The Comparison of Various Correlation Network Models in Studying Mobility Data for the Analysis of Depression Episodes

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Abstract: Depression is a serious mental health disorder affecting millions of people around the world. Traditional diagnostic approaches are subjective including self-reporting feedback from patients and observational evaluation by a trained physician. However, altered motor activity is the central feature for depressive disorder. Moreover, recent studies show that the analysis of motor activity is the best predictor in characterizing psychological disorders including depression. With the advent of wearable devices, an individual's motor activity can be monitored naturally using body worn sensors and feasible to distinguish depressed persons from healthy individuals. In this manuscript, we hypothesis to apply a methodology that takes advantage of motor activity recorded from wearable devices and process mobility patterns for a given group of subjects. Besides, employed a population analysis approach using correlation networks that evaluates mobility parameters of the population and identify subgroups that exhibit similar motor complexity. We have analyzed the mobility data of the given group by extracting three different sets of features using hour-wise, day-wise, and hybrid mobility data. Also, a comparison study of three models is presented by constructing a correlation graph and finding a cluster of individuals exhibiting similar mobility patterns. We found that mobility data using hour-wise features provides the best results compared to the other two models.

1 INTRODUCTION

According to World Health Organization (WHO), approximately 280 million individuals suffer from depression around the world which is equivalent to 3.8% of the total world population (The World Health Organization(WHO), 2021). Moreover, depression may impact any person regardless of their age, race, and socio-economic background. However, it is likely to affect adults than children. The onset of depression may not trigger by normal mood fluctuations or temporary emotional disturbance, rather when the sadness becomes recurrent with intense severity that leads to a major depressive disorder (Abuse, 2018). Depression is a serious mental health condition that may cause frequent mood swings which result in a deprived quality of life. Furthermore, recent studies show that there is a surge in suicides in depressed patients due to feelings of loneliness (Curtin et al., 2016). Depression often may influence the work-life balance and cause poor performance in studies. It is due to the symptomatic nature of illness which causes a gloomy mind, lack of pleasure in doing routine activities, feeling worthlessness, and hopelessness (The National Institute of Mental Health (NIMH), 2021). It is known that there is no precise pathology test such as a blood routine test to accurately diagnose depression, yet most of the existing clinical prognosis is largely dependent on visual observation. Numerous subjective diagnostic scales were proposed to measure the severity of the disease. For example, the Center for Epidemiologic Studies Depression Scale (CES-D) is a self-reporting method that measures the severity on a 4-point scale (Radloff, 1977). Similarly, the Montgomery-Asberg Depression Rating Scale (MADRS) measures the seriousness of the disorder on a 7-point scale which is exclusively designed for adults over 18 years of age (Montgomery and Åsberg, 1979). The drawback of these approaches is that these methods merely depend on human perception and comprehension skills. Therefore, it is important to develop a sophisticated methodology that is observer independent.

Although the main cause of depression is an abnormality in neurological functioning, altered motor activity is one of the common symptoms that ap-

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pear in patients suffering from depression. Besides, previous studies demonstrate that analysis of motor skills is an important aid in classifying depressed patients from healthy counterparts (Sobin and Sackeim, 1997). Moreover, the depressed group compose lower body reaction time and decreased body movements than healthy persons. This opens a door for new possibilities to categorize depression by utilizing their mobility data. Altered or lessened motor activity allows to distinguish depressed patients from healthy subjects. Proliferation in sensing technologies created tiny wearable devices to record motor behavior unobtrusively in a natural setting without disturbing the daily activities. Wearable devices are proved to be efficient, affordable, unobtrusive, and more convenient for they can even fit a newborn child and collect the data for several days (Heinze et al., 2010).

