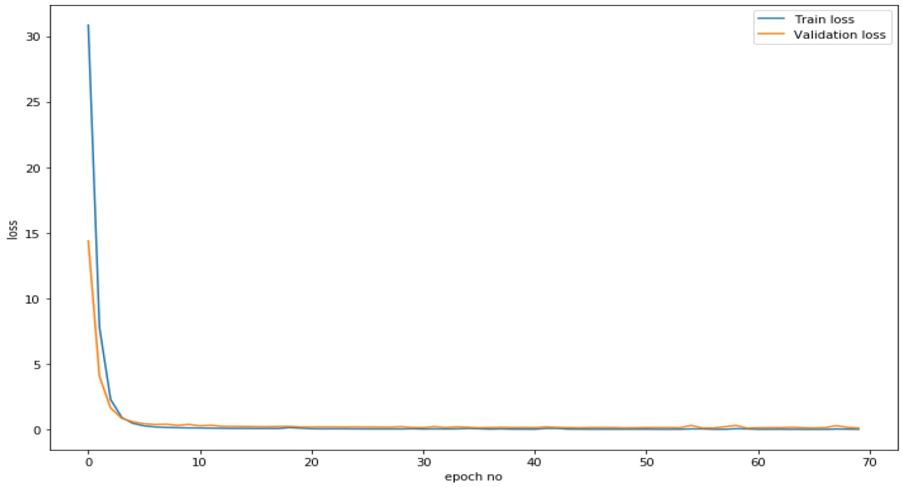

Figure 9: Graphical representation of training loss and validation loss outcome in performing human activity recognition.

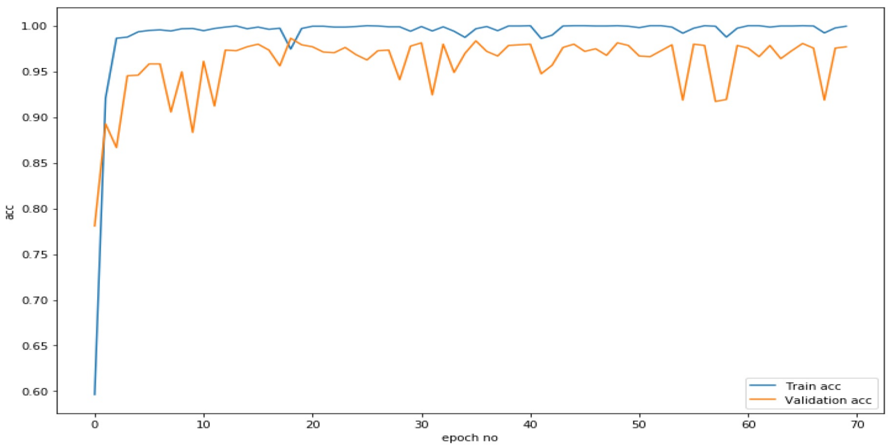

Figure 10: Graphical representation of training accuracies and validation accuracies outcome in performing human activity recognition.

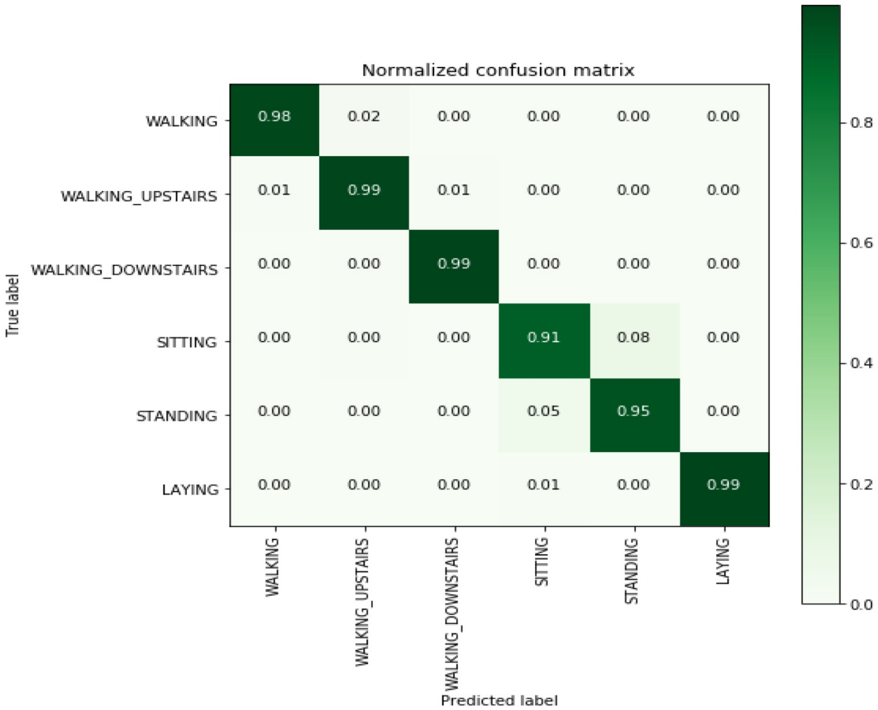

Figure 11: Graphical representation of ROC confusion matrix outcome in performing human activity recognition.

the three-axis acceleration and velocity. All the signals were normalized and then using the CNN-GRU model all the features were extracted automatically to detect the six day-to-day life activities such as walking, sitting, walking downstairs, walking upstairs and lying from the dataset. The overall accuracy of the open UCI dataset achieved using existing CNN-based HAR model is 95.99%, respectively; however, our CNN-GRU HAR model achieves an accuracy of 96.79%. The final results showed that the CNN-GRU HAR model can be used to detect the activities of the human using the sensors. This model can be used for the estimation of the rehab exercises of different individuals who have less mobility, like the patient who undergo the dialysis. The proposed model and the algorithm work efficiently and is feasible. Future work would consider improving performance of proposed HAR detection model considering more diverse dataset. Further, validate the CNN-GRU model for solving regression problems.

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