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Title: Unobtrusive monitoring of behavior and movement patterns to detect clinical depression severity level via smartphone

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Ethical approval: This study was approved by the Institutional Review Board of Institute of Allergy and Clinical Immunology of Bangladesh [Ref No: IRBIACIB/CEC/07201803]. Formal informed consent was obtained from participants prior to participating in the study after informing them concerning the details of the nature and purpose of the study, the procedure, and the right to withdraw their data at any time. Anonymity and confidentiality of data were also ensured to all participants.

Regular research paper

Title: Unobtrusive monitoring of behavior and movement patterns to detect clinical depression severity level via smartphone

Abstract:

The number of individuals with mental disorders is increasing and they are commonly found among individuals who avoid social interaction and like to live alone. Amongst such mental health disorders is depression which is both common and serious. The present paper, introduces a method to assess the depression level of an individual using a smartphone by monitoring their daily activities. The time domain characteristics from a smartphone acceleration sensor were used alongside a vector machine algorithm to classify physical activities. Additionally, the geographical location information was clustered using a smartphone GPS sensor to simplify movement patterns. A total of 12 features were extracted from individuals' physical activity and movement patterns and were analyzed alongside their weekly depression scores using the nine-item Patient Health Questionnaire. Using a wrapper feature selection method, a subset of features was selected and applied to a linear regression model to estimate the depression score. The support vector machine algorithm was then used to classify the depression severity level among individuals (absence, moderate, severe) and had an accuracy of 87.2% in severe depression cases which outperformed other classification models including the *k*-nearest neighbor and artificial neural network. This method of identifying depression is a cost-effective solution for long-term use and can monitor individuals for depression without invading their personal space or creating other day-to-day disturbances.

Keywords*:* Depression, Smartphone, Classification, GPS, Acceleration, Daily activities

1. Introduction

Depressive disorders are the most prevalent psychiatric comorbidities in populations among almost all age groups [1]. Depressive disorders can result in mood changes, feelings of guilt, insomnia, loss of appetite, decreased energy, increased fatigability, loss of interest, or enjoyment in day-to-day activities, poor concentration, and increased physical inactivity [2–5]. According to the World Health Organization, 322 million people suffer from depressive disorders. In Bangladesh (where the present study was carried out), over 6 million people are affected [1] and it has been claimed that depression will be the second most burdensome disease across the world by 2020 after ischemic heart disease [5]. In Bangladesh, the depression prevalence rates vary but have been reported as being as high as 65%, which is extreme in world contexts [4,6–8]. However, it is well established that psychiatric disorders (i.e., depressive episodes, anxiety disorders, trauma and stress-related disorders, adjustment disorders, dissociative disorders, etc.) have been suggested as the strongest mediators of suicide, where approximately 90% of suicide victims have at least one mental disorder, and where depression is the main mental health issue. Although there are no specific statistics of suicide and depression in Bangladesh, up to 52% of Bangladeshi people with depression have been reported to be exposed to suicidal behaviors [9,10]. Additionally, Bangladeshi individuals have reported to have a poor literacy status compared to other nations, which is a background factor for increasing the risk of developing depressive episodes and which can act as proximal suicide risk factor [2].

Most mental disorders are treatable by various effective methods (i.e., interpersonal psychotherapy, cognitive-behavioral therapy, clinical management, etc.) [11]. Therefore, the effectiveness of diagnostic tools is paramount in ensuring proper treatment. Although numerous self-report instruments have been evaluated for the diagnosis of depression [12], it can be troublesome to identify respective symptoms alone and use of self-report methods alone can lead to method biases, social desirability biases, and memory recall biases [13]. Furthermore, the high cost of treatment means that individuals in lower and middle-income countries often get less help than they need or no help at all [14]. Furthermore, depressed patients avoid inpatient treatments because they are not willing to persist in longtime supervision for their diagnosis and treatment or try to solve themselves own [15].

Depression is also difficult to monitor on a long-time daily basis because practitioners in some countries need to travel long distances to visit patients [16]. Therefore, a majority of individuals with mental disorders remain untreated, and in some countries fewer than 40% receive stable treatment [15,17]. Consequently, technological interventions (e.g., using smartphones) that monitor depression more effectively without the need to disturb an individual's day-to-day living at a minimal cost could be used. This could be combined with educational materials concerning depression knowledge including self-diagnostic testing [18]. Poor depression knowledge is a silent epidemic in some countries, which mediates as a key barrier for help seeking in mental health issues and founds to be associated with higher levels of stigma, but increased literacy can aid disease care, increase help-seeking behavior, help in the prevention of further complications, and reduce long-term suffering [2,19].

Smartphones have now become an integral part of individuals' daily lives. The number of smartphone users is forecast to grow from 2.1 billion in 2016 to 2.5 billion in 2019, with 36% of the world's population using a smartphone in 2018, up from 10% in 2011 [20]. In Bangladesh (where the present study was conducted), the number of smartphone users was estimated as being 26.8 million in September 2018 ranking 22nd in the world in terms of number of users [21]. Given the smartphone's advanced hardware, software computing capabilities, and powerful sensing tools, the device can be used to monitor health, physical activity, location and direction, and environmental conditions (i.e., detecting temperature, weather, climate, etc.).