For our tests, we have chosen the 'Depresjon' dataset downloaded from the public database (Garcia-Ceja et al., 2018). It consists of 55 subjects categorized into two groups: the first group has 23 patients diagnosed with either unipolar or bipolar depression (the condition group) and the second group contains 32 healthy control subjects (the control group). The main objectives of this study are as follows

1. Extracting three different categories of features that represent motor activity segmented by the hour, day, and combination of an hour as well as day.
2. Employing the population analysis-based correlation network approach to construct a graph where the group of persons with similar mobility profiles are strongly connected in the resultant graph.
3. Applying an appropriate clustering algorithm to obtain potential subgroups in which each subgroup represents a set of individuals exhibiting similar motor complexity.
4. Comparison study of results obtained from three different categories of features namely hour-wise, day-wise, and hybrid.

The rest of the paper is organized as follows. Section 2 covers the previous studies conducted on the dataset. Section 3 describes a brief description of the dataset, feature extraction, and correlation graph construction. Whereas experimental results are shown in section 4 and post hoc analysis of the obtained results is elaborated in section 5.

2 RELATED WORK

In the past, several investigators have performed different experiments with the dataset. The dataset was created by Garcia-Ceja et al. (Garcia-Ceja et al., 2018) and published baseline performance results. They tested with different machine learning algorithms but finally obtained higher accuracy of 73% with Linear Support Vector Machine (SVM). In another research carried by Rodríguez-Ruiz et al. (Rodríguez-Ruiz et al., 2020) processed motor data and divided it into three sets as day, night, and full-day activity data. The fundamental objective of this work is to compare the motor activity patterns across three different times of a day and draw profound insights. They concluded that the features used to build the nighttime motor data produced promising results compared to the other two features. They obtained the highest sensitivity and specificity of 99.4% and 99.9% respectively.

On the other hand, Zanella-Calzada et al. (Zanella-Calzada et al., 2019) extracted hour-wise features by segmenting the overall motor activity into the one-hour interval, trained the model using a Random Forest classifier. Their model achieved 87% accuracy while the sensitivity was 87% and specificity was 92% . Similarly, Galvan-Tejada et al. (Galván-Tejada et al., 2019) mined 38 statistical features belonging to the time and frequency domain. They have employed a genetic algorithm-based feature selection approach to identify the best features. They also used Random Forest to predict between healthy and depressed and obtained a sensitivity of 68% and a specificity of 61% .

Most of the researchers applied machine learning techniques such as Random Forest and support vector machines. Furthermore, they analyzed the data by using supervised machine learning methods by adding a class label manually for each subject (0/YES for condition group and 1/NO for control group or vice versa). The novelty of our approach is that we do not include known labels in the study, but we identify the group of subjects by utilizing their mobility. In such groups, condition subjects are gathered into a single cluster and control subjects into another cluster.

3 MATERIALS AND METHODS

3.1 The Pipeline

Fig. 1 depicts the processing pipeline for correlation graph analysis for mobility data acquired from Depressed patients. In the first step, a dataset is acquired from the public repository. In the preprocessing step, data is cleaned, normalized, and eliminated outliers. In the third step, three different types of features are extracted namely hour-wise (Model M1), day-wise

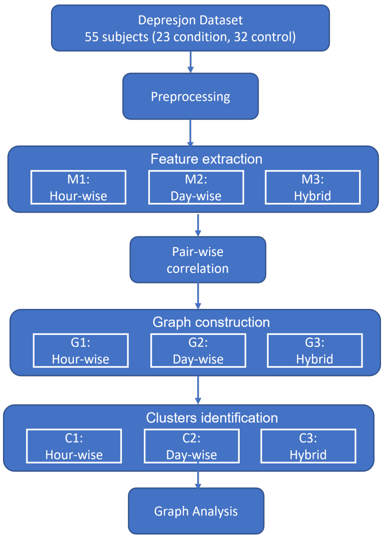


Figure 1: The pipeline for correlation network model.

