UTM UNIVERSITI TEKNOLOGI MALAYSIA
INTERNATIONAL JOURNAL OF INNOVATIVE COMPUTING
ISSN 2180-4370
Journal Homepage : https://ijic.utm.my/

Scrutiny of Mental Depression through Smartphone Sensors Using Machine Learning Approaches

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Submitted: 22/04/2020. Revised edition: 18/05/2020. Accepted: 18/05/2020. Published online: 20/05/2020
DOI: https://doi.org/10.11113/ijic.v10n1.259

***Abstract*—In addition to a variety of exceptional sensors, Smartphones now facilitates vigorous open entries in data mining and machine learning to scrutinize the Human Activity Recognition (HAR) system. The follow-up to the treatment of diseases, HAR monitoring system, can be used to recognize mental depression that until now has been overlooked for HAR applications. In this scrutinize, Smartphone sensor data were collected in the 1 Hz frequency from 20 data subjects of different ages. We drove the HAR by using basic machine learning strategies, namely Support Vector Machine, Random Forest, K-Nearest Neighbors, and Artificial Neural Network to recognize physical activities which are associated with mental depression. Random Forest outperformed to recognize daily patterns of activities with 99.80% accuracy of the validation data set. Along with, sensors data was amassed regarding the activities performed over the most recent 14 days continuously from target subjects' Smartphone. This data was fed to the optimized Random Forest model and quantified the duration of each symptomatic activity of mental depression. Here, a push was connected to figure the risk factor for the probability that an individual has been encountering mental depression. So, a questionnaire was surveyed to collect data from 50 patients who were suffering from mental depression. The questionnaire enquires for the duration of activities related to mental depression. Then, the similarity of these experimental subjects' activity pattern was measured with those of 50 depressed patients. Finally, data was collected from target subjects' and applied similarity approach to induce the relation between the target subjects' and depressed patients. Average similarity value of 90.94% for the depressed subject and 34.99% of the non-depressed subject justifies that this robust system was able to achieve a good performance in terms of measurement of risk factors.**

***Keywords*—Human Activity Recognition, Mental Depression, Smartphone sensors, Cosine Similarity, Depressive Symptomatic Activities**

I. INTRODUCTION

Nowadays, mental depression is a typical global disease that raised a strain of society. The statistics indicate that around 450 million people suffer due to the lack of early stages and proper treatment [1]. The worst is that depression contributes to suicide; each year, around 800,000 people committed suicide due to mental depression [2]. Researchers have found that mental depression has a colossal association with physical exercises. Many studies brought to light that people are not physically active, suffer from mental depression [3]. Not only a simple physical exercises but also there are alike manner various activities which gets a normal impact on headway of mental depression.

These days modern technologies lead us to a world that makes things easier for us; Smartphones are one such technology. Versatile advancements, specifically mobile sensing Smartphones, have the potential to conquer downsides with conventional psychological wellness appraisal and give more plenteous constant data about patients' daily patterns of activities, way of life, and manifestations. Perceiving human activities with a device or system is presently known as Human Activity Recognition (HAR). The HAR has a combination of employments; for instance, it might be used to figure the movement counts of an individual, computerized activity-observing framework, suspicious activity recognition, and so on. There could be various relevance of HAR, which are yet to be displayed. Diagnosis of chronic diseases and mental disorders are one of such perfect applications. There are different contaminations, which are genuinely associated with the proposed system works out, for instance, Diabetes, Mental Depression, Insomnia, Cardiovascular disease, Cancer, and so forth [4].

In this work, it is endeavored to improve the utilization of Smartphone sensors to lead the affirmation of physical activities which are directly or indirectly associated with mental depression. In the first phase of this scrutinize, tri-axial accelerometer and tri-axial gyroscope sensor were used to collect data from 20 data subjects of different ages in the 1 Hz frequency. To accomplish the first phase, at first, some activities were chosen which were positively associated with the depressive symptoms which were walking, sitting, lying, jogging, cycling, eating, drinking, speaking communication, and sleeping. Following, the activities which are regularly performed by an ordinary person were identified. An Android application was used for this data collection purpose. Forasmuch as an Android application was used to collect data, so there might be software issues which could generate erroneous data. The Smartphone also might get stuck up due to performance overload, which could also be responsible for generating null values. Therefore, several preprocessing techniques were applied such as checking for null values, checking outliers by box plot and replacing outliers by mean, normalizing the dataset with min-max normalization technique and then, Butterworth Low Pass filter for generating a smooth signal to overcome and eliminate these faulty instances.

