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Detection of Generalized Tonic Clonic Seizures and Falls in Unconstraint Environment Using Smartphone Accelerometer

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ABSTRACT The detection of Generalized Tonic Clonic Seizures (GTCS) and Falls is of utmost importance due to the increase in prevalence of epilepsy and Sudden Death in Epileptic Patients during CoVID-19 pandemic, and prevention of serious injuries in Fall risk groups such as elderly requiring continuous monitoring for disease management and assisted living etc. Monitoring of Activities of Daily Living (ADLs) can assist in the detection of symptoms and onset of neurological disorders such as Alzheimer's, stroke, and epileptic seizures. With a host of embedded sensors, improved memory, enhanced processing capabilities and availability to masses, smartphones can be used for Human Activity Recognition (HAR) through continuous monitoring of ADLs. This paper presents a tri-axial accelerometer-based approach to detect and classify activities performed by individuals by applying machine learning algorithms including RF, J48, NB, LMT and SVM to movement data. Movement data is collected in real-time from the embedded accelerometer of a smartphone worn by individual on upper-left arm in unconstraint environment. It is pre-processed using time and frequency domain analysis and spatial domain features are computed. Supervised machine learning techniques are applied to classify ADLs into five classes based on the intensity of movements: Stationary, Light Ambulatory, Intense Ambulatory, GTCS and Falls. We also used training data from MyNeuroHealth dataset collected from 23 individuals including epilepsy patients. Based on gathered results, Random Forest outperforms other classifiers with classification accuracy of 99.6% for stationary, 81.5% for light ambulatory, 99.8% for intense ambulatory and GTCS, and 97.2% for Falls corresponding to training data of 14000 samples. To date, activity classification in our system has been implemented on cloud instead of mobile phone application as subjects are using smartphones with dissimilar software and hardware specifications for assisted living applications.

INDEX TERMS Accelerometer, activity recognition, biomedical signal processing, assisted living, machine learning.

I. INTRODUCTION

Human Activity Recognition (HAR) through wearable sensors is gaining attention due to progress in automated feature extraction, classification, mobile and cloud computing for a number of applications [1], [2]. HAR is an ability to interpret human body gesture or motion via sensors such as accelerometer sensors, heart rate monitors and EEG etc. to determine type of activity or action accordingly [3]. HAR is one of the most active research areas with its applications in human computer interaction, healthcare, and security surveillance [4]–[6]. The accuracy of automated HAR is enhanced by using data from environmental and body worn sensors. In environmental sensing, sensors are placed in the surrounding environment of the person. Therefore, the detection of human activity depends on the person's interaction with the sensors. The sensor data can be collected in a constraint environment where the patient is lying or sitting in an idle state under controlled conditions or unconstraint environment i.e., without laboratory conditions, while

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the body worn sensors are attached to the person who is expected to perform different tasks [7]. Sensed data is used to characterize the activities into different classes based on ambulation, orientation, localization, and other appropriate classifications depending on the type and frequency of the activity being performed and recorded [8]. Furthermore, there are different approaches to use body worn sensors, placed in and on different parts of the individual's body; including waist, wrists, and thighs, to achieve a higher level of accuracy. Recently, smartphones are being extensively used to detect human behaviour using the inbuilt sensors like accelerometer, gyroscopes, microphone, proximity, light intensity sensor, and camera, etc. [5], [6].

The main goal of HAR is to have the ability to detect and classify the basic Activities of Daily Living (ADLs) such walking, running, eating, sedentary activities, office work etc. However, it offers a level of difficulty due to sensor motion, its placement, background management, and variations in the way activities are performed by an individual [9]. Monitoring of various ADLs is employed in treating various neurological disorders, detection of Falls and eventually helping to improve quality of life of individuals with various health issues [4], [5]. It is to be noted that several ADLs have common postures and levels of ambulation and it is very difficult to classify these activities correctly. For example, deskwork and having breakfast both require a subject to be in stationary sitting posture. In order to simplify the decision-making process, activities can be grouped together on the basis of movement into stationary class, light ambulatory class, intense ambulatory class, and abnormal class [1]. Data of an individual's body parameters can be extracted using wearables and mobile devices and it can be further processed for the classification of ADLs using machine learning algorithms and deep learning such as Convolutional Neural Network (CNN), K-Nearest Neighbor (KNN), Decision Trees (DT), Pruned Decision tree (J48), Random Forest (RF), Logistic Model Trees (LMT), Bayesian Network (BN), Naïve Bayes (NB), Multilayer Perception (MLP), Instance Based Learning (IBL), and Support Vector Machine Learning (SVM) [9]. Mentioned Machine Learning classifiers and deep learning techniques can be used to improve the classification and detection accuracy of HAR, and abnormal activities including seizure and Fall detection [2], [10].

Random Forest (RF) is a supervised machine learning algorithm employing a large ensemble of decision trees and it can be used for classification and regression problems. Several trees are originated from bootstrapped original data sets. It can easily handle a dataset with a large number of dimensions, and it is suitable for feature selection as it assigns an importance score to every feature based on the best binary split. Accelerometer data with respect to time is highly varying and with reference to [6], [11], [12], a trend is observable that RF is outperforming other classifiers and it is going to perform well for the detection of HAR using accelerometer.

Epilepsy is a neurological disorder that directly affects the nervous system. It is also known as seizure disorder which is diagnosed when a subject experiences one or two unprovoked seizure attacks within 24 hours. Seizures in epilepsy are caused by irregular activity of the electrical pulses of brain or disruption of communication between neurons [13]. It is third most common neurological disease, and more than fifty million people are suffering from epilepsy around the world [14]. Sudden Unexpected Death in Epileptic Patients (SUDEP) is the leading cause of death in patients suffering from epilepsy. It influences individuals of all age groups generally causing SUDEP fatalities (0.3-6) in every one of thousand individuals. In addition, SUDEP is also responsible for 8-12% of deaths in epileptic patients [15]. Epileptic seizures can be classified into motor or non-motor seizures based on the movement intensity such as Generalized Tonic-Clonic Seizures (GTCS) seizures that occur when there is a disturbance in both sides of the brain leading to unconsciousness and a series of jerking movements. Frequency of the GTCS is the most important risk factor for SUDEP [16].