(Model M2), and hybrid (Model M3). The models M1, M2, and M3 represent the average motor activity data segmented by the hour, day, and the combination of an hour as well as day respectively. Then, a pair-wise correlation is applied for each of the models to construct a correlation graph. Then, strongly connected clusters are detected from the correlation graph. Finally, resultant graphs are analyzed and discussed

3.2 Dataset Description

In this study, we have used the 'Depresjon' dataset (Garcia-Ceja et al., 2018). It is a public dataset consisting of motor activity collected from 55 participants including 23 persons belonging to the condition group and 32 subjects belonging to the control group. The persons in the condition group were diagnosed with either unipolar or bipolar disorder and they are under antidepressant medications. Whereas the 32 participants in the control group are healthy individuals. In this document, motor activity data and mobility data are used interchangeably throughout this document. Their motor activity was recorded using a body-worn wearable sensor embedded in an Actigraph watch (Name: Actiwatch, Manufacturer: Cambridge Neurotechnology Ltd, England, Model AW4). For the comfort of all participants, the actigraph watch was worn on the right wrist and their mobility data was continuously monitored in the natural environment. None of the participants were called to a pathology lab or followed any specific instructions. The actigraph measures the activity with a piezoelectric accelerometer that is designed to record the intensity, quantity, and duration of movement in all directions. The Motion data was captured with a sampling frequency of 32Hz and movements over 0.05g for every minute in the form of activity count. The actigraph records the motor activity in the form of an activity count. The higher activity count resembles the higher intensity in the motor activity.

The captured mobility data contains activity count along with its timestamp. Besides, each participant's mobility data was stored in a separate data file, and they can be identified with a unique contributor id. Moreover, all of them were participated and provided their data for a different number of days. However, on average every person has 12 days of motor activity. In addition to the data file, individuals' demographic characteristics are provided in a separate file (scores file). This file contains the important information of each person such as person unique id, days (number of days of data monitored), gender (1:female, 2:male), age (age range), afftype (1: bipolar II, 2: unipolar depressive, 3: bipolar I), melanch (1: melancholia, 2: no melancholia), In addition to this, every subject in the condition group was assessed by MADRS observational scale (Montgomery and Åsberg, 1979) at the start of the data collection and also at the end of the data collection. The MADRS scores are available under MADRS1 and MADRS2 columns respectively. Further, a statistical summary of all 55 participants and their demographic details are described in Table 1.

3.3 Preprocessing

The first step in preprocessing phase is combining the individual raw sensor data into a single dataset and preparing for further processing. The motor activity data was not measured for the same duration. However, on average 12 days of motor data is available for all the users. Furthermore, the number of days the data is available is not consistent between the user sensor data file and the scores file. Therefore, we have

Table 1: Demographic characteristics.

	Condition group		Control group	
Statistic	Mean	SD	Mean	**SD**
Days	12.6	2.3	12.6	2.7
Age	42.8	11	38.2	13
MADRS 1	22.7	4.8		
MADRS 2	20	4.7		
Statistic	Total	%	Total	%
Gender (Male)	13	57	12	38
Depression (Bipolar)	8	34		
Hospitalized (Inpatient)	5	22		

Table 2: Model-wise features.

Model name	Feature name	Features count	Feature description
M1: Hour-wise model	m0-m23	24	The Average motor activity measured for every hour for 0-23 hours
	sd0-sd23	24	The standard deviation of motor activity measured for every hour for 0-23 hours
M2: Day-wise model	dm1-dm19	24	The Average motor activity measured for each day for 1-19 days
	dsd1-dsd19	24	The standard deviation of motor activity measured for each day for 1-19 days
M3: Hybrid model	m0-m23	24	The Average motor activity measured for every hour for 0-23 hours
	sd0-sd23	24	The standard deviation of motor activity measured for every hour for 0-23 hours
	dm1-dm19	24	The Average motor activity measured for each day for 1-19 days
	dsd1-dsd19	24	The standard deviation of motor activity measured for each day for 1-19 days
	id	1	A unique id to represent each subject

taken the number of days mentioned in the scores file as the ground truth and deleted the additional days of motor data present in the sensor data file for each participant. In the next step, the activity signal is normalized, and removed outliers. The activity signal data is normalized between 0 and 1 using the Z-score standardization technique. Since the condition and control groups belong to two different entities, both groups' sensors data is normalized separately. In the next step, outliers are eliminated by utilizing the interquartile range (IQR) property. In this context, a data point is considered an outlier if it is below the first quartile or above the third quartile. In this process, outliers are not removed rather they are replaced with either the first quartile or the third quartile depending on whether the data point is above the third quartile or below the first quartile respectively. The resultant dataset is normalized and free from outliers.