Here, basic machine learning approaches such as Support Vector Machines (SVM), Random Forest (RF), K-Nearest Neighbors (K-NN) and Artificial Neural Network (ANN) were deployed to perceive symptomatic activities. RF outperformed to recognize daily patterns of activities with 99.80% accuracy of the validation dataset. RF has been the strongest of all classifiers to identifying the symptomatic activities, and RF was used as our prepared framework for further predicting the activities of target subjects. Together with the Android application, Smartphone sensor data was collected from the target subjects. Data from sensors involving activities was carried out on an ongoing basis over the last 14 days. Sensor Data was collected from target subjects' Smartphone; those data were preprocessed using the mentioned hereof preprocessing techniques and made those ready for predicting the activities performed by target subjects performed in last 14 days. For each subject, data was fed into a pre-trained classifier that was optimized RF model and predicted the activities. After classifying all the instances for each subject, it was measured how much time each target subject spent in performing each symptomatic activity.

To know about the activities of depressed patients, a questionnaire was surveyed to collect depressed patients' daily activity pattern data. The principal purpose of data accumulation about depressive symptoms is to find out the duration of performing our mentioned symptomatic activities. It was tried to know that how much time a patient is suffering from a depressive disorder spend in performing symptomatic activities. The purpose of recording the durations was for correlating subjects' daily activities with the durations.

In the last phase, the risk factor was figured for the probability of an individual has been encountering mental depression and applied Cosine Similarity approach to induce the relation of daily activities in between the target subject and depressive patients'. Applying the Cosine similarity method, the average similarity value was found for depressed and normal subjects. There were two target subjects for this experiment. The system diagnosed one target subject as depressed and another one as non-depressed based on the measured similarity of daily activity patterns of target subjects' activity and depressive patients'. The depressed subjects diagnosed as depressed and the non-depressed subject as well balanced. Doctors also diagnosed the target subjects as a prediction of the suppositional system. Interestingly, a targeted subject that doctor diagnosed as depressed, this system showed high similarity value for that subject. And, other target subject diagnosed as well balanced by a doctor for that this system inaugurates low similarity value.

II. Related WOrks

There is vast number of researchers who are chipping away at HAR utilizing Smartphone sensors and wearable sensors. In the medical services field constant observing of physiological parameters, human activities as well as abnormal activities is conceivable without admitting in clinics through savvy wearable sensors [5]. Edwards [6] utilized wireless sensors for precise observing patients' brain activity, muscle movement, temperature, pulse, and other basic information. Moreover, Yatani and Truong [7] built up a wearable acoustic sensor, named BodyScope with the F-measure of Support Vector Machines classification of 12 exercises utilizing just BodyScope they gained 79.5% precision.

Smartphone is a multipurpose gadget that can do numerous assignments simultaneously. Researchers perceived 10 human activities, such as jogging, walking, lying, walking upstairs and downstairs, sitting, squatting in the toilet, standing, cycling and fallen down with the assistance of gyroscope sensor, humidity sensor, accelerometer sensor and temperature sensor data from 3 subjects in 1 Hz frequencies [8-12]. In addition, an Android application was developed for gathering accelerometer, gyroscope, temperature and relative humidity sensors data [9]. They included some uncommon activities like fallen down and squatting in the toilet, which was perceived with a higher precision.

In the era of Smartphones, Shelke and Aksanli [13] displayed an ease and low vitality keen space which can perceive static and dynamic human activities that requires basic movement. They prepared dataset with six machine learning algorithms such as Decision Tree, Logistic Regression, Support Vector Machine, Random Forest, Artificial Neural Network and Naive Bayes. However, Bayat, e*t al.* [14] proposed a framework which comprises a digital low pass signal for disengaging the segment of gravity acceleration up from body acceleration of raw data. They trained and tested the framework on numerous people in real-world conditions. Utilizing statistical features, they tried a few classifiers. They obtained huge exactness of 91.15%. Designed an activity recognition system which uses tri-axial accelerometer [15]. Authors have classified the activities utilizing 4 machine learning classifiers i.e. K-NN, ANN, SVMs and Quadratic Classifier. During subset determination and feature extraction dimensionality reduction is performed. The framework's procession arrives at 84.4%.