There have been many causes of injuries among elderly and Falls are one of those. Over 64 people suffer at least one Fall per year out of 28% to 35% of the population [17], [18]. Fall incidents are becoming a major health care problem for elderly people with the percentage constantly increasing in the elderly population who live alone. Falls are also the leading cause of deaths for the elderly people who are over 65 years old and the annual incidence is approximately 35% [19], [20]. Falls may have serious consequences, but mostly emergency situations are not directly caused by Falls rather by lack of timely assistance and treatment [21]. Further damage caused by Fall can be prevented by sending an immediate alarm to the caregiver of an elderly person reducing the treatment costs and increasing the recovery opportunities. Therefore, it is of utmost importance and necessity to develop a reliable, convenient, accurate, and automated Fall detection system [22].

GTCS and Fall detection has gained considerable research impetus recently due to prevalence and deployment of e-health care solutions. This topic has become more relevant in the prevailing COVID-19 pandemic as continuous lockdown, monitory, social and societal losses, depression, and anxiety associated with the uncertainty of the pandemic has increased the number of reported emergency instances by neurological patients many folds [23], [24].

It has also been evident that 18-38% COVID-19 sufferers have neurological symptoms [25]. Clinicians do not know how common these neurological effects are. As per a recent report in nature [26], it is expected that 0.4 to 0.2% of the people are to face neurological complications as a result of COVID-19 and given that the current number of infections are of the order of 100 million worldwide, we can expect that between 200,000 and 400,000 people have experienced neurological disorders as a consequence of the pandemic.

Existing research on the automated detection of GTCS and Falls is hampered by lack of customized data sets and classifiers pertaining to unconstraint environments. To the best of our knowledge, no other data set exists in public domain

TABLE 1. Available datasets collected using accelerometer.

Dataset Name	*Activities*	*Instances/Sampling frequency*	*Subjects*	*Environment*
FallAllD [27]	26420 files of Simulated ADLs and Falls	Fs=238Hz	15 participants	Constraint
IoT based assisted human posture recognition [28]	Sitting, standing, and laying	37419 samples	6 participants	Constraint
Activity Recognition from single Chest-Mounted Accelerometer Dataset [29]	7 ADLs, scenarios limited to standing, desk work and walking.	Fs=52Hz	15 participants	Constraint
WISDM [30]	18 ADLs	15630426 samples	51 subjects	Constraint
UmaFall [31]	ADLs and Fall	-	17 subjects	Constraint
Motion Sense Dataset [32]	6 ADLs in 15 trials	Fs=50Hz	24 participants	Constraint
Dataset for ADL recognition with wrist-worn accelerometer dataset [33]	14 ADLs	Fs=32Hz	16 participants	Constraint

which has been collected in an unconstraint environment using wearable sensors to identify the anomalies in ADLs and their long-term manifestation as neurological disorders. In subsequent sections, we explain the basis and feasibility of a method that uses 3D Accelerometer data collected in an unconstraint environment from individuals performing different ADLs. Collected Data is pre-processed using time and frequency domain analysis for observing patterns in ADL classes. Furthermore, the data is used to classify the activities into five categories: stationary, light ambulatory, intense ambulatory, GTCS, and Fall using supervised machine learning classifiers such as J48, RF, LMT, NB, and SVM. These classifiers are implemented and compared to identify the most suitable classifier detection of ADLs, GTCS and Falls. Table 1 shows the summary of available datasets collected using accelerometer, activities performed by the volunteers, samples, number of subjects, and the environment in which the dataset was collected.

II. RELATED WORK

An accelerometer is a device that can detect changes in velocity and directions in x, y and z planes. Since seizures and Fall manifest an abnormal movement of limbs and body among subjects, 3-D accelerometers are used as motion sensors in the detection of motor seizures and Falls. The main challenge is to detect the difference between regular ADLs and abnormal activities. Accelerometers can be used to detect ongoing motor seizures but due to their inherent dependency on the changes in movement, they might generate false classifications in the absence of motor phenomena [7]. For example, a subject experiencing absence seizure might be classified as someone performing stationary activities if the decision is made solely on accelerometer data. A comparison of relevant work done on HAR using wearable sensors based on ADLs, type and placement of sensors, features, classifiers, and classification accuracy is presented in Table 2.

Automatic detection of ADLs, epileptic seizures, and Falls require systems which makes use of certain sensors for the collection of data such as Accelerometer, Electrocardiogram (ECG), Electroencephalogram (EEG), Magnetometers, Photoplethysmography (PPG), etc. These sensors are either employed in unimodal or multi-modal approach for seizure and Fall detection. Video-Electroencephalography technique is considered to be the gold standard for detection of epilepsy and stroke. However, it requires trained technicians to record video-EEG that is reviewed by medical experts for confirmation. Whereas, monitoring systems which use wearable 3D Accelerometer devices detect seizures and Falls efficiently with reasonable accuracy [34], [35]. By analyzing the data with appropriate machine learning classifiers, a seizure and Fall can be detected timely to prevent injuries or sudden death. The known classifiers for HAR and detection of ADLs using 3-axis accelerometer includes Rule-Based machine learning, Decision Trees, Bayes Networks, and SVM [36], [37].

Pannurat *et al.* proposed in [36] that position of wearable sensors does affect the classification accuracy of e-health care system used for the detection of neurological disorders and Ambient Assisted Living (ALL). They investigated the classification accuracy by placing the sensors on ankles, wrist, upper side of arm, thighs, head, chest, waist, waist front and waist side. Furthermore, machine learning techniques such BN, NB, J48, Partial Tree Rule Learning, MLP, IBL, KNN, and SVM were explored. It was concluded that waist side, waist front and chest are the best sensor positions by using NB achieving an accuracy of more than 96% for three mentioned optimal positions. While 1NN perform exceptionally for the sensors placed at thigh and achieved an accuracy of 99%.