Researchers have begun to investigate sensor-based solutions in monitoring individuals who live independently and the technology can extract features of an individual's behavior that can translate into the identification of depressive symptoms [22–27]. The integrating abilities of smartphone sensors can detect depressive symptoms via lassitude, anhedonia, and psychomotor retardation, which are related to physical activities (i.e. walking, running, sleeping etc.) [28], changes in behaviors (e.g., smartphone call patterns such as speech fluency and intonation [29], circadian movement [30], etc.), and social interactions [31]. One study examined psychiatric patients' physical activities via smartphone and monitored smartphone call patterns, acceleration, geographic location data and reported a correlation between mental state change and activities such as walking, running, and sleeping [29]. Another study developed a sensor-based monitoring method for detecting depression severity among the elderly using daily physical activities in their living space [32]. Additionally, a few studies have monitored individual's daily life movement and activities by using mobile GPS to assess the severity of depression [30,33–35]. This passively gathered information is arguably more effective than traditional self-reports because (as already mentioned above) it overcomes a variety of methods biases, social desirability biases, and memory recall biases. The collected data from mobile sensors can easily be used in the management of depression, for continuous diagnostics of at-risk individuals without typical treatment cost [18].

Although a few previous studies have differentiated depressed individuals from non-depressed individuals using smartphone sensors [22,23,29,30,33–35], there is a lack of studies assessing different depression levels (absence, moderate, and severe) [29,32]. Consequently, further study is needed to establish the validity of unobtrusive monitoring of depression levels via smartphone sensors. Therefore, the present study assessed individuals' depression severity levels by tracking their movement patterns (i.e. distance variance, stepping, entropy, transition time, quotidian movement etc.) and physical activities (i.e., exercising, resting, stationary smartphone usage etc.), via individuals' geographic location and acceleration sensor data.

2. **Method**

The present study attempted to develop a model for classifying depression severity level using smartphone sensor information to assess an individual's physical activity behaviors. Figure 1 presents a flowchart describing the development of the system which consisted of four phases. In the data collection phase (Figure 1a**)**, three types of data were collected. From the data collection phase, acceleration and GPS data were filtered as shown in Figure 1b to ensure that all the collected data were evenly sampled without noise. Extracted features from filtered data were then used in the activity recognition phase to detect individuals' activity patterns. The data filter and activity recognition phase are described in the data preprocessing section below. The final depression detection phase extracted features from activities (Figure 1c) which were then used in the regression and classification model to estimate depression scores and depression severity levels (Figure 1d).

2.1 Data collection

Figure 2 summarizes the data collection and storage procedure. Data from 33 participants (19 males and 14 females) were collected focusing on their activity for 11 weeks, resulting in over 2500 days of mobile sensor data from April to June 2018. All the participants were from Dhaka (Bangladesh) and above 18 years of age [mean age=24 years; SD±5). Participants used an *Android*-based smartphone operating system *Lollipop 5.0* or higher which was configured with a *Data Collector* (an *Android* platform-based mobile application). The application can access hardware sensors (i.e., accelerometer, GPS, gyroscope, etc.). The accessible sensor information can be stored on the device and transmitted to the back-end server when data connection becomes available. Physical activity and different types of movement in the present study were calculated by collecting information from the accelerometer and GPS sensor via *Data Collector*. All participants in the present study were instructed to keep their smartphone fully charged and carry it with them at all times.