Depression is a state or temperament when individuals feel low [16], this state influences the individuals so seriously that they can't think appropriately, changes their conduct and in some extreme cases make them self-destructive. Besides, Hosseinifard, *et al.* [17] ordered depression patients from the ordinary subjects by contemplating the exhibition of various classifiers. They utilized power spectrum of frequency band alpha, beta, theta and the entire groups of EEG as features. For feature selection, they used Support Vector Machine (SVM) characterization system utilizing Genetic Algorithm where precision was 88.6% on ordering depression patients. Likewise, Alghowinem, *et al.* [18] gathered data from 60 genuine subjects. They analyzed three classifiers, Support Vector Machines, Gaussian Mixture Model and Multilayer Perceptron just as Hierarchical Fuzzy Signature classifier. Gaussian Mixture Model and Support Vector Machines gave the best classification results. Contrasting decision fusion, score, and feature, score fusion performed better for Gaussian Mixture Model, Hierarchical Fuzzy Signature and Multilayer Perceptron, while choice combination worked best for Support Vector Machine.

Tacconi, *et al.* [19] proposed a structure that helps semi-automation identification of mental sickness determination. Besides, Matic, *et al.* [20] employed self-rating questionnaire for revealing day by day state of mind varieties of activities. Also, Tacconi, *et al.* [21] proposed an idea utilizing activity recognition and setting mindful association to automate the bipolar issue. Utilizing Hamilton Depression Scale, known as HAMD and Bech-Rafaelsen Mania scale explicit conduct were recognized that should be identified by the proposed framework.

Based on previous studies of associations among human activities with mental illness and fostering of the HAR, our research objective is selected stressing that HAR should carry any potential performance improvements. Lower power consumption is regarded as a very significant necessity in modern technology. Moreover, the data amassment process conducted with a frequency of 1 Hz. Furthermore, to make HAR process more versatile, data regarding activities was amassed by putting the subjects in different situations such as walking in some market or crowded place, jogging in roads or parks with a number of changes in directions, lying in different positions, sitting at different places. Data also collected with residing the Smartphone in different positions so as to diminish the problem regarding different positions of Smartphone in pockets. In addition, since the classifier was trained with a huge number of instances, it achieved a power of exhibiting a high-level performance. Another point to be mentioned, effective preprocessing techniques converted the data into smooth esteems. As a result, any issue regarding the domination of a particular dimension was barely faced.

In terms of similarity measure, it is observed that this novel process of finding out the risk factor actually exhibited a superior performance. So, it is concluded that this system had a peak success rate in case of finding out the risk factor from the activity pattern. Proposed method could actually categorize all the target subjects' correctly and it can be said that with further modification this system may work in the case of other diseases with an exhibition of higher performance.

III. METHODOLOGY

In this scrutinize, firstly, we tried to enhance the application of Smartphone sensors to conduct the recognition of physical activities which are directly or indirectly associated with mental depression. The activity recognition process was conducted by employing a machine learning method on sensors data. Later, the physical activities related to mental depression being recognized, we exerted an effort to compute the risk factor regarding the possibility of a person has been suffering from mental depression. Fig. 1 shows a pictorial view of the methodology of this paper.