In [4], tri-axial accelerometer data is collected from 35 healthy individuals performing ADLs including jumping, lying down, sitting, walking, Falls, etc. Spatial frequency domain features were extracted from the data and a final feature vector was generated as the concatenation of the computed features. The extracted vector was used to train machine learning model for the detection of ADLs and Falls. The classification methods were designed in two different ways; classification into 7 activity classes and binary classification into Fall and No Fall. Supervised machine

TABLE 2. Summary of related work.

Source	*Activities*	*Subjects*	*Sensors*	*Placement*	*Features*	*Classification Algorithms*	*Max. Accuracy*
T. Althobaiti et al. [4]	6 ADLs and Fall	35	Accelerometer	Chest	Frequency Domain	KNN, SVM, LDA, DT	99.05%
A. T. Özdemir et al. [37]	16 ADLs and Fall	14	Accelerometer, Magnetometer, Gyroscope	Head, Chest, Waist, Right wrist, Right thigh, and Right ankle	Time Domain	KNN, LSM, SVM, BDM, DTW, ANN	99%
M. M. Hasan et al. [40]	12 ADLs	-	Smartphone Inertial sensors	-	Frequency and Time Domain	KPCA, LDA, DBN, SVM, ANN	95.85%
C. A. Ronao et al. [1]	7 ADLs	30	Smartphone, Inertial sensors	-	Frequency Domain	CNN	95.75%
S. Kusmakar et al. [41]	5576hr seizure recordings	79	Accelerometer	Wrist	Time Domain	Kernel SVM	95.23%
V. Bojanovsky et al. [42]	ADLs, simulated Falls, and convulsions	15	Smartphone, Smartwatches	Wrist	Time Domain	C4.5 DT	98.5%
A. Gumaei et al. [43]	12 ADLs	10	Motion sensors and ECG	Right wrist, Left ankle, and Chest	Time Domain	Deep SRUs-GRUs neural network model	99.8%
S. Zia et al. [8] [2]	15 ADLs, GTCS and simulated Falls	16	Smartphone Accelerometer	Upper-Arm	Time Domain	NB, RF, ZeroR OneR	99%

learning techniques including KNN, SVM, Linear Discriminant Analysis and DT used for the classification of ADLs and Falls led to a higher classification F1-score of 98.41% for the binary approach instead of multi-class classification approach. Whereas the multi-class approach was proven to be slightly better for Fall detection with a sensitivity of 99.05%.

A trial to detect Tonic Clonic seizures was conducted in [38], tri-axial accelerometers were attached to both wrists of the patients who were undergoing Video-EEG. False Positive Rate (FPR) and sensitivity are used as a performance parameter learned through the Linear Kernel Support Vector Machine (LKSVM), Random Forest (RF) and K-Nearest Neighbors (KNN). KNN performed best by attaining a sensitivity of 100% and RF did well in terms of False Positive Rate (FPR) and attained an FPR of 0.01 FPR/h. Jose R. Villar *et al.* suggested a 3D-accelerometer based non-invasive seizure detection system in [39]. A 3D-accelereometer was placed on the wrist of an epileptic patient for the detection of Myoclonic seizure stimulated movements of upper limb and lower limb. Principal Component Analysis (PCA), Locally Linear Embedding and a distance based PCA are used for extracting features from the collected data. The extracted features are used for training machine learning model using KNN and DT to detect seizures accurately. PCA-based methods outperformed others by achieving the geometric mean of 98.43 %. Table 2 gives a detailed summary of existing methods for detection of ADLs, seizures and Falls.

III. METHODOLOGY

The proposed system uses 3D-accelerometer data collected from the smartphone of the user in order to classify activities into 5 different classes. The data gathered is pre-processed to extract spatial domain features such as mean, variance and standard deviation. The time and frequency domain features help us analyze the trends of various ADLs, Seizures and Falls for further classification of the activities using Machine Learning Classifiers. The proposed methodology for accurate detection of ADLs is presented in Figure 1.

A. DATA COLLECTION

Proposed system includes the collection of data from the user using MyNeuroHealth application. The architecture of the application is presented in [8]. The application uses accelerometer in the mobile device to collect data from the patient's body. It had been noted that as operating systems tend to regulate the sampling rate of embedded accelerometers and these results in nonuniformly sampled data. During data collection we noticed that the operating system changed the sampling rate from 8 samples/sec to 20 samples/sec based on previously recorded acceleration values and the battery power levels. So, the data is pre-processed in real-time to maintain a uniform sampling rate of 15 samples/sec through linear interpolation. The resulting data is stored in a remote database alongside user's mobile device. Using our developed application, we have collected the data for all activities that are listed in the UCI dataset used in [44]. All recorded activities were performed in an unconstraint environment and data is collected by 11 volunteers suffering from neurological disorders and 12 healthy individuals. Collected dataset is available at IEEE DataPort [45] and the comparison of both datasets is given in Table 3. The mobile device was worn by the mentioned 11 patients for a long duration of time and from that we segmented the accelerometer data of ictal state. All volunteers were required to perform ADLs, and they were also asked to simulate Falls while performing various ADLs.