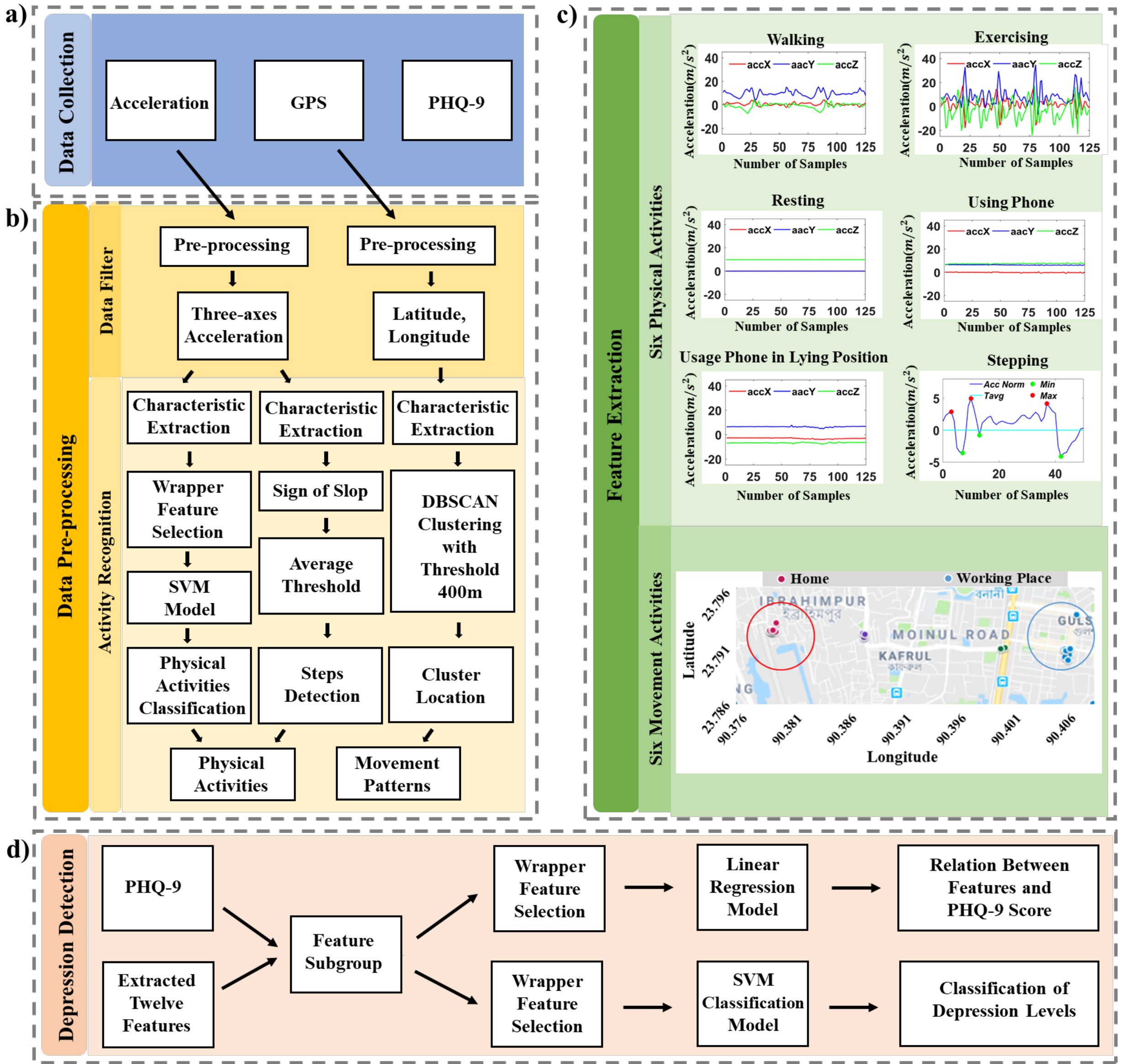

Figure 1. Research flowchart comprising (a) data collection, (b) data pre-processing, (c) feature extraction, and (d) depression detection.

Table 1. Distribution of depression scores

	PHQ-9 < 10	10 ≤ PHQ-9 < 15	PHQ−9 ≥ 15
Participants	24	7	2
Depression Level	Absence	Moderate	Severe
Gender	Ten females; Fourteen males	Three females; Four males	One female; One male
Age, mean±sd (years)	24 ± 4	25 ± 5	24 ± 4
No. of weeks activity recorded	198	64	19

Participants' mental health status in terms of depression was assessed using the nine-item Patient Health Questionnaire (PHQ-9) [36], which was validated into Bangla by Chowdhury et al. [37]. In the present study, the participants depression levels were categorized into three types based on PHQ-9 score: absence of depression (combined score of minimal and mild; PHQ-9 <10), moderate depression (10 ≤ PHQ-9 <15) and severe depression (combined score of moderately severe and severe; PHQ-9 ≥ 15) [36]. Every week, PHQ-9 scores were collected from participants via email prompts or smartphone text messages. Based on the PHQ-9, the distribution of the depression scores for the first week is shown in Table 1. The dataset comprised 281 weeks activity data from 33 participants. However, 82 weeks activity data were excluded because of inadequate information provided by participants, application errors, smartphones being turned off for a long period, and/or data connection problems.

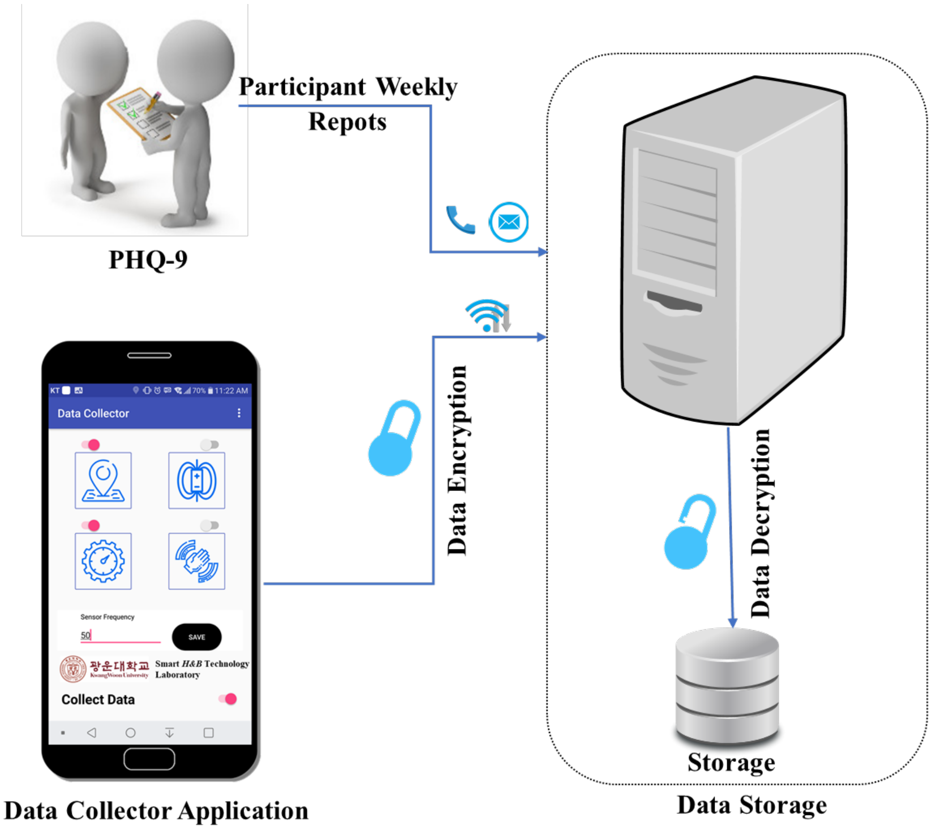

Figure 2. Overview of the data collection process.

2.2 Data preprocessing

In the data preprocessing stage, the objectives were to classify physical activities, detect the number of footsteps, and cluster location for simplifying the extraction of features from recorded phone sensor data. The raw acceleration data was taken at a constant sampling rate 50Hz and the location information was taken at 300 samples per hour. Due to the *Android* operating system power saving mode, the accelerometer and GPS sensor were turned off during the periods of no activity. Therefore, data from the last reported signal from the GPS sensor were retained until new physical activities was performed. This acceleration data sample was fixed at a sampling rate of 50Hz. After sampling, it was preprocessed for noise reduction using two steps. In the first step, a third order low-pass Butterworth filer with a 20Hz cutoff frequency was used to remove unwanted noise spikes due to the acceleration. This is sufficient for capturing body acceleration since 99% of the energy is contained below 15Hz. In the second step, gravitational component was filtered and subtracted from body acceleration data. The gravitational component has low frequency, therefore a third order low-pass Butterworth filter with 0.3Hz cutoff frequency was used for separation [38]. Two types of location data sample were obtained (i.e., participants in a stationary state or in a transition state). The raw location data was filtered with a threshold speed of one kilometer/hour to remove transition state and ensure these data were from the stationary state [30]. The filtered data was not evenly sampled, therefore the data were downsampled at the rate of 15 samples/hour [33].