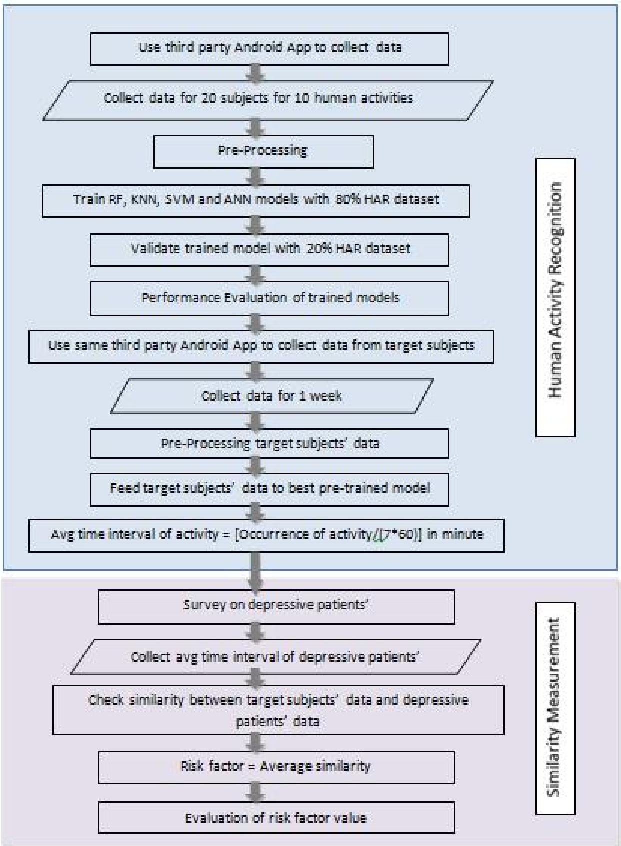

Fig. 1. Outline of the methodology

A. Data Collection

In this system, Samsung Galaxy S4 was used that has tri-axial accelerometer sensor and gyroscope sensor for collecting users' data. Data was collected from twenty subjects for 10 human activities: walking, sitting, lying, jogging, cycling, eating, drinking, speaking communication, sleeping and irrelevant activities.

We culled data for about 10 minutes of each work. Walking data was collected while subjects walking through a busy road, empty road, supermarket and so forth. Sitting data was collected while sitting in bed, chair and sofa. Jogging and cycling data were collected in high, medium and low speed. Speaking communication data was collected from subjects in different circumference like when walking, sitting, running and lying. Sleeping and lying data were collected from different body position. Irrelevant activity data was collected from subjects during their talking via phone, charging the phone, phone out of pocket and when the phone was on a flat surface. The mobile has been put into the subject's pocket while collecting data. For all activities, we culled 1 Hz frequency of sensor data. Data from Smartphone sensors were accumulated in a csv-format file for each activity.

B. Data Pre-Processing

Since a pre-installed Android application was employed to accumulate sensor data, software problems can cause faulty data. The smart phone could also be stuck because of the overload in results, which could also produce null values. Here, some preprocessing methods such as checking for null values, checking for outliers by boxplot and replacing outliers by mean, Min-max normalization and Butterworth low pass filter were used.

The null value of the data set or table demonstrates that no value is shown in the particular field. Different drawbacks, such as system errors, defective sensors, noisy atmosphere or movement, etc., can lead to missing value or a null value. Consequently, it is checked whether there were any null or missing values in our data set to keep our data safe from the curse of null values. The cumulative data showed no missing values and that therefore no pre-processing was required to handle missing values.

Outliers refer to these data values in a database, which cause the distribution of information on an irregular basis. Outliers are more often than not statistically unusual values in the dataset. Box plot uses the quartiles to set both the top and the bottom limits. The definition of these two thresholds allows values above or below the top limit to be considered as outliers. Because the box plot is a very effective technique for detecting the existence of outliers, used box plot was used to depict whether there were any outliers in the dataset. The dataset consisted of 70,000 instances; among them 6999 instances were detected as outliers. The basic technique for handling outliers suggests that these outlets are excluded from the whole dataset. However, it would not be a good choice to delete most instances observed as outliers. So, the outliers were replaced by the mean. Furthermore, identified outliers and evacuation of the outliers are portrayed in the Fig. 2.