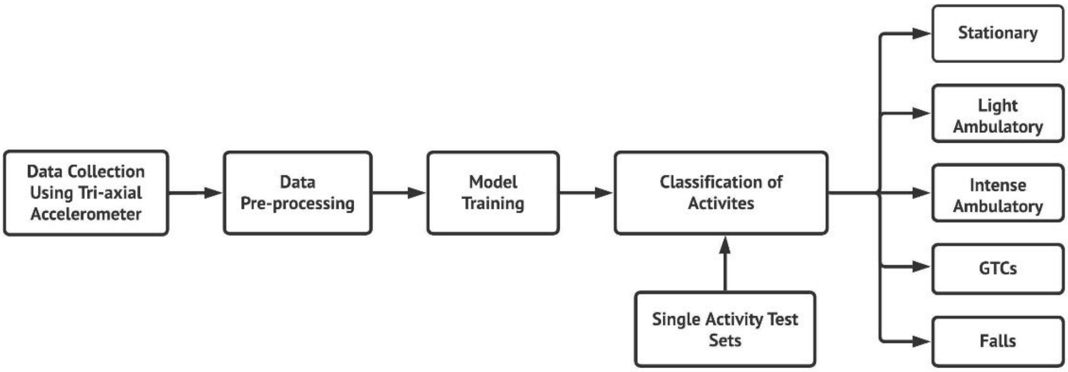

FIGURE 1. Overview of the proposed methodology for detection of activities.

TABLE 3. Summary of datasets [2].

Activity	*UCI Database Sub-Activities*	*MyNeuroHealth Sub-Activities*
Desk Work	-	Writing, Working
Eating/Drinking	Breakfast, Brunch, Coffee, Break, Dinner, Lunch, Snack	Meal
Housework	Cleaning, Tidying Up	*
Meal Preparation	-	Cooking
Movement	Go for a Walk, Go Home, Go to Work	Stairs Up and Down, Laying, Running, Sitting, Standing, Walking
Personal Grooming	-	*
Relaxing	Playing, listen to Music, Watching TV	Watching TV
Shopping	-	*
Socializing	Bar/Disco, Cinema at Home	Watching Movie
Sleeping	-	*
Sports	Basketball, Bicycling, Dancing, Gym, Gymnastics, Ice Hockey, Jogging, Soccer	Jogging, Playing
Transportation	Bicycle, Bus, Car, Motorcycle, Scooter, Skateboard, Train	Bus, Car, Motorcycle
Postures	Climbing (1), Jumping (2), Laying (3), Running (4), Sitting (5), Standing (6), Walking (7)	Stairs Up and Down, Laying, Running, Sitting, Standing, Walking
Abnormal Activities	*	Seizure Attack, Fall

Note: - indicates single activity and * indicates not included

1) PLACEMENT OF THE MOBILE PHONE

The data is collected with the mobile phone placed at the upper-left arm of the individual as represented in Figure 2. The device is placed on upper left arm to avoid any discomfort that may hinder the activity performance as the most stable part of the body is upper torso [46]. The x, y and z acceleration data for a particular activity can also be visualized in Figure 3.

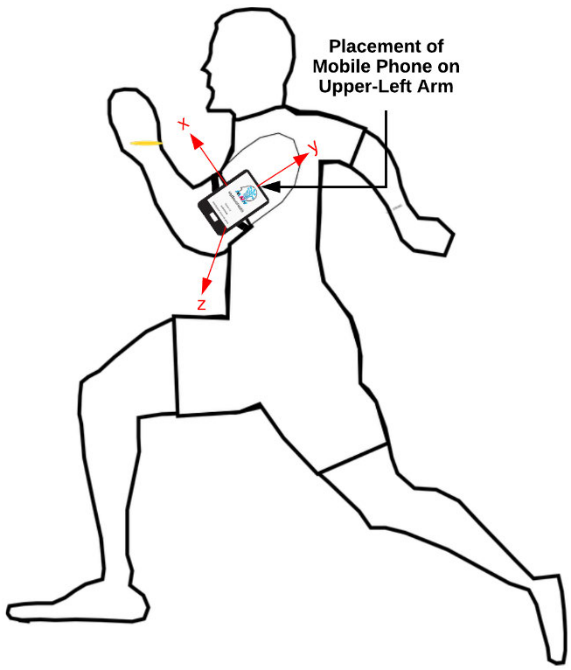

FIGURE 2. Placement of mobile phone for recording of data from the volunteers.

B. DATA PRE-PROCESSING

Abnormalities can be detected by monitoring different patterns of daily activities, seizure attacks and Falls. According to the Table 1, time and frequency domain analysis can be used for pattern recognition and extracting respective features for classification. The recorded 3D accelerometer signal from MyNeuroHealth consisted of a 3-dimensional vector with a sampling frequency of 15Hz, each component corresponding to each of the three axes x, y, and z respectively. The various computed features for the trend detection of ADLs, GTCS and Fall are defined below. Where i is the corresponding x, y and z of accelerometer, n are the samples of the time series and N is 500 which represents the total number of samples of a single ADL.

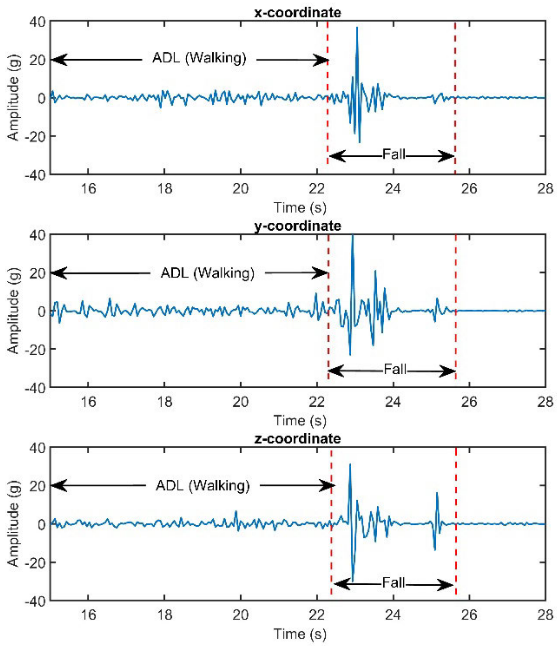

FIGURE 3. Transition of activity from walking to Falling, the red lines represent the segment of Fall with a duration of 3 seconds.

