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# Deep Learning Model to Predict the Behavior of an Elder in a Smart Home

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## Abstract

**Objective:** The aim of smart home is to create an environment that is aware of the activities of elderly, disabled people within home and then predicting their behavior which aids for further actions like alerts. Predictive Intelligence environment gathers information from Wireless Sensor Networks (WSN) from various parts of the home which includes daily activities, interactions with the objects within the monitoring environment. **Methods/Statistical Analysis**: Assistance independent living of the elderly helps them to lead the daily life independently in a self-regulating way. Based on the key daily living activity like preparing food, showering, walking, sleeping, watching television, reading books etc., their routine and their wellness can be tracked. Behavior of occupant of smart home different times using prediction methods is collected based on which the extraction of patterns is done leading to classification of activity and rating the activity as normal or abnormal. A novel behavior prediction model for daily activity and analysis in monitoring has been designed and developed. **Findings:** The datasets are being experimented with the support vector machines and deep learning networks. Based on the best performance results, deep learning network with SVM linear kernel is capable of making correct classification of datasets accurately with the average accuracy of 88.20% and the prediction time is 5.178 sec. The results show that daily normal and abnormal patterns can be identified with behavioral changes. **Application/Improvements:** The deep learning model of smart home system is a useful approach for learning the mobility habits at the home environment, with the potential to detect behavior changes that occur due to health problems. A deep learning based system can successfully identify and predict the activity of the elder people.

**Keywords:** Predictive Analytics, Senior Analytics Care, Smart Home, Wearable Sensors

## 1. Introduction

As the average age of the urban population increases, cities must adapt to improve the quality of life of their senior citizens[1]. The smart home gloal market is expected to grow to USD 119.26 billion by 2022 by Mordorintelligence[2]. They are providing innovative services and products to take advantage of the growing market. Despite the growing need, smart home service has not been widely implemented. High device prices, limited consumer demand, and long device replacement cycles are the major barrier in establishing the infrastructure of a smart home[3].

Elderly and disabled people encounter problems in their everyday life while most of other people do not knowledgeable of their difficulty. One of the biggest needs and required for disabled people is to continue their daily life activities when they are alone at home and there is nobody to help them. There are many studies about smart houses system aims to help elderly and disabled people. In this paper, the form of smart home focuses on making it possible for disabled people to remain their life at home, safe and comfortable. The normal elderly person daily activities need to be tracked. The analysis of data in real-time will determine whether any change of

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regular activities have taken place and if any preventive action is required. This precautionary measure may help in reducing the future health-care cost[4]. Also monitoring and modeling of elderly activities of daily living were included[5]. There is a increasing interest in smart homes and predicting behaviors of inhabitants is a key feature for the success of smart home services. Sungjoon et al has proposed a deep learning algorithm for predicting the smart home applications[6].

The smart home system need to do identification of basic behavioral activities by heterogeneous sensors of in-home monitoring[7]. Smart home system to detect postures, detect the presence and track the people in environment. Detection of anomalies (including falls and too long time spent in bathroom) follows a set of manually designed rules with adjustable thresholds. The manually kept logs of geriatric centers for patient monitoring, to derive observations that go beyond the simple content of the logs and to detect anomalies[8].

The merit is the cluster activities is in unsupervised fashion, labeled. Uses a sequential pattern mining approach to determine abnormal events based on the labeled events, the demerit is to tend to be complex, with temporal gaps, replete with inconsistencies and noise.

Detection and classification Using Wearable Sensors is mainly used in identifying the activities but elders may feel discomfort in wearable sensor[9]. There are a number of projects present on wearable health device, personal wellness monitoring and safety comes with sensors to provide continuous monitoring of person's health related issues and activity monitoring[10]. Usually people are ackward to wear a system continuously on their body. So, it may not be a suitable for a healthy elder people. This situation may be agreeably for a patient under rehabilitation. If many sensors can be installed in the system for the monitor of all appliances used by the elderly in a new constructed house, it provides needed data for elderly monitoring[11]. Systems like human monitoring with remote monitoring using wireless sensor networks were introduced and however technology are effectively implemented but, these systems are limited to a few activities[12].

Smart automation contains multiple interconnected smart devices and entertainment consoles, etc. Intelligent devices are available to the system to provide control, convenience, comfort and security to the end users. With advancement in technology can control the levels and also to give more comfort to end users.

