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Healthcare Monitoring System forpatients in Smart Homes using Bayesian Classification

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Abstract--Migration of people from villages to smart cities is quite common in today's world. Health care services are the standout for the people living in corporate areas for maintaining good health habits to the one who are being sick. Now a day's many technological advancements are going with IoT in the smart homes, for example the automation of electronic devices through the sensor or smart meters. Although there exists several improvements in these sector, very limited research under the progress of the same technology in the view of healthcare. The sensors or smart devices are able to capture the regular activities of the patients living in a smart home to their continuous health monitoring. We proposed a software system that is able to capture the activities of the patients and transfer this information to the doctor by considering the state of the different appliances in a smart home. The useful frequent patterns and association rules are extracted from the sensor data and this can be used for predicting the behavior of the patient. Our proposed contributions are at first, the regular activities are recorded through the sensor at regular intervals with a specific threshold. Association rules are extracted using frequent pattern mining from this relational data. K-means clustering applied for this resultant information. Finally we used the Bayesian network model is utilized to predict the behavior of the patient and to control the health habits remotely by the supervisor.

Keywords – Smart meters, IoT, Big Data, Healthcare Application, Bayesian classifiers

1. Introduction

The everyday communication between ubiquitous sensors and devices to map the things physically and virtually through virtual network is called as Internet of Things (IoT). There are some probabilities provided by IoT that made this possible to offer various related applications. From these the smart home is highly enhanced domain in smart home automation systems with the motto of increment of users comfort and assurance for their safety and its criteria with low operation costs. Since smart home is an automated environment it can do monitor, detect and record daily activities by using variety of sensors and communication technologies. The user's daily activities develop patterns that play a key role in smart home environment [1, 2].The detection of user's daily activities is done on remote monitoring. It is having applications in many domains such as health care and daily care [3]. Hence the research on finding home activity is achieving more interest, specifically due to recent trends to shift healthcare from hospitals to patient's homes and make them to live independently. Few applications in this era include detecting daily activities also helps in supporting home automation and saving energy in smart homes. Home activity recognition depends on making an inference by data fusion from different sensors and uncertainty relevance due to stochastic nature of human behavior and bad sensing equipment. The important constraints include privacy, recognition with minimized cost and the sensors which are non-intrusive are considered. Those are the challenges in recent research.

According to the theory of D-S, couple of activity recognitions are done related to the smart homes. The author's Lee et.al. Demonstrated that their hypothesis of proof improves the vulnerability effectively. The D-S hypothesis of confirmation alongside with the lattice structure is utilized for finding the fundamental human activities like toilet flushing [4].In this paper we assume that many significant daily life activities can be found only with the utilization of energy monitors like smart meter information. Expecting that by the end of 2030, most of the houses in India will be provided by a smart sensor device for capturing the whole activities inside a smart home similar to the developed countries. As every home will be equipped with sensors for activity recognition so it is not necessary to have additional hardware. The remaining sections described in the following structure. Section 2 has the conventional methods on this area and related works with literature study. Section 3 demonstrates the proposed work. Our experimental study is discussed in Section 4. At the end, conclusion is drawn in Section 5.

2. Related Study

Various researches introduced IoT related smart home technologies to increase the security and to make the comfort for the users with reasonable. Vividly the use of sensors in smart homes is indispensable to record user activities. These activities of users is captured continuously and frequent patterns are generated based on the location of the person and their corresponding operation over the appliances. With that normal or abnormal behavior of the person done in the smart home and such kinds of activities will be found. In [5], the EM-algorithm helps in grouping of similar objects. It is quite easy and fast in performance but the number of features and objects changes its efficiency. Jakkula et al. [6] uses k-means clustering strategy. Nevertheless this method efficiency computed based number of clusters, optimal selection of centroid and iterations.In [7] a hierarchical clustering algorithm is utilized and is evaluated with entropy, time and coefficient of time. There is no specific constraint is there to give the number clusters in before implementation. In spite of hierarchical algorithm produce clusters with low quality and consumes much time for execution. The SOM algorithm [8] produces the high accurate results related clusters and better than k-means and EM methodologies. Nevertheless as increment in the no. of clusters ‘k’ (number of clusters) consequently there is decrement in the performance which gives less accurate outcomes. In general, there will be some ambiguity while processing noisy data in existing clustering algorithms. Along with user behavior and activities are integrates is some cases. Some of the models for forecasting the activities include the sequential activity prediction by using decision trees, the k-NN. Alam et al. [9] used models based on probability such as HMM to model user activities. This model is extensively utilized to find spatio-temporal associations between the sensor data and also to identify time series prediction [10, 11]. It consumes more time for execution for huge data. In [12], on the basis of C4.5 classifier one more classification model is considered for activity recognition. This model gives better results. In preciseness of recognition the performance is not that much greater than using Neural Networks [13]. Here we discussed some more literature study of our work from last three years.[14] Presents an approach to data assembling from smart homes on using installed appliancesThe objective is regulating the utilization patterns of household’s structure, so by keeping the view of usage of smart metering systems it provides additional knowledge on their usage. Most of the unsupervised machine learning techniques is processed while observing the pattern’s usage at various households. This work yields the related outcomes to smart metering systems that contributes to sophisticated energy consciousness; it is suitable to predict the usage precisely and gives input to the demand response systems in households and suggests the users on energy saving periodically. In this paper there provided some results showing that determining the features of household from smart meter data is precise and is able to get usual trends in data.