3.4 Feature Extraction

Each participant has shared their mobility data for a certain number of days. But all of them were not collected their motor data for the same number of days. For example, participant 8 in the condition group has provided mobility data for 5 days, while person 2 has 20 days of motor data. In this manuscript, we propose to utilize three different types of features: hour-wise features (Model M1) that represent hourly motor activity in a 24-hour cycle, day-wise features (Model M2) that signifies overall day motor activity, hybrid features (Model M3) that combine both hour-wise and day-wise features. The detailed list of features is elaborated in Table 2.

In the hour-wise model (M1), motor activity is segmented by an hourly pattern. Although each participant generated motor activity for a variable number of days, the total activity of a person for all days is aggregated before extraction of the features. Then each person's motor data is divided by an hour interval. Further, the mean and the standard deviation (SD) are computed for every hour of aggregated data. As a result, 24 features are generated from mean and another 24 features are generated from SD. In the day-wise model (M2), a person's motor data of a day is aggregated, and this process is repeated for all days. Then mean and SD is calculated for each day. From the dataset, it is known that each participant's motor activity is collected for a variable number of days, yet a user has not more than 19 days of activity data. So, 19 features of as day-wise activity means, and 19 features of day-wise SD are processed. This process produces 38 features for each person. Since every participant does not possess 19 days of sensor data, the remaining days where the data is not present are filled with 0. To eliminate the bias of the number of days between two persons, the minimum number of days is considered during modeling. In the hybrid model (M3), 48 features from the hour-wise model and 38 features from the day-wise model are combined. Effectively M3 model generates 86 features.

3.5 Construction of Correlation Network Model

The objective of building a correlation graph is to understand the interrelationships among the participants concerning their mobility parameters. In previous experiments (Garcia-Ceja et al., 2018) (Zanella-Calzada et al., 2019), researchers have employed machine learning approaches and classified depressed patients from the healthy control group. Nevertheless, all these studies have utilized a known class label such as 0/NO for healthy control subjects, 1/YES for a depressed patient, then try to classify the subjects and measure the accuracy of the prediction algorithm. The inherent downside of this approach is that the learning algorithm works only if the known label is present in the dataset. Besides, these methodologies are label-driven. In this manuscript, we introduce a data-driven approach by employing a population analysis approach using correlation graphs. This approach does not require a label to be present in the dataset rather it analyzes the mobility parameters of the given group and identifies the subgroups that demonstrate similar mobility patterns. Our hypothesis is developed on the fact that subgroups in the given group compose similar motor activity which makes them distinguishable from other groups. This is further exemplified from the motor data of 55 subjects where the overall mean activity of the condition group is 284 while the condition group has 187.

The first step in the graph creation is to establish the relationship between each pair of subjects with respect to their motor activity data. Once the relationships are identified, their interconnections are represented using a graph. A graph G = (V, E) is an abstract mathematical representation of any system that depicts the relationships between the objects. In such a graph, nodes or vertices (V) denotes the elements of the system, and edges (E) represent the interconnection between the elements (Dongen, 2000). In this study, all 55 participants are denoted as nodes, and their relationship regarding their motor activity is represented as an edge. It implies that two participants are connected by an edge if they possess a similar motor activity profile.

