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Predicting Depressive Symptoms in Students using Smartphone-based Sensor Data

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Abstract To predict depression or mental health using smartphone-based sensor data is an ongoing research problem in the domain of mobile health (mHealth). We have created a scale, Depression Severity Index (DSI) to measure the level of depressive symptom of a set of students using their responses to the Patient Health Questionnaire 9 (PHQ9) and Perceived Stress Scale (PSS). A secondary dataset of 48 college students collected over a 10-week period from the study StudentLife is used. It comprises smartphone-based global positioning system (GPS) data and various survey data on personality, depression, loneliness, sleep quality, stress etc. Further, we have developed two predictive model one using logistic regression and other using K-Nearest Neighbour (KNN) classifier to predict depressive symptom severity in the students based on the characteristics of their movement as derived from the GPS data. Depressive symptom severity is estimated from their responses to the survey questionnaire. The prediction result is validated using k-fold cross-validation method. The results show that the characteristics of their movements are significantly correlated with their mental health scores like PHQ9, and PSS. The findings in this study are consistent with those reported in the literature. It points to a novel application of the smartphone sensor data to develop an early warning system for mental health issues.

Keywords Ubiquitous sensing, mHealth, Depression, Prediction, Classification, Students

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1. Introduction

Depression is distressing and disturbing. Prevalence of depression is rising. It is posing an enormous burden in terms of cost, morbidity, and mortality [9]. The prevalence of depression is on the rise worldwide. More than 300 million people are suffering from depression[1]. India is witnessing an increasing number of cases of depression, hypertension, stress, and suicide among adults and suicide have become a major mortality burden in India[14, 15]. The prevalence rate of hypertension for the adult population in urban India stood at 33% [5].

Depression is a common disorder and is treatable but the major problem is its early detection and a proper treatment follow up[6]. Primary healthcare centers often do not offer professional screening of depression and patients remain disillusioned with their medical condition[6]. Upon self-screening, the patient may relate their condition to mental health disorder and visit the psychiatric department. The treatment cycle is generally large and

most patient does not end-up follow complete treatment cycle[6]. The absence of policy and proper infrastructure makes the treatment availability even harder[5].
Indeed, to start the treatment and follow up, healthcare system relies completely on the patient themselves. On the other hand, a patient with depression feels hopeless, helpless, confused, unmotivated, and stigmatized which makes it even more difficult for them to present themselves for treatment. Therefore, whole process ends-up with poor results on the detection and treatment of patients and poor healthcare delivery by the healthcare system[13].
As mentioned that detection of depression remains critical in treating the problem, a ubiquitous device like a smartphone can be a useful tool in detecting depression. A mobile phone is perhaps the most ubiquitous sensing device a person carries with him. Further, its penetration among the population is ever increasing. Today, the smartphone is equipped with a wide variety of sensors that can sense various facets of a person's daily living like activity, mobility, sociability, web-usage, app-usage etc. Detecting behavioral patterns using mobile phone based sensor is a cutting-edge research domain [2, 3, 10, 11, 12, 13]. It can detect a wide range of daily-living behaviors which is an indicator of person's social, psychological and physiological behaviors. Therefore, a mobile phone based platform to detect depression could help in its management by allowing continuous and ubiquitous diagnosis of people who have and are at risk of having depression.
According to American Psychiatric Association, 2013, depression can be characterized by loss of interest and pleasure in most activities[4]. However, detecting depression from mobile phone sensor data is not easy. Daily behaviors like activity or sociability or sleep patterns are directly observable from the sensor data. But, depression is a more complex phenomenon. There is no sensor which can directly predict depression. The challenge is to extract features from various daily behavior that can enable the prediction of depression. These characteristics might be reflected in day-to-day behaviors like activity, sociability, sleep-pattern, mobility etc. Therefore, it is likely to develop mechanisms to extract features from daily behavior which can act as a predictor of depression.
Some studies have been done in which the features like location variance, circadian movement, entropy, number of location cluster etc. are derived from GPS data [18]. We extended a previous study[17] which deliberated the possibility to predict depressive symptom severity using correlation analysis of smartphone based geographic location (GPS) data features and Patient Health Questionnaire 9 (PHQ9). In an another study, correlation between these GPS data features and PHQ9 is carried out and results in quite strong correlation [17]. However, to confidently predict depression from these features is still in the naïve stage. Correlation with an only single survey like PHQ9 may not consider as the only prominent option. We should also consider other survey data like stress, sleep quality, loneliness etc. in addition to PHQ9 to study correlation with sensor data. In this study, two predictive models have been developed. To develop these models, logistic regression classification and KNN classification methods have been used. We created two classes i.e. Normal and Depressed and based on the values of features derived from GPS data a subject is classified into one of the two class. Our findings are consistent with those reported in the literature and indicates towards a novel application of mobile phone sensor to predict depressive symptom severity.