## 2. Methodology

### 2.1 Senior Analytics Care Model

Wellness determination process through monitoring daily activities and the Figure 1 shows the lifestyle oriented model. The data collection is done using the following steps:

- The sensing data for different events are collected with tem- poral information. The data are stored in a file for further processing.
- Activities are annotated by applying conditional probabilistic method as given below: The best activity identification for the

The different features used in Prediction are as follows

- Time of sleep
- Time to getup
- Number of times to bath room during sleep
- Duration at bathroom
- Number of times movement in bed during sleep
- Total static time during sleeping
- Maximum duration of static
- Door usage
- Electrical appliances usage
- Based on the features extracted the normal and abnormal conditions can be classified. The Figure 1 shows the different response level of the person. Real-time processing of activities of daily living data is a must for recognizing activity behaviour and predicting abnormal situations of the elderly. Based on the time log window Data driven approach identifies Actvity daily log is classified to normal and abnormal. The severity level is considered as low, medium and severe and given in the Figure 2.

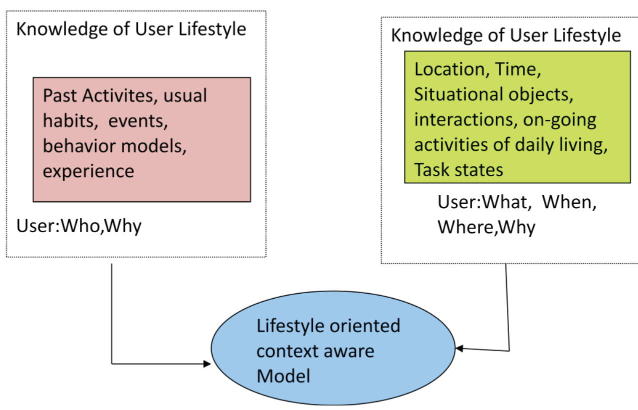



**Figure 1.** Life style oriented context aware model.

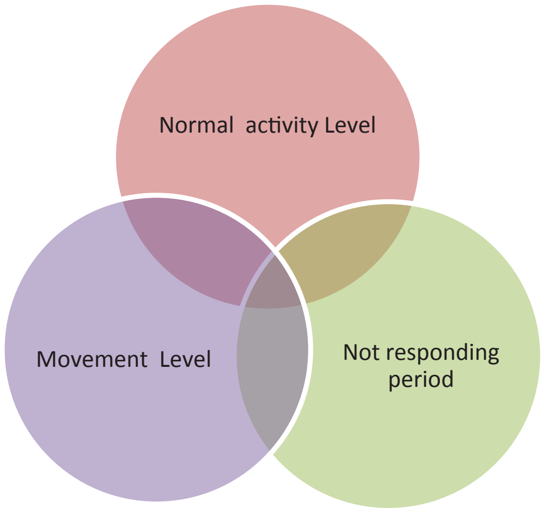



**Figure 2.** Activity of daily living log classification.

Components for discovering, modeling and recognizing the patterns of activity

- Monitor the daily routines of the house–mate using environmental sensors.
- Using Sensor data, the information about ADLs (Activity of Daily Living) and environment contexts are derived, analyzed and controlled.
- Monitor the behavior of people and control IoT devices when abnormal situations are detected.
- Deep Learning is used to analyze the activities are rich enough to exhibit idiosyncratic variations.
- Under non- trivial situations to improve detection and prediction rates.

## 2.2 Predicting Behavioral Model

In machine learning, support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Support vector machines along with kernel based algorithms provide good classification result. The different kernel functions available in SVMs are the Polynomial kernel, Radial Basis kernel. On selection of the kernel function, the different parameter has to be varied in order to obtain higher classification accuracy. The predicting model is given in the Figure 3.

