An Efficient Probability Proto form Summary Technique for Finding Mental Health Condition

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Abstract:

Now a day's to every person is give an importance to monitor our life style in every day or weekly or monthly. By performing monitoring process we can user sensors which record our walking habits and smart watches which along motion can measure heartbeat. After measuring those information can be taken into data format and used those data for finding changes in certain activity patterns may signal changes in person's physical or mental health condition. Recognizing these changes ahead of time may help in preventing forthcoming health problems. A common way to understand and extract information from this data and make decisions based on them. Several studies to test the hypothesis that health problems lead to changes in sensor data pattern. In this paper showed that mental illness such as depression and dementia influences the patterns recorded by sensors monitoring in-home activity and the amount of time residents spend outside the apartments. By finding mental illness in this paper we are implement probability proto form summary technique. By implementing this technique we can find out mental ill ness of person.

Keywords: *Mental Health, Periodic Sensor Data, Training data set, Quantitative.*

I. INTRODUCTION

As with other medical problems, the risk of depression and dementia in the elderly increases with other illnesses and with declines in functional abilities. One conceptual framework that may be employed to assist in the detection of changes in mental health status is the Early Illness Detection Model. This model can be used to identify typical patterns of decline including plateaus and step downs that depict functional changes. Coupled with the deployment of sensor systems in the homes of older adults, and utilizing density mapping, changes in activity patterns that are likely to be associated with depression and dementia can be detected earlier with the goal of alerting health care practitioners of changes in medical conditions. Early alerts allow for medical interventions to be addressed sooner, which assists in the management of disease processes. This article will describe the Early Illness Detection Model and the density mapping technology produced from a passive sensor system. Using a retrospective perspective, a case by case study analysis will be presented using the model and technology to track activity patterns associated with dementia and depression. This approach is used in an attempt to illustrate the use of this model for the management of behavioural health issues.

This study applies the model to detect early onset and exacerbations of episodes of dementia and depression. Technology in the form of sensor networks, offers an alternative approach that may be more feasible, cost effective and less intrusive in monitoring such illnesses. Our revised version of the Early Illness Detection Model has been modified for use with dementia and depression (Figure 3). This model guides the sensor system refinement and tracks the outcomes which are specific to early illness detection and clinical management of two behavioural health issues and the exacerbations of these illnesses. The same major premise drives this revised model-detection of early onset and/or exacerbations of mild dementia or depression, providing opportunities for early clinical treatment of these behavioural health problems. Changes in activity patterns serve as an alert that further assessment is in order. Once activity pattern changes are identified then additional assessments can occur earlier. If illnesses and exacerbations are detected and managed at an earlier stage, it can prevent excessive visits to physicians' offices with undifferentiated complaints, ER visits, hospitalizations and/or transfers to intermediate care facilities.

To detect activity pattern changes, a precursor for both dementia and depression, the identification of changes in participants' level of regular or baseline activities is key to early recognition of changes in mental health status. Dementia and depression can both present with either decreases in activities and normal patterns of behaviour or increases in activities and normal patterns of behaviour. For instance, early symptoms of depression can manifest as an increase in sleep activity or a decrease in sleep activity. Early onset of dementia can present with increase in wandering out of the apartment or it might present with decreases in venturing away from the apartment. Therefore, it is important to measure each participant’s regular or normalized patterns of behaviour in a baseline information assessment that can be obtained through medical assessments, interviews, clinical observations and technology enhancements. This baseline can then be compared with any changes in activity or patterns of behavior that are indicated by the sensor data and clinical observations. This baseline will change over time with each episode of functional decline.