2.1 DM algorithm in Healthcare

Healthcare includes all the processes regarding diagnosis, treatment and disease prevention, injury and other physical and psychological impairments in humans [15]. In most of the countries the healthcare industries are at quick development. These healthcare industries are considered as places with better data quality as they constitute huge amount of data [16] and it is not utilizing well. The industries of healthcare utilize various methods and those are discussed in the following.

2.1.1. Anomaly Detection

It helps in finding the key variations in a dataset [17]. Bo Lie et al [18] introduced anomaly detection methods based on SVM and density vector method and other Gaussian models to predict the anomaly over different datasets on identification of liver disorder. The calculation of this method is performed on the basis of UCI accuracy. The results for a balanced dataset are obtained with 94% aggregate. To the same dataset 2.63 is the average standard deviation. The uncertain datasets are ignorable in the available datasets. To overcome this issue the anomaly detection provides better way. In this paper we are not concentrating on the effectiveness of this method.

2.1.2. Clustering

The authors in [19] used vector optimization for clustering to predict readmissions in intensive medicine and is similar to k-means. Whatever the datasets used in this study are retrieved from diagnosis process of a patient and laboratory reports. With the use of Davies-Bouldin Index each and every paradigm is evaluated. The algorithms k-means, x-means and k-mediods yields better, fair and poor outcomes respectively. On the basis of these outcomes the researchers selects the good result which could be used in characterizing different patients with high probability of readmission. We focused only on the vector quantization method in this paper.

2.1.3. Classification

It refers to the process of identifying a learning function that performs classification of data item into one of dissimilar predefined classes is called as Classification. The below subsections cover the related work of classification.Many studies examined the methods of decision tree to analyze clinical data. Authors Sharma & Om [20], Wang et al. [21] and Zolbanin et al. [22] utilized the decision tree technique in their work.. To perform prediction it is needed to explore the data and making a tree and the conditions of it are utilized. All the works mentioned above used decision tree for dataset to improve the performance regarding accuracy. We used a balanced dataset in this research work.

2.1.4. Swarm Intelligence

Authors Yeh et al. [23], Fei 2010 [24] and Abdi&Giveki [25] implemented swam intelligence method for diagnosing.Partial Swarm Optimization algorithm detects the optimal or approximate solutions in large search spaces efficiently. The authors worked for solving the optimization problem which involves with the features of classification problems. If lesser features are utilized then the process for classifying becomes speedy and more accurate. From studies this PSO related approach proved to improve the total outcomes of classification since PSO is used for selecting related parameters in the included classifiers.

2.1.5. Bayesian Classifier

Bayesian classifiers are widely known for its computational efficiency. These have ability to manage missed data efficiently. By this advantage the researchers attained fair accuracy from the generated models. Since models are implemented with the utilization of Bayesian classifiers also proved that the model is suitable because the average rate of this model led to improve accuracy in prediction and helps the authors to get more features.In Bayesian Networks though the relationships between parent-child need not to be casual and used in medical field[Beinlich 1989; Good 1961a; Good 1961b]. So that the demographic factors like age, often not having parents; these factors affects the probabilities of diseases or syndromes, which in turn affect the probabilities of symptoms or other measures of outcomes.The usage of Bayes Network is huge in real time applications includes Gene Regulatory Networks, Medicine Document Classification and numerous image processing applications.