The degree of similarity between each pair of subjects is measured using the Pearson pair-wise correlation coefficient (ρ). The Pearson pair-wise correlation coefficient measures the linear dependence between a pair of objects. Usually, the value ranges between -1 and +1 where -1 indicates a negative correlation and +1 signifies a strong positive correlation. To construct the correlation graph, the ρ value is computed between each pair of users by utilizing their motor activity data. This operation outputs a correlation matrix with pair-wise correlation coefficient values. The ρ value between a pair of users signifies the degree of similarity with regards to their motor activity. The higher the ρ value the stronger the relationship between the pair of users. To create the graph from the correlation matrix, strongly correlated pairs are identified by using the significance matrix. A significance matrix is obtained by setting a predefined threshold k using equation 1.

$$\begin{aligned} \text{significance matrix}(i,j) &= 1, \quad if(\rho(Pi,Pj)) \geq k \\ &= 0, \quad if(\rho(Pi,Pj)) < k \end{aligned} \tag{1}$$

A predefined threshold k indicates the correlation at which a pair in the matrix is significant. Intuitively, when 55 participants are represented by a significance matrix then two persons (Pi, Pj) are said to be associated if their correlation constant exceeds or is equal to k. Therefore, Pi and Pj are connected by an edge in the resultant correlation graph. Since the significance matrix will have either 0 or 1, it is equivalent to the adjacency matrix. As the last step in graph creation, an adjacency matrix is translated to a correlation graph.