II. RELATED WORK

Glascock and Kutzik proposed the use of motion sensors to infer activities of daily living [1]. The Independent Life Style Assistant (ILSA) developed by Honeywell was also an early system which proposed passive monitoring (e.g., mobility, sleeping, and toilet usage), as well as the learning of environmental preferences (e.g., temperature) [2]. Ogawa et al. monitored two participants for over a year, logging motion activity, sleep time, and appliance use (with wattmeters) [3]. Beckwith studied nine residents with dementia in assisted living housing, using motion and door sensors, and bed load cells; residents and staff each wore a badge for location tracking [4]. Barger et al. report a monitoring system with eight PIR sensors to infer a person’s behavioural patterns using probabilistic mixture model analysis [5]; the approach was validated with one user and a manual log documenting activities such as sleeping, changing clothes, and meals. Lundell et al. proposed a medication prompting system that uses context and previous behavioural patterns [6]. Cuddihy et al. collected data in the homes of seniors, using motion sensor density to determine the level of movement; family members could be alerted when the motion density was very low, indicating little or no movement [7]. Kaye et al. introduced a system to estimate walking speed from noisy time and location data collected by PIR sensors; walking speed was investigated as a proxy to detect early signs of cognitive problems [8]. Wearable health monitoring devices have also been proposed. Actigraphy is a method of monitoring human rest/activity cycles, typically used with a wrist sensor worn like a watch [9]. Paavilainen et al.studied a telemetric actigraphy system to monitor the circadian activity rhythm of elderly nursing home residents [10]. Howell et al. investigated the daily maximum activity collected using actigraphy to evaluate the clinical utility in patients with heart failure [11]. Philipose et al. used RFID gloves in the home to recognize activities through object proximity [12]. Korhonen et al. introduced a model which used wrist-worn sensors to measure health and wellness status of an individual Sensing has also been incorporated into textiles for wearable systems . There are advantages to wearable sensing systems, such as the ability to collect data outside of the home. However, there are problems in relying on wearable sensing for continuous, long-term monitoring of seniors, as many find them intrusive . Also, older adults with cognitive problems may either forget to wear the devices or intentionally remove them. There have been a variety of machine-learning approaches applied to in-home sensor data. Kim et al. compared hidden Markov models (HMM), conditional random fields, skip chain conditional random fields and emerging patterns in activity recognition, and proposed a topic model based on daily routine discovery. Rashidi et al. introduced an adaptive smart home system and the frequent and periodic activity miner algorithm to find patterns of daily activities. Helal et al. introduced a smart environment to monitor activities, diet, and exercise compliance of diabetes patients, using HMMs for task recognition.

III.PROPOSED SYSTEM

In this section we are describe our technique for finding mental ill ness of person. By performing this process we can effectively get efficient details of ill ness and also provide best output result. By implementing this process we need two data sets i.e. training data set and testing data set. In the training dataset contains all information related person with contains mental ill ness. The testing data set contains all information of test result. By taking test result from sensor and find out mental ill ness of person. Finding mental ill ness of person we are implementing probability proto form summary technique. The implementation process of probability proto form summary technique is as follows.

1. Read training data set from data base containing information related to mental ill ness of persons.

2. Read testing data set from data base containing information related to sensor data of person.

3. After that take the first record test result from testing data set and calculate similarity of each attribute in the training data set. The calculation similarity can be done by using following formula.

$$Sim(Attr_i) = \sum_{i=1}^{n} com(Test(Attr_i, Training(Attri_i)))$$

4. By counting all similarity of in the training data set and also count non similarity of training data set.

5. After that we can find out similarity probability of each attribute wise by using following formula.

Prob(Attr$_i$) = simarlarity(Attr$_i$)/ Total (Attri$_i$)

6. We can also find out probability non similarity of attribure by using following formula.

Prob(non sim(Attr$_i$))= non similarity(Attr$_i$)/total (Attri $_i$)

7. After calculation of probability of similarity and non-similarity of attributes check the probability. If the probability of similarity is more than non-similarity the get mental ill ness status and put that value to specified record in the testing data set. If the similarity is the less than one equal non similarity then the status of training data set take and put into testing data set.

8.If the this process repeated until all test records completed.

By implementing this process we can effectively get classification result and provide best result.

IV. CONCLUSIONS

In our proposed system we are implementing an efficient classification approach for finding mental illness status of patient. In this paper we are taking periodic sensor data of each patient and perform the classification process. By implementing classification process we can easily find out metal ill ness of each patient. In this paper we are implementing probability proto form summary technique for finding mental ill ness of patient. Before finding mental ill ness of each patient the user will take training data and take the testing result. By taking testing resulting we can apply the classification process on training data set we can got mental illness status based on testing result. By implementing probability proto form summary technique we can efficient classification result of mental illness of patient.

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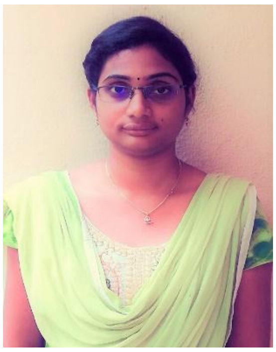

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