2.2.1 Classifying physical activities

The acceleration data along with the three axes were used to classify five physical activities. For classifying these physical activities, a classification model was developed using a support vector machine. The classification model used time domain characteristics and these characteristics were extracted from a participant's acceleration data. A fixed-width sliding window of 2.5s seconds (125 samples) was considered enough to calculate the characteristic set for a specific activity. The time domain characteristics extraction process is described in Table 2 where x is the signal, w is the window size, and N is the total data points. A characteristic subset was selected by using the wrapper method for the classification model. The characteristic selection process was discussed above. The overall classification accuracy for activity detection was 99% in the present study.

2.2.2 Detecting footsteps

To identify the participant's number of footsteps, independently filtered acceleration data were used. When participants moved arbitrarily, steps information distributed along three axes. Therefore, the Euclidean norm of the acceleration data was calculated, which represented the movement of all the axes. In order to maximize the accuracy of footstep identification, the present study subtracted the average Euclidean norm with moving window size 20 from the calculated Euclidean norm [39]. It was calculated as follows:

$$A_{acc}(t_i) = E_{acc}(t_i) - \frac{1}{N}\sum_{k=i-N+1}^{i} E_{acc}(t_k) \qquad (1)$$

Where $A_{acc}(t_i)$ filtered Euclidean norm at time t_i, $E_{acc}(t_i)$ Euclidean norm and N was moving windows size.

Participants' footsteps in the Euclidean norm is specified as consisting of a peak alongside its valley. A sign of slope and average threshold was applied on the filtered Euclidean norm data to identify the local maximum and minimum values. A footstep was counted by checking if the condition of the local maximum should come before the local minimum or vice versa. The number of footsteps was defined by counting the number of pairs of the local maximum and local minimum. This model estimated the number of footsteps with an accuracy rate of 99.2%.

Table 2. Acceleration signal time domain characteristics

Feature	Abbr.	Extraction Process
Arithmetic mean	AM	The arithmetic mean is the summation of all the data points of the acceleration signal in the window, divided by the window size N. It is defined as $$AM = \frac{1}{N}\sum_{i=1}^{N} x_i$$
Standard deviation	SD	The standard deviation measures the Variation of the data. It is defined as $$SD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$
Harmonic mean	HM	The harmonic mean of the data is defined as $$HM = (\frac{1}{N}\sum_{i=1}^{N} x_i^{-1})^{-1}$$
Root mean square	RMS	The root mean square is defined as $$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert^2}$$
Skewness	SK	Skewness measures the asymmetry of the data distribution points around the sample mean is defined as $$SK = E\left[(\frac{x-\mu}{SD})^3\right]$$
Kurtosis	KT	Kurtosis measures the tailedness of the data distribution points around the sample mean is defined as $$KT = E\left[(\frac{x-\mu}{SD})^4\right]$$
Willison Amplitude [41]	WA	The Willison Amplitude counts the number of changes in the acceleration sample amplitude that exceeds a predefined threshold and calculated as $$WA = \sum_{i-1}^{N} f(\lvert x_i - x_{i+1}\rvert)$$ $$f(x) = \begin{cases} 1, & if\ x > threshold \\ 0, & otherwise \end{cases}$$
Slope Sign Change [41]	SSC	The Slope Sign Change measures the number of changes sign between positive and negative slope. It is initialized as zero and the slope sign change count increased if $$\{x_i > x_{i-1}\ and\ x_i > x_{i+1}\}\ OR\ \{x_i < x_{i-1}\ and\ x_i < x_{i+1}\}, \quad 1 \le i \le N$$
Count below zero [41,42]	CBZ	The count below zero is the number of times acceleration data crosses below zero and is defined as $$\{x_i < 0\ and\ x_{i+1} > 0\}$$
Entropy of signal [43]	EOS	The entropy of signal is a statistical measure of randomness.
Maximum Value	Max	The maximum value measures the maximum peak value of the acceleration data and is defined as $$Max = \max(x_i)$$

2.2.3 Clustering locations

To identify places (home, workspaces, parks), the density-based spatial clustering of applications with noise (DBSCAN) clustering method [40] was applied to filtered stationary sample data. Here the number of cluster sizes was unknown, and its size was dependent upon the participants' movements. Consequently, DBSCAN was more suitable for clustering participants' locations. Some previous studies have used K-means clustering method with fixed threshold distance [30,33]. However, the present study observed that the DBSCAN method outperformed K-means clustering method. DBSCAN requires two parameters, epsilon (distance between points) and within each cluster a minimum number of cluster points. For considering 400m a threshold distance between clusters, an epsilon of e = 0.4/R (R is the radius of the earth) was used. Five was considered as the minimum number of points for each cluster.

2.3 Feature extraction

A total of 12 features were extracted from participants' classified physical activities, identified footsteps, and clustered location information. The participants' activity features extraction process is shown in Table 3. The distance variance (DV) measures the variability of a participant's GPS location distance. The resting, stepping, walking, exercising, transition time, and staying at home features measures the activeness of each participant. The entropy and normalized entropy calculated the diversity of spending time in each location cluster. The quotidian movement represents the periodical information of the participant's location. A high quotidian movement indicates that participants have a more regular pattern of movement between locations.