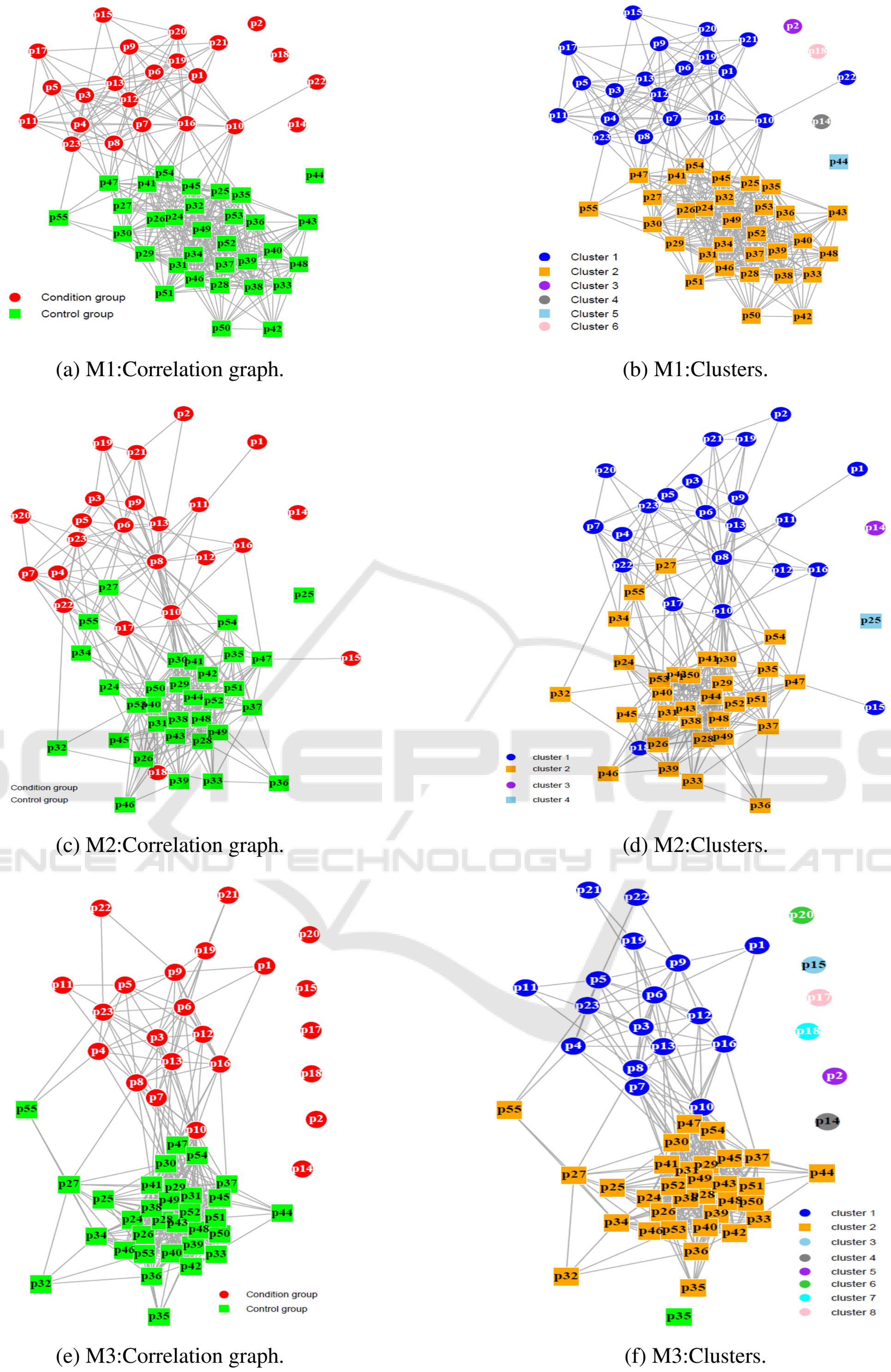
3.6 Clustering

Even though the correlation graph is built, it is necessary to find the potential clusters in the resultant graph. Often, the terms Clustering and Community discovery are used interchangeably by the scientific community. In biological networks, clustering or community discovery is a method of classifying the elements into groups (clusters) wherein members of each group are similar by means of certain characteristics (Girvan and Newman, 2002) (Ali et al., 2019). In the current study, clusters are identified according to the motor complexity of all the subjects under the study. So, all the persons in a cluster are expected to have similar mobility patterns. A cluster in the correlation graph signifies a group of subjects that are strongly interconnected through mobility patterns. Also, the discovered clusters naturally hold two principles: Homogeneity and Separation. Homogeneity alludes to the similarity among persons within the same cluster while separation indicates persons in different clusters exhibit different characteristics.

To uncover the hidden communities in the correlation graph, MCL (Markov Clustering) technique is applied. The MCL algorithm is a popular unsupervised clustering algorithm that is well suitable for extracting communities in biological networks (Dongen, 2000). The MCL algorithm works by a random walk property of a graph where all nodes are randomly visited to find the strongly connected components in the graph. A good clustering algorithm typically produces high-quality clusters with distinct non-overlapping boundaries. Yet, achieving perfect separation is practically not possible.

4 RESULTS

This study includes 55 participants with 23 from the condition group (patients suffering from depression) and 32 from the control group (healthy counterparts). The final dataset used for correlation analysis has 55 observations where each observation corresponds to a person. However, the number of feature variables is different for each model. The hour-wise model (M1) has 48 features, the day-wise model (M2) consists of



(a) M1:Correlation graph. (b) M1:Clusters.

(c) M2:Correlation graph. (d) M2:Clusters.

(e) M3:Correlation graph. (f) M3:Clusters.

Figure 2: Correlation graphs and discovered clusters.

38 features, and the hybrid model (M3) has 86 features. The Pearson correlation coefficient is applied to three models then M1 outputs 55x48 matrix, M2 outputs 55x38 matrix, and M3 yields 55x86 matrix. In the next step, a predefined threshold of 0.7, 0.6, and 0.55 are set to the models M1, M2, and M3 respectively, to get the significance matrix. A correlation graph is generated from the three significance matrices. The obtained correlation graphs of M1, M2, and M3 models are shown in Figure 2 (a, c, e). To recognize each person a unique id is used where control subjects are numbered from 1 to 23 and condition groups are numbered from 24-55. Furthermore, control group participants are colored in green whereas condition group subjects are colored in red. Each vertex in the resultant correlation network represents an individual while the edge between two vertices signifies the degree of similarity in terms of their movement pattern.