1) MEAN

Mean (μ) of the tri-axial accelerometer is computed using the following equation.

$$\mu \left(Acc_i\right) = \frac{1}{N}\sum_{n=1}^{N} Acc_{i,n} \tag{1}$$

2) VARIANCE

Variance (σ^2) of the tri-axial accelerometer is computed using (2).

$$\sigma^2 \left(Acc_i\right) = \frac{1}{N}\sum_{n=1}^{N} \left(Acc_{i,n} - \mu \left(Acc_i\right)\right)^2 \tag{2}$$

3) STANDARD DEVIATION

Standard deviation (σ) of the tri-axial accelerometer is computed using the following equation.

$$\sigma \left(Acc_i\right) = \sqrt{\frac{1}{N}\sum_{n=1}^{N} \left(Acc_{i,n} - \mu \left(Acc_i\right)\right)^2} \tag{3}$$

4) FREQUENCY ANALYSIS

The signal of each ADL contains some unique dominant frequencies and a magnitude belonging to each frequency. Based on the fundamental frequencies and their magnitudes of a signal, ADLs can be recognized. The data acquired using accelerometer is processed using Fast Fourier Transform (FFT) and respective frequencies are observed.

The thresholds for different activity classes are based on trend detection techniques. The classified activities along with their calculated spatial domain parameters are stored in the remote database and user's mobile devices. The stored data is used for further processing and classification. The instances are further labelled according to four different classes described in [1] and the idea of classification is already presented in [47]. The classification of the activities according to their classes are presented in the Table 4 based on the patterns and intensity of movement involved in each activity.

TABLE 4. Classification of activities [1] [47].

Major Activities	*Sub Classes*	*Accelerometer Data Movement Intensity*
Stationary	Sitting, Breakfast, Writing, Desk Work, Watching TV, Laying, Standing.	Low
Light Ambulatory	Walking, Stairs Up and Down, Riding Bike	Moderate
Intense Ambulatory	Jogging, Running	High
Abnormal	Fall, GTCs	High

5) TRANSITIONAL ACTIVITIES

Given the nature of Fall, it is likely that a subject may encounter Falling while performing ADLs such as working, walking, jogging, or driving etc. The activity will transit from a regular ADL to a Fall as shown in Figure 3. It is necessary to find the epoch of the activity to be extracted and for this purpose resolution of the sensory data can be improved by subtracting data values from its previous index. This can be achieved by using delta modulation [48].

C. MODEL TRAINING AND CLASSIFICATION

UCI dataset and the data collected using MyNeuroHealth is used for model training and further collected activities using MyNeuroHealth are used for real-time testing. As per the sampling rate, each activity contains 500 data samples of x, y, and z acceleration, respectively. The data after pre-processing is used for training three models with increasing the number of samples per activity in training data to achieve the best possible accuracy of detection. The training models are then validated using 10-fold cross validation and further the model is tested against the five classes of activities. Accuracies of training and testing of the data are compared against different machine learning classifiers including RF, NB, LMT, J48 and SVM. The breakdown of the training models is presented in the Table 5.

IV. RESULTS

The data gathered is processed using time and frequency domain analysis to identify a difference in trend between the activity classes. Training models are tested in terms of accuracy of classification for ADLs through Machine Learning Classifiers and tested against each activity as discussed below.

A. TREND DETECTION

Mean, Variance and Standard deviation of the collected data is presented in Table 6. From the table it can be clearly seen

TABLE 5. Breakdown of training datasets.

Sr. No.	Training Data	Activities	No. of Samples
1	4000	Stationary	1000
		Light Ambulatory	1000
		Intense Ambulatory	1000
		GTCS	500
		Fall	500
2	9000	Stationary	2000
		Light Ambulatory	2000
		Intense Ambulatory	2500
		GTCS	1500
		Fall	1000
3	14000	Stationary	3000
		Light Ambulatory	3000
		Intense Ambulatory	4000
		GTCS	2500
		Fall	1500

that Seizure exhibits significant difference in the features with respect to other ADLs. Whereas it is difficult to distinguish between activities that belong to the same class and exhibit similar movement intensity such as stationary class activities of Watching TV and Having Meal have significant correlation. The difference in the trends of different ADLs, GTCs and Falls can be observed by time and frequency domain plots. The results can be observed in Figure 4, characterizing sitting by frequencies between 0 to 1 Hz, Figure 5 shows dominant frequencies of light ambulatory activity i.e., 1 to 2 Hz, Figure 6 shows intense ambulatory can be categorized by the frequency between 2 to 3 Hz, GTCS is characterized by frequencies between 4 Hz to 6 Hz as seen in Figure 7 and Figure 8 shows the time and frequency domain results of Fall with dominant frequencies between 0.5 and 1.5Hz.

B. MODEL TRAINING AND CLASSIFICATION

Data sets obtained from different ADLs are processed in WEKA and machine learning algorithms are applied for classification of activities to achieve maximum accuracy. For further validation of the training models, 10-fold cross

TABLE 6. Spatial domain features of activities.