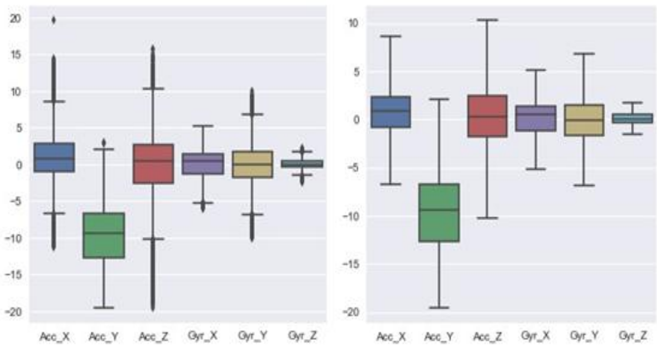

Fig. 2. Detection and handling outliers with box-plot

Min-max normalization refers to the automatic scaling of a data series into a range of 0-1. Min-max normalization can be carried out to an indifferent degree, making it easy to use the learning algorithm for attributes of different scales or measurements. The dataset contains multiple attributes of different units, such as ms^{-2} for Accelerometer or radian s^{-1} for Gyroscope. The dataset was normalized so as to diminish the problem due to the presence of divergent scales. In consequence, min-max normalization effectuated to scale them in the same range in between 0 and 1. The scaling the dataset wound up like the Fig. 3.

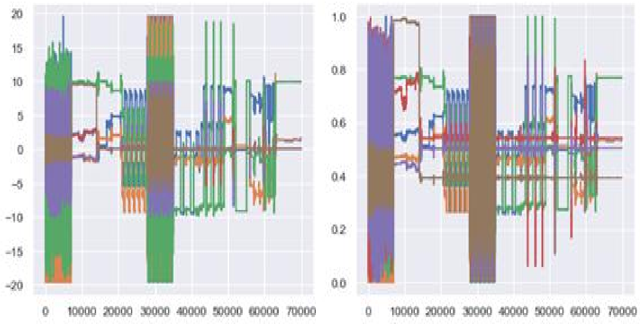

Fig. 3. Scaling the dataset with Min-Max Normalization

Signal filtering can be described as a kind of signal processing course of action that can transform a generated frequency into a smooth frequency. The Butterworth low pass filter takes a minimum value during filtering and removes all signal values above it. It was assumed that the research would face some inconsistencies in the dataset due to earth's gravity and the signals could lose their smoothness and fluctuations lose during data collection process. Therefore, the Butterworth low pass filter was dispatched to remove irregularities due to the gravity of the earth. After employment of this filtration process, a valuable outcome achieved which can be depicted by the Fig. 4.

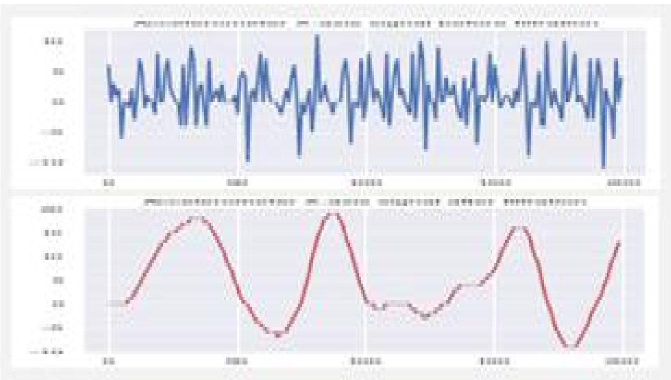

Fig. 4. Employing Butterworth low pass filter on Accelerometer X-axis data to generate smooth signal

C. Applied Machine Learning Algorithms

Modern times require contemporary alternatives to ancient problems. One of these is the statistical analysis and the supporting documentation in that whole data. Machine learning algorithms are available to render the classification process in supervised dataset. For this intended task, SVM, K-NN, RF and ANN approaches were exercised.

In ANN, identically biological neurons are supplanted by certain nodes additionally called artificial neurons. Like the biological neurons, the artificial neurons are associated with one another and they can exchange signals to one another. Upon the firing of signals of the biological neuron, distinctive kinds of motions or developments or responses are displayed. These responses can be viewed as the relevant output as per the neuron's input. Typically an ANN has three parts: an input layer, with units representing the input fields; one or more hidden layers; and an output layer, with a unit or units representing the target field(s). The units are connected with varying connection strengths (or weights). Input layer may consist of one or more than one neuron. Number of neurons in the input layer depends on the dimensions of the input dataset. No computation takes place in the input layer; the only input is fed through it. Suppose x1, x2 and x3 represents a three-dimensional input. The hidden layer is one of the largest parts of the neural network, as it is accountable for all input calculations provided by the input layer. The nodes in the hidden layer also transfer the data to the output layer. On a typical hidden layer, each hidden node calculates the weighted amount of the input that multiplies the input to a hidden node and then sums up it. The calculated I1 input can be,