Unraveling hidden clusters in a correlation graph is a crucial step at this stage. MCL algorithm is utilized to discover the potential clusters from three graphs as depicted in Figure 2 (b, d, f). In this graph, nodes with similar colors signify that they belong to the same community. we can comprehend from the graph that controls and condition subjects are fairly separated into two dense communities (condition group in red color and control group is in green color). Analyzing these communities provides numerous insights into the connections between the individuals. Section 5 further elaborates on commonalities between the persons in the same community.

5 DISCUSSION

In this section, a post hoc analysis is carried out on the results obtained from the three models. The input dataset consisting of mobility data collected from 55 subjects also provides classification labels that correspond to the diagnosis of the person. It is known from the dataset that participants numbered from 1 to 23 belong to the condition group and they are diagnosed with either unipolar or bipolar depression, whereas subjects numbered from 24 to 55 belong to the healthy control group. Previous studies that employed machine learning techniques had obtained higher accuracy in terms of predicting the persons with and without disorder (Garcia-Ceja et al., 2018) (Zanella-Calzada et al., 2019) (Rodríguez-Ruiz et al., 2020). However, our hypothesis is not established based on known labels rather we built the network by taking advantage of the motor activity data itself. Therefore, subgroups extracted from the correlation model are more intuitive in terms of their movement patterns.

The main objective behind creating three models is to understand the granularity of the mobility that can best describe the overall movement patterns of the subjects under study. From Figure 2, results obtained from hour-wise mobility data are more promising than the other two models built on day-wise and hybrid mobility data. Comparing three models shown in Figure 2, M1 and M3 produced 6 clusters and M2 produced 4 clusters. However, all three models have two dense clusters, and they mostly differ with respect to the number of singleton or dual node clusters that are not connected to the network. Model M1 has 6 clusters in which persons P2, P14, P18, and P44 are isolated from the group. The phenomenon of isolation highlights the peculiarity of these persons. They are isolated because their mobility is not comparable with any other person in the group. Nonetheless, from the available information in the dataset, it is not possible to determine the exact reason behind their separation. Hence, we believe that having additional information such as clinical parameters might be helpful in further analysis. Additionally, the hourly features employed for the M1 model separated condition and control groups into two well-separated subgroups according to their mobility but without using known labels. Even though the M3 model divided condition and control groups, P15 who is supposed to belong to the condition group is clustered into the control group. Similarly, in the M2 communities' graph, P15 and P18 are classified as condition groups but they are strongly correlated to control subjects than condition subjects. By utilizing these rich insights, it is plausible to comprehend the severity of the disorder provided if there is additional clinical information such as medical history.

Another aspect of constructing three different models is to realize the best method that can distinguish the subgroups according to the degree of mobility. The creators of the dataset did not mention the actual setting of the subjects under study. If all the subjects are residing in the same community and have the same daily routine, then day-wise segmentation of the mobility data is helpful than the hourly segmentation. Conversely, if the participants are living in different communities with diverse daily routines, then hourly features might produce better results than day-wise features.

6 CONCLUSION

Mobility is considered one of the important influential factors that determine the overall health of an individual. However, certain medical conditions such as depression can impact the mobility pattern. Consequently, the affected individual's movements are significantly altered compared to their healthy counterparts. However, the degradation in mobility can be used as a vital parameter in characterizing the disorder. In the past, physicians assessed the depression by an observation followed by self-reported feedback from the patients. Yet, with the latest innovations in wearable devices, it is possible to diagnose the illness by collecting mobility data from depressed patients using wearable sensors. In this study, we proposed and built a correlation network model by utilizing the movement data collected from the group consisting of depressed as well as healthy subjects. Earlier studies predominantly focused on prediction of the depression by incorporating known labels. However, our hypothesis is built on the concept of population analysis and correlation network by utilizing the mobility data. We treated all the subjects belonging to one group then explored similarities and differences between each pair of subjects by utilizing their movement data. Then we constructed a correlation network model that has the potential to discover the subgroups of those who are suffering from depression and healthy subjects. We have extracted three different granularity of features and we found that hourwise features are the best set of feature parameters that can fairly identify the subgroups.

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