2.4 Feature subgroup

Based on the extracted features of days, the present authors recognized that working and non-working day's features have some relationship with their depression scores. Therefore, extracted features were separated into three subgroups (i) baseline, (ii) weekdays, and (iii) weekend days.

$$F_n = \sum_{i=1}^{n} D_i \tag{2}$$

Here, F_n represents the feature subgroup, n is the total number of days depending upon feature subgroups: baseline, n=7; weekdays (Saturday to Thursday), n=6; and weekend day (Friday), n=1. D_i is the *i-th* day features.

Table 3. Participants' activity features

Feature	Abbr.	Extraction process
Distance variance	DV	The authors first considered one starting stationary state location point and then measured other stationary state location points distance compare to the starting point location by using Haversine Formula [44]. Following this, the logarithm of the distance variances was calculated as follows: $a = sin^2(\frac{\Delta\varphi}{2}) + cos\varphi_1 * cos\varphi_2 * sin^2(\frac{\Delta\lambda}{2})$ $c = 2 * a * tan2(\sqrt{a}, \sqrt{(1-a)})$ $distance = r * c$ $\text{DV} = \log(\sigma(distance)) \times N$ Where $\Delta\varphi$ is change in latitude, $\Delta\lambda$ is change in longitude, φ_1 starting latitude, r is the radius of earth approximately 6371 km and N is the number of clusters.
Resting	RE	The amount of time a participant spends during the resting activity.
Using phone	UP	The amount of time a participant interacted with their smartphone.
Phone usage in lying position	PLUP	Phone usage in lying position indicated the amount of time the participant spent using their smartphone in lying situation.
Stepping	ST	Stepping indicated the total number of footsteps a participant made.
Entropy	EN	Entropy of each cluster was calculated using the Shannon entropy formula [43]. It was calculated as: $\text{Entropy} = -\sum_{l}^{N} p_l \, log p_l$ Where l = 1, 2, 3, …., N represented a location cluster, total clusters size N, and p_l represented percentage of the time each participant spent at the location cluster l. Location Cluster percentage of time was calculated by taking the number of samples each cluster and a total number of location samples.
Normalized entropy	NEN	The Normalized Entropy was calculated by dividing the logarithm of the total number of clusters [30]. $\text{Normalized Entropy} = \frac{\text{Entropy}}{log\ N}$ Its value ranges from 0–1, where 0 indicates participant spent all their time in the same cluster and 1 indicates time spent equally in all the clusters.
Walking	WL	The amount of time a participant spent walking.
Exercising		The amount of time a participant spent exercising.
Transition time	TT	Transition time was calculated as the percentage of time the participant spent in a moving state. Transition time measured as the following way: $\text{Transition Time} = \frac{\sum_{i}^{n} T_i}{\sum_{j}^{N} S_j}$ Where i=1,…….., n is the transition state GPS samples and j=1 ……. N represent respectively all GPS samples.
Staying at home	HS	Staying at home is considered a participant's total percentage of time spent in home relative to the other places. Every participant's home location points previously known and according to this location we identified which the cluster represented the participant's home. The percentage was calculated by taking a total number of samples in the home cluster.
Quotidian movement	QM	Quotidian Movement calculates the sequence of location's information followed the circadian (*circa* = about, and *dia* = day) cycle. Lomb-Scargle periodogram was used [45] on GPS location to obtain the spectrum and then we calculated each cluster energy within a 24±0.5-hour cycle [30] followed as: $E = \sum_{i=1}^{N} \frac{psd(f_i)}{(N)}$ $\text{Quotidian Movement} = \log(E_{lat} + E_{lon})$ Where i= 1, ..., N represents the range of frequency bins in between 24.5 and 23.5 hours, psd represent power spectral density, f frequency bin. After that, quotidian move obtained by calculating separately logarithm of the latitude and longitude power spectral density.

2.5 Feature selection

Feature selection is a method to select an optimal feature subset from all feature sets which improves classification performance with less complexity and computational cost. Therefore, feature selection can be used for better performance as a preprocessing tool prior to the classification problem. Features were selected using a wrapper feature selection method [46,47] of physical activities' classification model, depression severity regression, and the classification model. Regression and a classification algorithm were used to evaluate the selected features performance after tenfold cross-validation of the data. Regression model features were selected using root mean square deviation (RMSD) of the PHQ-9 score estimation. The physical activity classification model and depression severity classification algorithm feature subset were selected using a genetic algorithm. This method increases the performance of the classifier and also prevents the problem of overfitting.

2.6 PHQ-9 score estimation

The PHQ-9 score was taken at the outset of the study and represented the participant's depression severity. The present study observed each extracted feature had some correlation with depression symptoms that can differentiate participants as having depression or not. The PHQ-9 score was estimated by using a linear regression model [48] on extracted features. The standard linear regression model was used:

$$\widehat{D_i} = \beta_0 + \beta_1 f_1 + \beta_2 f_2 + \cdots + \beta_n f_n \tag{3}$$

Where $\widehat{D_i}$ is the estimated PHQ-9 score for i participants, f_n is the n number of features, and where $\beta_0, \beta_1, \ldots, \beta_n$ is the coefficient of the linear regression model. To minimize the error between the estimation score and the true PHQ-9 score for high dimensional features, the lasso regularization [49] was used. This prevents the regression model coefficient becoming too large. The lasso regularization performed well in the model because all the features had strong correlations.

2.7 Depression severity level classification

Depression was classified into three levels (Table 1) and for observing the classification performance, three popular classification algorithms Support Vector Machine (SVM), *K*-nearest neighbor (KNN), and Artificial Neural Network (ANN) were considered.