$$I1 = w11x1 + w12x2 + w13x3 \tag{1}$$

When the weighted input amount is calculated, it is supplied to the activation feature. The activation feature squashes the hidden node input to a value within a particular range. A hidden node generated output can be communicated through,

$$O1 = Activation(\,I1\,) \tag{2}$$

The output layer processes the output obtained from the prior layer and calculates the correct output for a particular input and concludes the final category/value. Some inputs from the priority layer are weighted also by the input of the nodes in the output layer. For further processing of the obtained data, the output nodes may also be activated. It can convey it through,

$$Net\ Output = Activation(\,I1w41 + I2w51\,) \tag{3}$$

K-NN, a non-parametric learning algorithm, uses a dataset with the data points in various groups to predict the alignment of a new sample. Since it is not parametric, it evaluates a model structure without making any assumptions about the distribution of data [22]. K-NN specifies an integer k for a new sample. When, k=11, maximum accuracy can achieve from our model structure. In a normalization process, each attribute value was regenerated by the following manner:

$$new_x = x_{mean} - old_x \tag{4}$$

Where, old is the old attribute value, mean is the average of old attribute values and new is the new attribute value. It was done to avoid the domination of a single feature. For the normalized value of the new instance, the following formula was used:

$$new_{normalized_{x_i}} = \frac{|x_i - x_{mean}|}{Standard\ Deviation} \tag{5}$$

Where, x_i is a new sample. It allows me to metaphor all features to bring them in a new level to facilitate comparison between them. For discrete value, the closeness of discrete values is computed by measuring the dissimilarity among their frequencies. Finally, KNN uses the similarity measure between the training data sample and the new data sample for the prediction.

RF is an ensemble learning methodology that can improve performance of a weak learning methodology (i.e. decision tree) with divide and conquer the whole complex model. Ensemble, a bagging method, is a set of weak learning methods that merge all weak learners to build a final learner in a high learning rate [23]. RF generally uses Gini Index to find the impurity for a selected feature with respect to the classes. In a training data set with M instances, selecting one case randomly belongs to C_i class, the Gini Index refers as:

$$\sum\sum(f(C_i, M)/|M|)(f(C_i, M)/|M|) \quad (6)$$

Where, (f (C_i, M) /|M| is the pruning probability with the class C_i. RF classifier need to generate parameter which is the number of feature(s) used at each tree to generate a tree and the number of trees to be grown. Only highly evaluated features generated by Gini Index value are searching for the best split at each tree node. N is the number defined by the user which implies the RF classifier consists of total N trees, where N is the total number of trees to be expanded.

SVM is a discriminatory classifier defining a hyperplane for classification separation. In our research work, SVM has been used for classification problem [24]. Therefore, the SVM marked with the training data with the independent attributes of the Gyroscope sensor data. And, the variable which depends on our machines is the operation that was recognized. Then set the kernels, the parameter for regularization and the gamma where the last 2 were the SVM classifier tuning parameters. Suppose, there is two data points x and x', then the Euclidean distance between this two input is,

$$d = \|x - x'\| \quad (7)$$

When the Euclidean distance between the two inputs is zero that is d = 0, then, it defines that the two input points are same, and the rbf kernel will give a result showing "1". It means the maximum similarity. And, if the two points are very dissimilar then it will give a result showing "0" and otherwise something between 0 and 1. The term "very dissimilar" depends on a special parameter that is the Gamma parameter that determines how much dissimilarity will be considered as "very dissimilar". For two input samples x and x', the rbf kernel is defined as follow:

$$k(x - x') = exp(-\gamma\|x - x^{1'}\|^2) \quad (8)$$

Here, the gamma parameter is a tuning parameter for SVM. Higher value for Gamma defines that two points can be considered similar even if they are considerably far from each other and a low value of Gamma defines the two points will be considered similar if they are considerably closer to each other.