Sr. No.	ADLs	X_Mean	Y_Mean	Z_Mean	X_Var	Y_Var	Z_Var	X_StD	Y_StD	Z_StD
1	Sitting	0.033902	0.01525	-0.03016	0.02988	0.02625	0.09667	0.17287	0.16201	0.31092
2	Standing	0.012743	-0.0164	-0.00349	0.09981	0.10191	0.0714	0.31593	0.31923	0.26721
3	Walking	-0.08955	-0.4714	-0.01372	0.66312	0.76344	3.22881	0.81432	0.87375	1.79689
4	Riding Bike	-0.04598	0.01784	-0.10194	0.55484	2.13381	0.42903	0.74488	1.46076	0.65501
5	Desk Work	-0.03657	0.03768	-0.03928	0.24762	0.17473	0.19154	0.49761	0.41801	0.43765
6	Driving Car	-0.02447	-0.1624	-0.05942	1.06254	0.59903	1.20034	1.0308	0.77397	1.0956
7	Having Meal	-0.01322	-0.1684	0.090913	0.7548	0.44082	0.78543	0.86879	0.66394	0.88624
8	Jogging	0.371306	-1.2485	0.471634	31.2808	17.4444	93.3526	5.59292	4.17665	9.66192
9	Laying	0.033619	-0.0279	-0.0276	0.03156	0.02635	0.03247	0.17766	0.16232	0.18019
10	Playing	0.085983	-0.0798	-0.36335	1.83262	2.05878	2.48975	1.35374	1.43484	1.57789
11	Running	0.150058	0.20284	-0.15821	3.21795	5.7307	3.74226	1.79387	2.39389	1.93449
12	Seizure	0.290057	-3.0447	0.064862	75.388	22.159	58.1819	8.68263	4.70733	7.62771
13	Stairs	0.006184	0.0585	-0.0751	0.05683	0.08835	0.13031	0.23839	0.29724	0.36098
14	Watching TV	-0.06237	-0.0036	-0.10063	0.12017	0.16931	0.14292	0.34666	0.41147	0.37805
15	Writing	-0.00794	0.00424	-0.00924	0.0793	0.18535	0.08465	0.2816	0.43052	0.29095

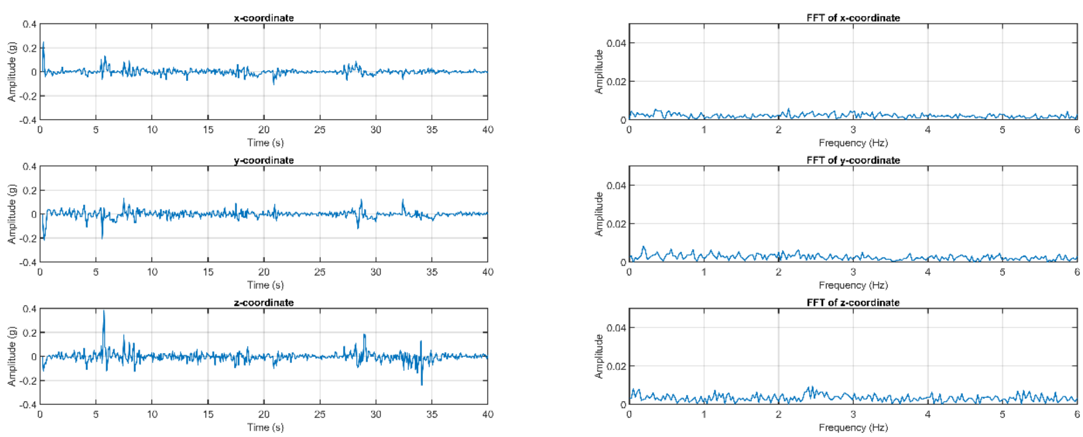

FIGURE 4. Time and Frequency domain representation of stationary activity (sitting).

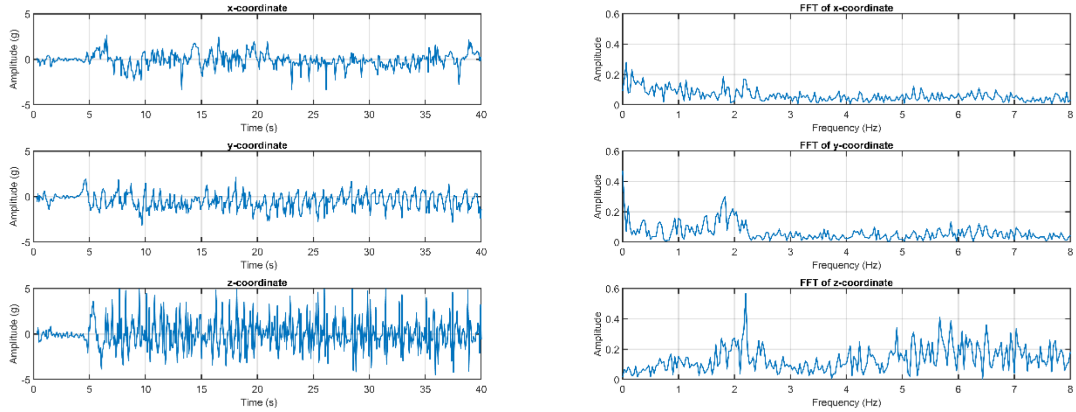

FIGURE 5. Time and Frequency domain representation of light ambulatory activity (stairs up and down).

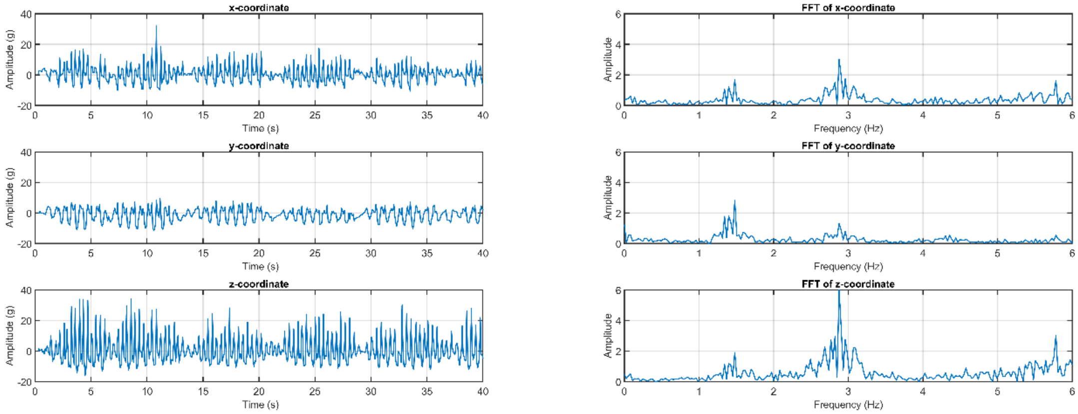

FIGURE 6. Time and Frequency domain representation of intense ambulatory activity (jogging).