2. Methodology

2.1. Data

The data in this study is obtained from a study known as StudentLife[19]. The data was collected passively using a ubiquitous smartphone sensing system from the students of a class of Darthmouth College, USA. There were 48 number of undergraduate and graduate students participated in this study for a period of 10 weeks. Gender-wise, 38 participants were male and 10 were female. The study was approved by the Institutional review board at Darthmouth College, USA. Any type of mental health condition was not considered to enroll participants in the study. All the participants completed the psychological survey like PHQ9, PSS, Loneliness, and PSQI. In addition, there was automatically collected data using smartphone which include physical activity, conversation, GPS, phone-charge, phone lock etc. The frequency of GPS data was once in every 5 minutes collected for a period of 10 weeks. The GPS data contains two variables i.e. latitude and longitude position along with a timestamp. The psychological surveys as mentioned previously were conducted before the start of the study and at the end of the study.

2.2. Description of Survey Items used in the study

2.2.1. Patient Health Questionnaire 9 (PHQ9) [14] It is an instrument to screen the existence and severity of depression by using a questionnaire consist of 9-questions. The PHQ9 score can range from 0 to 27. Each of the 9 questions can be scored from 0 (not at all) to 3 (every day). The results of the PHQ-9 can be used to diagnose depression as per DSM-IV criteria. It takes less than 3 minutes to complete.

2.2.2. Perceived Stress Scale (PSS) [8] This measure is used to find individual stress level. It measures the degree of a stressful situation in one's life.

2.3. Depressive Severity Index (DSI)

In previous studies[18, 17], only PHQ 9 survey response is considered to find correlation of depressive symptom with that of GPS data features. The predictive model developed in a study [18] also considered only PHQ9 to classify the depressive or normal state of subjects. In this study, we first conducted a correlation between all the survey items which in some way are the marker of unhealthy psychological states like PHQ9, PSS, Loneliness, PSQI, and Panas_Negative. The results are shown in Table 1. The results in the table are sorted as higher correlation coefficient to lower. The correlation coefficient between PHQ9 and PSS is very significant which indicated the closeness between the two markers of depressive symptom severity. But, PHQ9 describes the mental health of an individual based on several factors such as hopeless feeling, least interest in doing things, over/under sleeping etc., on the other hand, PSS captures the stress level of an individual. Since PHQ9 doesn't consider stress level of the individual, we have created another scale (DSI) using PHQ9 and PSS together. We first normalized both the survey items in the range of 0 to 1. Since PHQ9 captures more depressive factors so it has been given more weightage as compared to PSS which only captures stress level of the individual. The DSI is calculated as:

$$DSI = 0.75 * PHQ9_{Normalized} + 0.25 * PSS_{Normalized}$$

$$The\,two\,classes\,of\,depression\,based\,on\,DSI\,are\,defined\,as:$$

$$\mathit{Normal};\ \mathit{if}\ \mathit{DSI} \leq 0.30\ \mathit{and}\ \mathit{Depressive};\ \mathit{if}\ \mathit{DSI} > 0.30$$

2.4. Characterizing the Movement of Individual

The movement characteristics of individual are derived from GPS data which have been adopted from the study by saeb et. al. [17]. They have derived 11 features from the GPS data namely, Location variance, Circadian movement, Speed mean, Speed variance, Total distance, Number of clusters, Entropy, Normalized entropy, Raw entropy, Home stay, and Transition time. Since this is a work in progress we are only including three features in this study to develop the classification model. These are Location variance, Number of clusters, and Entropy. Furthermore, these are the only features which have shown a good correlation with PHQ9 in the literature. Selecting these features for further analysis makes a valid argument. The details of the selected features are as follows:

Table 1: Correlation between various survey item

Correlation Study	Corr. Coeff. (r)
PHQ9 vs Percieved Stress	0.54
PHQ9 vs PSQI	0.43
Loneliness vs Percieved Stress	0.38
PHQ9 vs Lonelines	0.38
Percieved Stress vs PSQI	0.35
Panas_Neg vs Percieved Stress	0.20
PHQ9 vs Panas_Neg	0.18
Loneliness vs PSQI	0.11
Panas_Neg vs PSQI	0.06
Loneliness vs Panas_neg	0.02

2.4.1. Location Variance As defined in the baseline, location variance measures the variability in the respondents GPS location. Only stationary state location data have been used. Location variance is defined as:

$$Location\ Variance = log(\sigma_{lat}^2 + \sigma_{long}^2) \quad where\ \sigma_{lat}^2\ \&\ \sigma_{long}^2$$

$$are\ the\ variance\ of\ latitude\ and\ longitude\ respectively$$

The logarithm is applied to compensate for the skewness in the distribution of location variance across participants.

2.4.2. Number of Cluster The k-means clustering algorithm has been used to find the total number of location cluster. The stationary location data is used while applying clustering algorithm. A distance based version of k-means clustering algorithm has been used[2]. To define a cluster, we set a threshold distance of 500 meters as the diameter of the cluster.