IV. Evaluation on classification methods

In the proposed method, the training and testing stage primarily operates for HAR with 70,000 samples for all ten activities. 80% of the dataset was used in the training echelon while the remaining 20% was used in the testing stage. Training dataset was fed with preferred classifiers and optimized all models with hyper-parameter optimization in random selection and later tested the models with test dataset. From the discourse referenced above, it is an unmistakable picture to be seen that HAR demonstrates turned out to be well trained. So, if the entire performance evolution picture is summarized, the following information is found in Table I,

Table I. Performance evaluation of exercised classifiers

Model Name	Train Accuracy (%)	Test Accuracy (%)
ANN	99.41	99.34
K-NN	99.94	99.70
RF	100	99.80
SVM	92.34	92.27

Among all the classifier, RF performs best. So, predicting target subjects' activity, RF was utilized as our prepared model. Besides, in Table I, absolute execution of the practiced classifiers locating the accompanying information.

V. Risk Factor measurement

Here, an Android application was employed to collect sensors' data from target subjects for 14 days with a frequency of 1 Hz. Sensor data were regarding the activities performed over the most recent fourteen days in a continuous manner. For each the pre-trained RF model it was recommended them to keep the device in their slash pockets as long as possible. So, for each subject data was saved in target subject's Smartphone when the application turned off by the subject. Data was collected from two subjects, the data was preprocessed using the mentioned preprocessing techniques and made those data ready for predicting. For each subject, data was fed into optimized trained classifier that is RF and predicted the activities. After classifying all the instances for each subject, how much time a person spent in performing each activity was measured. To do this, the number of each specific activity has been calculated to found out the time spent in performing each activity in last 14 days. The data was accumulated in the 1 Hz frequency. The total number of instances for each activity actually defines the number of seconds a subject performed activity. The time in minutes from seconds was converted by dividing 60. In addition, the total minutes for each activity were divided by 14 to find out the average time for each activity per day. Following the above process, the average time spent per day in performing each activity for every subject was computed. The number of occurrences of every activities of target subjects demonstrates in Fig. 5.

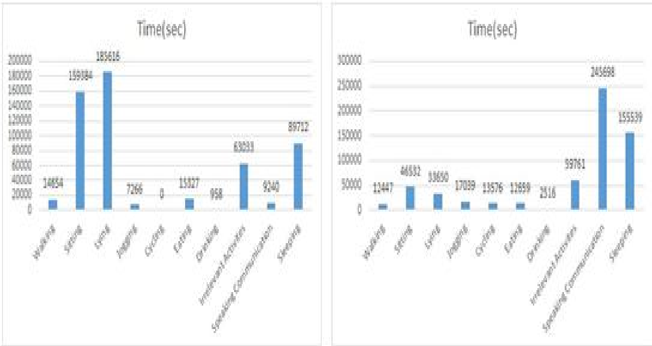

Fig. 5. Activities performed by depressed and normal target subject

The main purpose of data collection on depressive symptoms is to determine the duration of performing mentioned symptomatic activities by depressed patients. Here, it was tried to know how long a depressive subject spends for these symptomatic activities. The purpose was to record the duration to correlate the daily activities of a subject with the duration. So, to collect data from the patients, we applied to the competent authority to collect data from patients. For about a month, data was collected from 40 depressed patients using a questionnaire.

The Cosine similarity calculating method measures the cosine angle between two multi-dimensional vectors of an inner product space. Euclidean distance measures the ruler distance between two multidimensional objects where the cosine similarity considers the angle between those two objects considering their attributes as components of the vector. Generally, Cosine similarity is used for finding the similarity between two documents. There are many more implementations of cosine similarity, such as information retrieval, biological taxonomy, gene feature mapping, and so forth. The Cosine similarity can be used in those areas where the value of attributes actually defines the frequency of the attributes. Suppose, we have two objects A and B with p number of attributes such that, $A_i = (a_{x1}, a_{x2}, .., a_{xp})$ and $B_i = (b_{x1}, b_{x2}, ..., b_{xp})$. Let θ be the inclined angle of these two vectors. Then the cosine similarity between these two objects can be defined by,

$$\cos\theta = \frac{A.B}{\|A\|\,\|B\|} = \frac{\sum_{i=1}^{p} A_i B_i}{\sqrt[2]{\sum_{i=1}^{p} {A_i}^2}\sqrt[2]{\sum_{i=1}^{p} {B_i}^2}} \tag{9}$$

Where A_i and B_i are components of vectors A and B and $\|A\|$ and $\|B\|$ are Euclidian norm of vector A and B. Depending on the values of θ the similarity measurement is actually defined. When, $\theta = 0$ then $\text{Cos}\theta = 1$ puts the two vectors are totally similar. When, $\theta = 90$ then $\text{Cos}\theta = 0$ refers that the two vectors or objects have no similarity at all.