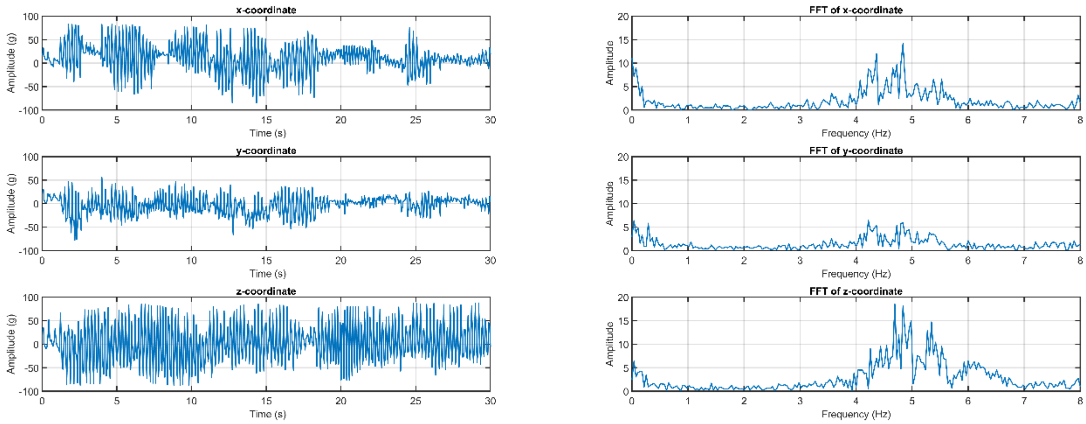

FIGURE 7. Time and Frequency domain representation of GTCS.

validation is applied, and accuracies of different classifiers are compared. Test sets are supplied to the trained model and accuracy of detection of each ADL, GTCs and Fall is computed using different classifiers and a comparison is presented in terms of accuracy of detection.

From Figure 9(a), we conclude that training model accuracy using Random Forest Classier results in 100%. Figure 9(b) shows confusion matrix of 10-fold cross validation of the training data with Random forest classifier, it results in 80% of detection accuracy with a certain overlap

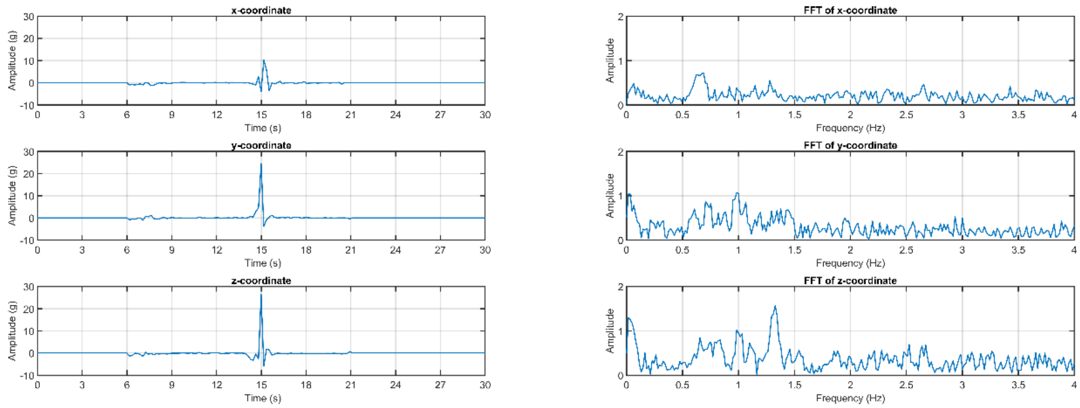

FIGURE 8. Time and Frequency domain representation of Fall.

TABLE 7. Training model accuracies (%).

Training Model/ Classifiers	*4000*	*9000*	*14000*
Random Forest	100	100	100
J48	86.9	85.4556	85.7643
LMT	78.575	80.0556	77.7143
Naïve Bayes	67.45	62.8222	63.5571
SVM	70.9	73.5333	73.6214

TABLE 8. 10-FOLD cross validation accuracies (%).

Training Model/ Classifiers	*4000*	*9000*	*14000*
Random Forest	77.475	76.7	79.75
J48	72.725	72.4667	73.55
LMT	73.3	73.5222	74.0571
Naïve Bayes	67.3	62.8889	63.4643
SVM	68.85	70.8	71.6357

TABLE 9. Machine learning performance metrics (Weighted AVG.).

Classifiers	*Precision*	*Recall*	*F-Measure*
Random Forest	1	1	1
J48	0.858	0.858	0.856
LMT	0.781	0.777	0.775
Naïve Bayes	0.645	0.636	0.631
SVM	0.738	0.736	0.729

TABLE 10. Stationary activity test set.

Training Model/ Classifiers	*4000*	*9000*	*14000*
Random Forest	94.831	94.6322	99.6032
J48	94.2346	92.0477	99.4048
LMT	99.2063	93.6382	97.2222
Naïve Bayes	99.4048	99.6024	99.6024
SVM	99.4048	93.0556	99.6032

of Intense Ambulatory ADL with Light Ambulatory and GTCS has significant overlapping data with Intense ambulatory. In Figure 9(c), we observe the classification of Light Ambulatory has significant overlap with stationary as the movement intensities of both activities are similar at certain data points, this results in difficulty during detection of that ADL and accuracy is affected.

Similarly, the accuracies of the training models presented in Table 5 are computed using RF, J48, LMT, NB and SVM and the summary of Training Models and 10-fold Cross Validation is presented in Table 7 and Table 8, respectively. From the tables it can be observes that as we increase the samples from 9000 to 14000 there is a less significant difference in the accuracies of training models and their validation. Table 9 shows the weighted average of the performance metrics for training model with 14000 samples. The values of precision, recall, and F-measure shows that RF performs better in comparison to other machine learning algorithms used as it classified all instances correctly.