2.7.1 Support vector machine (SVM)

The support vector machine [50] is a widely used machine learning technique for classification and regression. It constructs a complex model as simply as possible so that it can be easily analyzed mathematically. SVM takes less computing time to detect a hyperplane in an N-dimensional space (N being the number of features) that individually classifies the data. The present study used a sequential minimal optimization (SMO) algorithm with the polynomial kernel to optimize the SVM classifier model. SVM was considered for handling the problem of overfitting of high-dimensional data.

2.7.2 K-nearest neighbor (KNN)

The *K*-nearest neighbor classifier [51] is mostly used a model-free classifier, whose learning approach is instance-based. The classification of the data is calculated according to the labels of the class of neighboring instances. The KNN classifier assigns the parameter of k and the best number of k depends upon the data. The larger number of k minimizes the effect of noise, but makes boundaries between classes less remarkable. In the present study, leave-one-out cross-validation was applied to identify the best one for the classification. Class was determined by using the weighted voting scheme [52], where closer neighbor instances have a higher weight.

2.7.3 Artificial neural network (ANN)

Artificial neural networks [53] are an interconnected assembly of preprocessing simple feed-forward elements of node networks that iteratively learn a set of weights to predict the class label. This feedforward network consists of three layers: an input layer, a hidden layer, and an output layer. There are a total ten hidden layers placed between the input and output layer. The input layer features data multiplied by weights W, which is learned iteratively from the training set data. The error was minimized by adjusting the weight using gradient descent. Initially, the present study considered weights value randomly with a learning rate of 0.1 and a total of 100 iterations were used to minimize error.

2.8 Model validation and evaluation

The linear regression model and classification model were evaluated by using the leave-one-out cross-validation (LOOCV) method. To validate the model, a participants' weekly label data were used for testing, and the remaining participants' weekly label data were used for training the model. This process was repeated for every participant to achieve the overall result. In relation to detecting depression severity levels (where the classes were not equally distributed), the data samples of one class were clearly more than the data samples of other classes, therefore the training [I changed 'tanning' to 'training'. Is this correct?] data were synthesized by subsampling the over-represented (majority) class that applied to the leave-one-out cross-validation method. To calculate the error between the estimated score ($\widehat{D_i}$) and true score (D), root mean square deviations (RMSDs) were used. The RMSD value defined the model performance, and was calculated as follows:

$$\mathrm{RMSD} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(D - \widehat{D_i})^2} \tag{4}$$

The present study evaluated each classification model sensitivity, specificity, F1-Score, accuracy, and receiver operating characteristic (ROC). In general, the high value of sensitivity, specificity, F1-Score, accuracy, and ROC indicated that the classification algorithm performed well in identifying depression. The ROC, which plots the values of the false positive rate (FPR) and true positive rate (TPR) together in a diagram, is represented as a single parameter to measure the performance of the classifier.

3. Results

3.1 PHQ-9 score prediction

Considering participants' activities, 12 features were extracted and divided into three subgroups. Each feature corresponding depression score was estimated individually using a linear regression model. According to the depression levels' score, three groups were categorized (absence [PHQ9<10], moderate [10≤PHQ9<15], and severe [PHQ9≥15]) [36]. Each subgroup's feature data distribution had a relationship with depression symptoms. The baseline subgroup features data distribution according to the depression severity are shown in Figure 3. This demonstrates that the data distribution median between depression levels has a clear deference in most of the features. It was also found that seven features (distance variance, resting, phone usage in lying position, stepping, normalized entropy, exercising, and staying home) had a high correlation with depression symptoms.

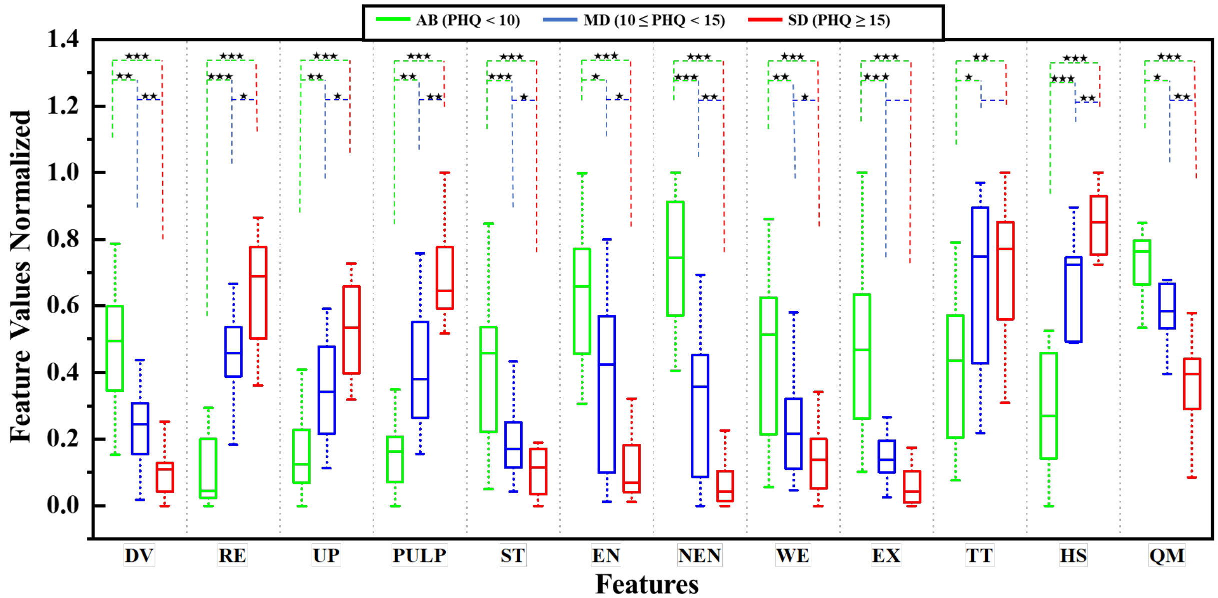

Figure 3. The distribution of values of the base subgroup features according to the three different depression levels: absence (green), moderate (blue), and severe (red). Features values were normalized between 0 to 1 and the inter-quartile range (IQR) in the box between 25% and 75%. The median line 50% of the features values falls between lower 25% to upper 75%. Here, the asterisks indicate the significance of the correlation coefficient between depression level and feature respectively: one asterisk = $p<0.05$, two asterisks = $p<0.01$, and three asterisks = $p<0.001$.