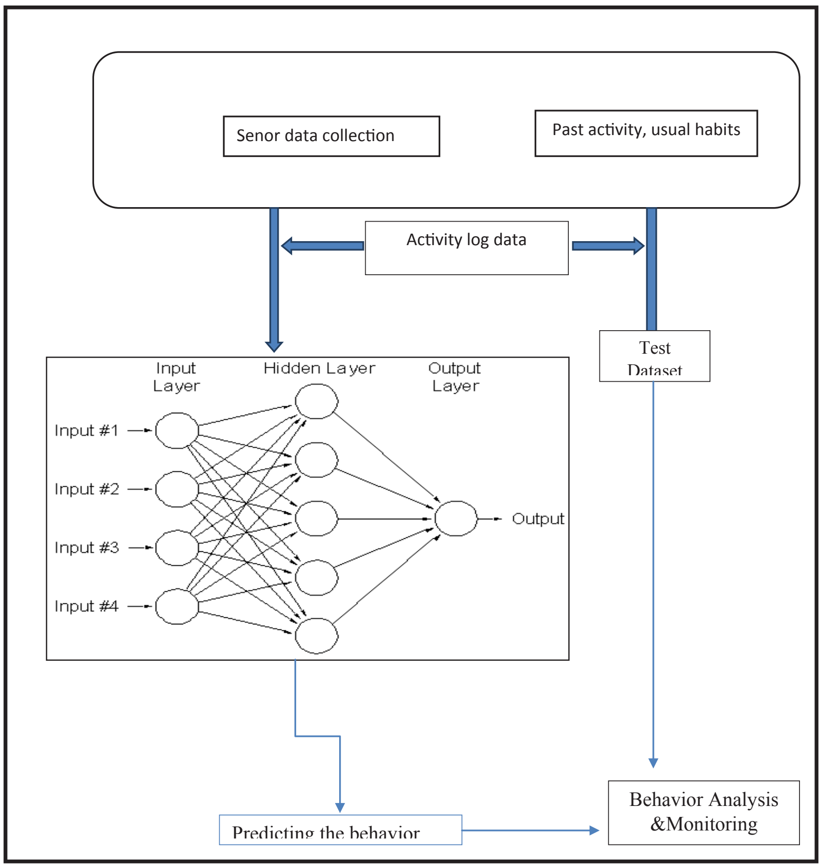



**Figure 3.** Deep model architecture for behavior analysis.

## 3. Experimental Setup

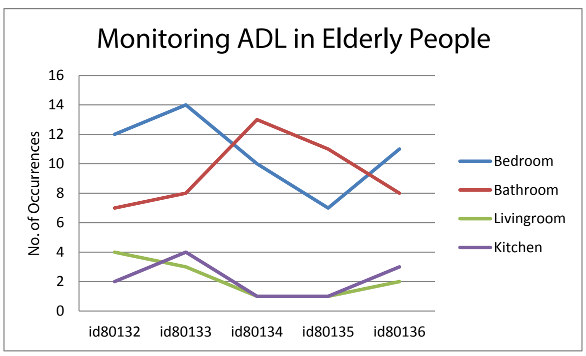
The data sets have been created of various lengths, ranging from 10 days to 70 days. The dataset collected based on the situation and features given in Table 1. These datasets contain a sequence of (x,y)-coordinate pairs, as well as a time-stamp and are captured with an interval of one minute. These coordinate pairs are then apped on regions of interest in the environment of the agent, which act as our observations. We assume that activities generally are executed in a specific location (e.g. cooking near the stove, sleeping in bed). These specific locations can be seen as regions of interest. We are not interested in the specific activity conducted at a particular location, because we cannot infer this from location information alone. Our movement between the different regions of interest, however, should provide us with enough information to infer a general behavioral (or movement) pattern.

**Table 1.** Situation and features design

| Situation | Basic Features | | | Special Features |
|---|---|---|---|---|
| | Start time | Duration/ End time | Times per day | |
| Sleeping | 2017-10-03 11:00:11 | 381 | 3 | Times to Bathroom at night. Duration in Bathroom, Getting up times and duration, Naps in daytime and Duration of Naps |
| Midday sleep after a lunch | 2017-10-03 11:13:54 | 2814 | 1 | Times to Bathroom during sleeping, Duration in bathroom, Total static time during sleeping, Maximum duration of static |
| Going to the rest room | 2017-10-03 13:12:19 | 66 | 2 | Times per hour and at night |

## 4. Results and Discussion

In order to validate our algorithm, we have used the dataset published in UCI Machine Learning repository: Activity Recognition system based on Multisensor data fusion (AReM) Data Set (https://archive.ics.uci.edu/ml/datasets/). The daily activities of the person are recorded. The quality of the learning module is determined by identifying the normal and abnormal behavior of the person and tracked is shown in Figure 4.




Model is validated after training using k fold validation. In k fold validation, 1/k fraction of data is used for validation and the rest is used for training the model. 20% of the data is hold for validation, the actual training data size is 80% of the data size. The error rate drops with increasing data size as expected and converging around 500. For the training process, the dataset was split into a training set (80% of the dataset) and a validation set (20% of the dataset) of continuous days. These sets were composed by the raw sensor data provided by. In order to make the training process more streamlined, we apply the sensor to action mappings offline. This allows us to train the deep neural model faster while still having the raw sensor data as the input. After the 1000 epochs, best model is selected using the validation accuracy as the fitness metric. The test runs for 3 different training data size. Table 2 shows the data set errors identified during the testing.

**Table 2.** Data set error level

| Data set size | Error | False positive error | False negative error |
|---|---|---|---|
| 1000 | 0.125 | 0.024 | 0.101 |
| 3000 | 0.117 | 0.020 | 0.097 |
| 5000 | 0.101 | 0.019 | 0.082 |

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