2.4.3. Entropy According to Information theory, entropy is the expected value of the information contained in each message in relation to the importance of the message. Here, entropy measures how each participant's time was distributed over different location clusters. It is defined as:

$$Entropy = -\Sigma_{n=1}^{n} p_i log(p_i),$$

$$where\ p_i\ is\ the\ percentage\ of\ time\ spent\ at\ location\ i,\ and$$

$$n\ is\ the\ total\ number\ of\ location\ clusters.$$

3. Results

3.1. Logistic Regression Model

In this model, movement features derived from the GPS data is used to predict the depression class of individuals. DSI is the dependent variable and features derived from GPS data like location variance, number of cluster, and entropy are the independent variables. We made four logistic regression models for classification of respondent based on DSI. One is aggregated of all the three features and other three models considering each feature individually. Since a small dataset with only 45 students is used to develop the classification model, k-fold cross validation method is used to estimate the goodness of fit of our model. The results of the classification models with their evaluation based on several parameters of the goodness of fit are depicted in Table 2.

Table 2: Estimation of Logistic Regression prediction model based on DSI and movement features of GPS aggregated and individually

Model	Mean Accuracy (SD)	Mean Precision (SD)	Mean Recall (SD)	Mean f1 Score (SD)
All Features	0.770 (0.145)	0.770 (0.128)	0.975 (0.075)	0.855 (0.094)
Loc. Var.	0.750 (0.153)	0.755 (0.138)	0.975 (0.075)	0.845 (0.099)
No. of Cluster	0.696 (0.067)	0.696 (0.067)	1.000 (0.000)	0.819 (0.483)
Entropy	0.696 (0.067)	0.696 (0.067)	1.000 (0.000)	0.819 (0.048)

Table 3: Estimation of KNN prediction model based on DSI and movement features of GPS aggregated and individually

Model	Mean Accuracy (SD)	Mean Precision (SD)	Mean Recall (SD)	Mean f1 Score (SD)
All Features	0.696 (0.130)	0.713 (0.114)	0.966 (0.100)	0.814 (0.087)
Loc. Var.	0.646 (0.096)	0.680 (0.062)	0.933 (0.133)	0.781 (0.072)
No. of Cluster	0.596 (0.146)	0.655 (0.077)	0.866 (0.221)	0.735 (0.130)
Entropy	0.526 (0.173)	0.620 (0.091)	0.766 (0.260)	0.671 (0.159)

3.2. KNN Classification Model

To have a comparative ground to compare the classification of DSI using movement features of GPS data, we further developed a classification model using KNN classification method. The results of estimation of this classification model is given in Table 3.

3.3. Performance Evaluation Measures

In this study, four measures are used to evaluate the models, they are:

3.3.1. Accuracy

$$Accuracy = (TP + TN)/(TP + TN + FP + FN)$$

3.3.2. Recall

$$Recall = (TP)/(TP + FN)$$

3.3.3. Precision

$$Precision = (TP)/(TP + FP)$$

(Note: TP, TN, FP and FN denotes true positives, true negatives, false positives and false negatives, respectively)

3.3.4. RMSD The Root Mean Sqaure Deviation (RMSD) signifies the sample standard deviation of the differences between predicted values and observed values.

4. Discussions

This was a preliminary work to predict depressive symptom severity using movement features of GPS data like location variance, number of location cluster, entropy collected via smartphone. These features have shown a significant correlation with PHQ9 in the literature. In this study, we further included the PSS survey response along with PHQ9 and developed a depressive severity index which scales the depression level of individual from normal depression to severe depression. This index accounts various depressive symptoms as gathered via PHQ9, in addition also account the stress level of the individual. Considering

DSI as a dependent variable and movement features of GPS as the independent variables, a classification model is developed using logistic regression classification method and KNN classification method. Our results indicate that logistic regression classifier outperforms the KNN classifier. The accuracy in logistic regression is 77% when the model is built using all the three features combined. The accuracy of 77% is encouraging, considering the smaller sample size. The classifier may result in better accuracy on a larger sample size. Furthermore, the accuracy in both models (LR and KNN) using location variance as the feature vector are 75% and 64.6% respectively which indicates that the location variance of an individual can be a good marker to predict their depressive symptom severity. Still, due to limiting the size of the data nothing can be stated confidently. A further analysis on a larger data set is required as a future direction. Further, other smartphone based feature can also be included like sociability, app usage pattern, physical activity, sleep pattern to develop a more robust model of depression prediction.

5. Conclusion

In the presented work, two classifiers are developed to predict the depression using smartphone based sensor data. In this work, only some movement features of students are derived from their smartphone-based GPS data. The features are used to build the model. There are more features which have been reported in the literature could also be used in future. In addition, the smartphone provides a range of sensor data which captures various aspects of daily life of individuals. These sensor data could be used to derive the physical activity, sleep, mobility, and sociability behaviors. These behaviors are the first-hand markers of the overall well-being of the individuals. They can be utilized to build models of early prediction of an anomaly in mental and physical health. In this paper, we presented our work in progress in this direction. Further analysis on more features in addition to GPS data and on a larger sample size could result in more fruitful findings. These can be used in developing an early warning system for mental as well as physical health issues.

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