The relationship between the regression model estimated PHQ-9 score and actual score is shown in Table 4. The relationship was evaluated using RMSD. The error was minimized using the lasso regularization method as discussed above. In Table 4 each of the feature results are calculated by using leave one out cross validation. Table 4 shows the smallest RMSD for the weekday resting feature and staying at home weekend feature using a linear regression model. Among 36 features from three subgroups (base, weekday and weekend), a subset was selected by using the wrapper feature selection method and showed lowest RMSD of 3.256. This demonstrated that the predicted PHQ-9 score had stronger correlations with the actual PHQ-9 score.

Table 4. Error rate between actual and estimated score

Feature	Base subgroup (RMSD)	Weekday subgroup (RMSD)	Weekend subgroup (RMSD)	Wrapper selected features (RMSD)
DV	4.201[a]	4.377[c]	4.417[c]	3.256
RE	4.321[c]	4.125[a]	4.258[a]	
UP	4.568[b]	4.441[c]	4.305[c]	
PULP	4.364[c]	4.321[c]	4.205[a]	
ST	4.445[c]	4.328[c]	4.253[a]	
EN	4.808[b]	4.568[b]	4.303[c]	
NEN	4.341[c]	4.257[a]	4.311[c]	
WL	4.463[c]	4.415[c]	4.210[a]	
RU	4.312[c]	4.339[c]	4.303[c]	
TT	5.046[b]	4.774[b]	4.625[b]	
HS	4.106[a]	4.258[a]	3.984[a]	
QM	4.418[c]	4.372[c]	4.205[a]	

Note: RMSD value range was divided into three groups and indicated by: a $<$ 4.3, 4.3 ≤ c < 4.5, and b ≥4.5

3.2 Depression level detection

In terms of the three depression levels – (i) absence, (ii) moderate, and (iii) severe – the classification algorithm results are shown in Table 5, where classification performance was demonstrated by showing the results of accuracy and top classifiers highlighted in bold. In Table 5 high sensitivity, as well as high specificity, and high F1-Score represented a good detection algorithm. Depression level identification was difficult due to data imbalance. In Table 5, and based on the accuracy results, it shows that SVM generally outperformed other classification algorithms. On average, SVM showed better performance in identification of three levels of depression level because of the overfitting of data. ANN showed better performance than the other two algorithms in identifying absence (no signs of depression), but in severe and moderate depression, SVM predicted well with high accuracy. Overall, SVM performed well on all three depression levels.

Table 5. Summary of classification results

Severity Level	Classifier	Sensitivity	Specificity	F1-Score	Accuracy
Absence of depression	SVM	94.2	82.2	93.8	91.9
	KNN	92.2	80.5	91.9	89.3
	ANN	95.8	84.6	94.2	**92.5**
Moderate depression	SVM	76.8	86.3	82.1	**83.8**
	KNN	68.9	89.2	69.7	80.9
	ANN	72.9	82.9	65.8	74.8
Severe depression	SVM	84.3	89.7	91.4	**87.2**
	KNN	69.5	84.6	87.8	82.5
	ANN	76.7	91.5	90.3	85.4

The performance of the SVM classifier using the receiver operating characteristic (ROC) curves is shown in Figure 4. As shown in Figure 4a, by considering absence of depression as a negative test sample, the ROC curve in terms of depression level reached a maximum true positive rate of approximately: (i) 80% for moderate depression, and (ii) 83% for severe depression. Figure 4b summarizes the comparative ROC results under the SVM classifier with and without the feature selection method. Considering the standard SVM without feature selection method, the performance of the SVM for detecting depressed (PHQ−9 $\geq$ 10) and non-depressed (PHQ-9 < 10) participants shown in Figure 4b, the ROC curve shows that it is possible to reach approximately 83.4% identification of depressed and non-depressed participants. On the other hand, the SVM classifier of an eight-feature subset was selected using a genetic algorithm (GA) and outperformed the performance in detection depression and non-depression with more than 84% of ROC. Although the number of features of the standard SVM classifier is more than the GA-SVM classifier, the ROC value is low and has high computational cost.