1) SINGLE ACTIVTITY TEST SETS

After validation of training model, each ADL, GTCS and Fall is supplied as a test set to the training model and accuracies are observed corresponding to RF, J48, NB, LMT and SVM. The summary of stationary, light ambulatory, intense ambulatory, GTCS and Fall as a test set is presented in Table 10, 11, 12, 13, and 14 respectively. From the tables, it can be concluded that RF is giving the best accuracy of detection

St.	LA	IA	GTCS	Fall	**Class**
3000	0	0	0	0	St.
0	**3000**	0	0	0	LA
0	0	**4000**	0	0	IA
0	0	0	**2500**	0	GTCS
0	0	0	0	**1500**	Fall

(a)

St.	LA	IA	GTCS	Fall	**Class**
2665	182	32	12	109	St.
129	**2335**	264	55	217	LA
25	339	**3474**	112	50	IA
17	129	529	**1816**	9	GTCS
172	262	140	36	**890**	Fall

(b)

St.	**LA**	IA	GTCS	Fall	**Class**
0	0	0	0	0	St.
27	**380**	7	2	84	**LA**
0	0	**0**	0	0	IA
0	0	0	**0**	0	GTCS
0	0	0	0	**0**	Fall

(c)

FIGURE 9. Confusion matrices for Random Forest Classifier for classification of St. (Stationary), LA (Light Ambulatory), Intense Ambulatory (IA), Falls and GTCS with training model 14000, (a) Training Model, (b) 10-fold cross validation, (c) Test data of LA (walking).

for each of the respective activities and the model with 14000 data samples outperforms the other two in terms of detection accuracy.

TABLE 11. Light ambulatory test set.

Training Model/ Classifiers	***4000***	***9000***	***14000***
Random Forest	81.1508	75.3968	81.5109
J48	71.173	64.2857	78.7276
LMT	79.7217	70.4365	82.505
Naïve Bayes	39.9602	50.9921	54.5635
SVM	44.246	45.6349	52.1825

TABLE 12. Intense ambulatory test set.

Training Model/ Classifiers	***4000***	***9000***	***14000***
Random Forest	60.0398	99.6024	99.8012
J48	61.4314	87.4751	88.0716
LMT	63.8171	72.3108	74.9503
Naïve Bayes	58.0517	71.3718	74.5527
SVM	76.3889	71.627	87.1032

TABLE 13. GTCS Test set.

Training Model/ Classifiers	***4000***	***9000***	***14000***
Random Forest	87.4751	82.5482	99.8016
J48	81.3121	83.499	83.6951
LMT	51.0934	59.841	58.5317
Naïve Bayes	76.3419	62.2266	65.2087
SVM	86.2823	73.7575	78.1312

TABLE 14. Fall activity test set.

Training Model/ Classifiers	***4000***	***9000***	***14000***
Random Forest	52.5794	97.619	97.2222
J48	56.5476	70.2381	75.5952
LMT	47.8175	52.7778	53.7698
Naïve Bayes	25	28.9683	31.746
SVM	18.9	38.2937	40.2311

V. IMPLEMENTED MODEL

Figure 10 shows our implemented system to date. The data is transferred to the cloud for classification of the activities and the results are sent back to the application as subjects were using phones with dissimilar hardware and software specifications as listed in Table 15.

With all the evidence provided earlier regarding the accuracies of classification using various machine learning algorithms, we conclude that a complete health care framework for the detection and classification of GTCS and Falls may be implemented on the mobile phone which can perform in app processing on the sensed accelerometry data with the deployment of our trained model.

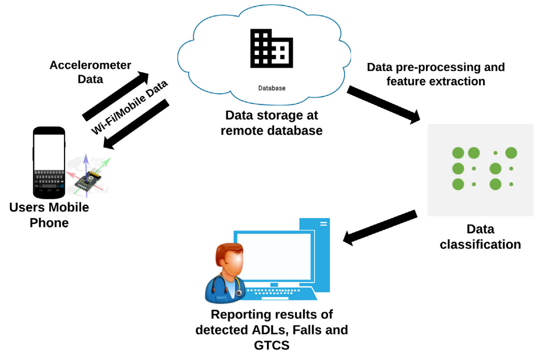

FIGURE 10. A Healthcare Framework for Automated Detection of GTCS and Falls.

TABLE 15. Smartphones used for data collection.

Mobile Phone	*Processor*	*RAM*
Samsung Galaxy A7	1.9 GHz octa-core processor	3GB
Nokia 6.1	2 GHz octa-core processor	3GB
Huawei Honor 5x	Snapdragon 616	2GB
Sony Xperia z3	Quad-core 2.5GHz Krait 400	2GB

VI. CONCLUSION

Smartphone accelerometer can be used for detection and classification of ADLs, GTCS and Falls to prevent any consequences of Fall or seizures leading to death or serious injuries. It is concluded that data from wearable sensors collected in an unconstraint environment, can be used for accurate classification of ADLs and abnormalities leading to neurological disorders. In the work presented, data from MyNeuroHealth application is pre-processed and further classified based on their movement trends. Based on the results of classification of different activities using RF, J48, LMT, NB and SVM classifiers, it is shown that RF performs 16% better than other classifiers for detection of GTCS and 22% in detecting Fall. It is observed that there is a certain overlap between the data points of light ambulatory and stationary activity, and the detection accuracy of light ambulatory is therefore minimum i.e. 81.5109% using RF classifier. Future work includes the integration of RF in MyNeuroHealth app and improvement in the detection accuracies by inclusion of more sensors such as heart rate, EEG, skin conductivity etc. in decision making process and the release of stand-alone application to facilitate patients suffering from neurological disorders.

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