The Cosine similarity was employed for measuring similarity between target subjects' and depressive patients' daily activity pattern. For each target subject and patient, there were nine dimensions, namely age, weight, running, sitting, lying down, walking, eating, jogging and cycling. Here, dimensions of every value were preprocessed using min max normalization so as to eliminate the domination of a single dimension. After normalizing the data, when conducting the similarity measurement process each row was converted into its' corresponding vector representation. Let, T be a vector representation of target subjects' activity patter and P be a vector representing an instance of depressive patients' activity pattern. Each vector has nine vector components resembling nine dimensions. The Cosine similarity between these two vectors can be defined as,

$$\cos\theta = \frac{T.P}{\|T\|\|P\|} = \frac{\sum_{i=1}^{9} T_i P_i}{\sqrt[2]{\sum_{i=1}^{9} {T_i}^2}\sqrt[2]{\sum_{i=1}^{9} {P_i}^2}} \tag{10}$$

As similarity measure, the Cosine similarity was employed since the regarding the activity duration from the subjects actually defines the frequency of those particular activities' occurrences. Here, similarity measurement process was conducted for every target subjects with all the instances gathered from 40 depressed patients. Performance measurement was separated for those two target subjects. Average similarity value for the depressed subject was 90.94% and 34.99% was for the non-depressed subject. Similarity value for depressed target subject and non-depressed target subjects are provided separately in line graph accompanying Fig. 6.

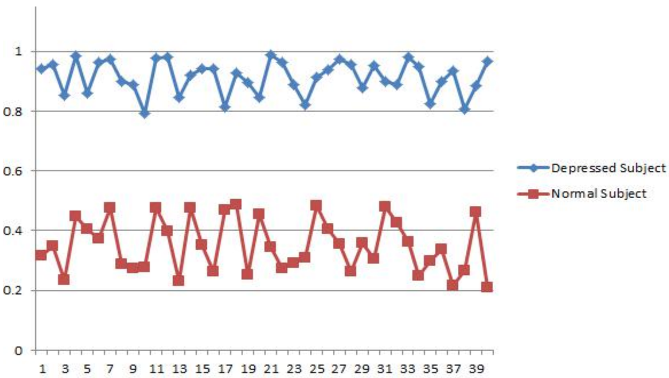

Fig. 6. Similarity value of target depressed and normal subject with 40 depressed patients data

To categorize the similarity measure resulted from the subjects' activity pattern into divergent levels of risk factor, clinical physiology along with the result produced by this proposed suppositional system was considered. In this connection, the system diagnosed one target subject as depressed and another one as non-depressed based on measured similarity among depressive patients' and target subjects' activity patterns. Doctor also diagnosed the target subjects and he diagnosed the target subjects as the prediction of this contemplated system. That means, the target subject who was diagnosed as depressed by the doctor, this system showed higher similarity value as well as a higher risk factor for that subject. Together with, other target subject diagnosed as non-depressed by doctor for whom this system prognosticated lower similarity value over and above a lower risk factor.

VI. Conclusion and Future Work

This study was about the employing of HAR using Smartphone sensors to scrutiny the risk factor of mental depression. We anticipate some changes to our approach throughout the future so that our system is implemented every day in daily practice. The method proposed should serve as a significant beginning to work on human activity to classify the possibility of disease discrepancies. Apart from some unavoidable circumstances, some future scopes include, conducting the same process by resetting the device in other possible positions of our body, accomplish the same goal with the employment of hand worn devices; working on computation of risk factor other diseases related to human activities, testing our process by collecting data from more subjects, trying out other similarity measures just to compare with our current process to see if there is possible development can be brought in. Data collection and preprocessing along with effective classifiers were used to achieve greater accuracy in case of HAR. In this work, the risk factor of two subjects from their activity pattern was successfully determined. Moreover, the availability of data also influenced the work to be a successful one. If it ultimately transforms into a benefit for humans with more successful experiments, this prognosis would serve the aim to convey the use of HAR to necessarily entail relative prevalence of mental depression.

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