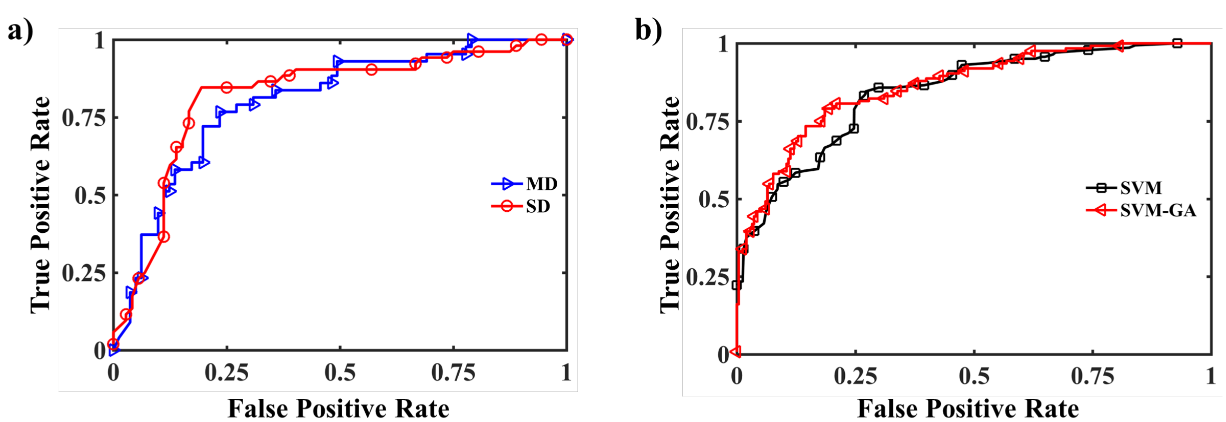

Figure 4. (a) The ROC curve demonstrates the performance of the classification of each depression level. (The blue curve (moderate depression) shows lower performance, while the red (severe depression) has a better result.) **(b)** The plot on the right shows the performance of SVM classifier under feature selection genetic algorithm (GA) method.

4. **Discussion**

The present study used geographical data and acceleration data to extract information about participants' behaviors and mobility patterns. To improve model performance, 'leave-one-out cross-validation' was used, where all the features for a participant were used for testing while the model was trained on the features of the rest participants. The model was able to detect three different depression levels (i.e., absence, moderate, and severe) with 86.4% accuracy. Extracted features from sensor data showed a strong correlation with PHQ-9 score, and was found in the regression model. Higher levels of depression severity strongly correlated with less distance variance from any starting point, greater resting time, greater time using the phone in a lying position, fewer footsteps, less normalized entropy, less exercising, and greater staying at home. This passively sensing platform was able to differentiate participants who had depression or not with an accuracy rate of 92%, which was higher than in previous studies that recorded accuracy rates of 85% [30] and 86% [33].

The study by Grunerbl et al. [29] was based on individuals living in a hospital where participants' movements were limited and used three types of data (GPS, acceleration, and phone call patterns) for detecting mental state change, whereas the studies by Saeb et al. [30] and Palminus et al. [33] used participants' GPS data for differentiating whether the individual was depressed or not. Other studies have also developed unobtrusive monitoring of daily living activity techniques using smartphone sensors [54–56]. In these studies, less physical activity, less exercise, and resting were typical symptoms of clinically depressive disorders [2,5]. Research has also demonstrated that greater regular exercise and physical activities have a positive effect on reducing mood disorders and anxiety symptoms [57]. In the present study, the resting feature on the smartphone assessed the participants' activity levels throughout the day. High resting patterns were indicative of higher depression symptoms among participants.

It has been reported by the Pew Research Center [58] that teenagers spend more than one-third of their day using a smartphone and like to stay at home [59]. For a small minority, excessive smartphone use can be potentially addictive alongside comorbid symptoms such as depression, stress, anxiety, and sleep disturbances [60,61]. Based on the self-medication hypothesis [62], technological addictions (i.e., non-chemical addictions that involve excessive human-machine interact) [63] such as smartphone addiction, gaming addiction, and internet addiction appear to be associated with an individual's attempts to 'self-treat' their stress, anxiety, depression etc. [64–66]. Therefore, the use of smartphones in respect to coping with depression is noteworthy. However, in the present study, the smartphone usage data, especially the use of smartphones while lying down demonstrated a strong correlation with depression severity, which is similar to previous study [67].

In the present study, the use of the wrapper method made the model stronger in achieving higher accuracy classification performance between each depression level (absence, moderate, and severe). To evaluate the classification performance, the present study used three popular classification algorithms: SVM, ANN, and KNN. Differentiating moderate depression from absence of depression and severe depression is a challenging task, and SVM only showed better accuracy in detecting moderate depression (83.8%). The KNN classifier showed the second-best accuracy in identifying moderate depression (80.9%) and the ANN showed better performance in identifying absence of depression (92.5%).

Limitations: Although the model in the present study predicted depression severity level with high accuracy there are some limitations to take into account when interpreting the results. The study did not assess a clinically depressed population because the sample only comprised students and the assessment used to assess depression was a self-report scale (i.e., the PHQ-9) rather than a clinical assessment. Staying in a single place for a considerable amount of time was one of the key behavioral predictors of depression, but non-depressed individuals may also stay in one place for long periods of time for educational and/or occupational purposes. Furthermore, some individuals may not have followed all the instructions all the time (e.g., forgetting to carry the smartphone in the left-hand side of their front pocket during activities alongside the fact that women do not always have pockets in their clothing, forgetting to keep their smartphone charged, switching off the phone due to lack of power etc.) which would lead to data errors. Additionally, smartphones are not always carried by individuals. Those dependent upon their smartphones are more likely to have their smartphones with them wherever they are compared to those less dependent. Consequently, the geographical location may not have been as accurate as it could have been.

5. Conclusions

Although the smartphone sensor system in the present study has some limitations, the present study demonstrated the capability to passively detect depression symptoms by monitoring day-to-day activities and behavior patterns. Given that the detection of depression level is not dependent on traditional self-report psychometric instruments, such a method may improve the identification of depression. As smartphones have become an integral part of individuals' daily lives, such mobile devices can be used as a way of collecting data with little effort on the part of the smartphone user. For those with mental health issues, the earlier they can be detected, the better the chance of recovery [34]. Therefore, the system described in the present paper can examine the totality of the data not just at specific stages. Furthermore, adding a wrist band fitness tracker device in future studies would act as an additional external source of data collection to that of the smartphone and would lead to an even higher level of data accuracy.

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