3. Proposed Work

Our proposed work flow is represented in Figure 1. It initiates by data preprocessing like data cleaning and data preparation and later we applied FP mining to find the relationships between various appliances. It helps in finding which appliances are working together. At this point, we utilized cluster analysis to identify the relationships between appliance and time. Next to these steps, now the system is able to retrieve the appliance's pattern and this will be given as input to Bayesian network for short and long duration predictions. The result of the framework is utilized by healthcare applications depending on intended use. We briefly explain the theoretical concepts of techniques used in next section.

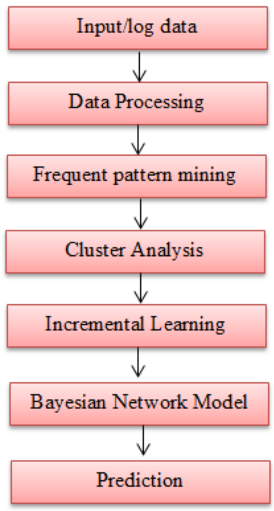


Figure 1: Flow of proposed work

3.1 Data Preprocessing

Data pre-processing is ignorable sometimes, but not in data mining process. If our dataset has irrelevant and noisy data, it becomes difficult to perform knowledge discovery process on training the data. The input data quality affects the final results. To get the precise outcomes finally, data should be efficiently preprocessed and we might use data cleaning, integration, transformation and data reduction for making the process easier. The stages are shown in figure 2. For our work we gathered attribute values, so the data may not have any empty values and we considered stipulated time for our work and that produces accurate results due to consistency. We are gathering the patient's information and everyday activities with the inclusion of several appliances in smart home. We considered binary values as the values for these appliances. Consider television is an example appliance and the value '1' indicates it is in 'ON' state and '0' indicates it is in 'OFF' state.

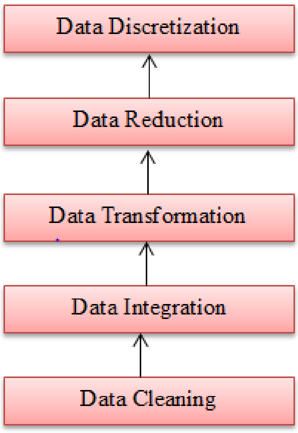


Figure 2: Data Pre-processing stages

3.2 Mining Frequent Patterns from Log Data

Our work main objective is to find patterns on the basis of human activities from smart meters. There are having various activities assume that 'Watching Television', 'Using Laptop', 'Using Micro Oven' and so on. We have to find the frequent patterns form the available activities, which are required in healthcare applications that monitor the immediate changes in the patient's behavior. The doctor could see the log data and suggest measures to patients by observing the generated association rules. In the essence, if the patient is in rest for a long period, the doctor can suggest to the patient based on the association rules and is more significant for heart patients. We set the different time intervals 30-60 minutes; the patient is able to upload smart meter information and frequent patterns will be generated accordingly. The numbers 1, 2 and 3 indicates the different every day activities. We have taken this concept from [24], [25] that use FP-growth technique using divide and conquer paradigm. Assume $\{I_1, I_2$, and $I_3 \ldots I_n\}$ are the item sets having 'n' number of items. I_k indicates the 'k'th item in the item set I_n. The association rules are generated in the form of X➔ Y in support and confidence framework. The preprocessing our data set using numeric to binary is shown in Figure 3.We used the FP-growth algorithm to find frequent item sets and the algorithm is shown in Algorithm 1.We can generate association rules from the frequent item sets. The goal of mining association rules is to form all rules which have support and confidence greater or equal than some predetermined minimum support and minimum confidence thresholds respectively.

Algorithm : FP-growth

```
Procedure FP-growth (Tree T, A)
{
if Tree T contains only one path P
    consider for every combination of the nodes in P do
      generate frequent patterns
else for each Hi in T
{
    generate pattern B= Hi U A with support= Hi support;
    construct B's patterns and B's frequent item sets i.e. FP-tree
then call FP-growth (tree B,B)
}
}
```

The general form of association rule is in the form of $X \Rightarrow Y$. The support, confidence and Lift are computed as from equation (1), (2) and (3).

$$\text{Support}=\frac{\text{frq (X,Y)}}{\text{N}} \quad (1)$$

$$\text{Confidence}=\frac{\text{frq (X,Y)}}{\text{frq (X)}} \quad (2)$$

$$\text{Lift}=\frac{\text{frq (X,Y)}}{\text{Supp (X)}*\text{Supp (Y)}} \quad (3)$$

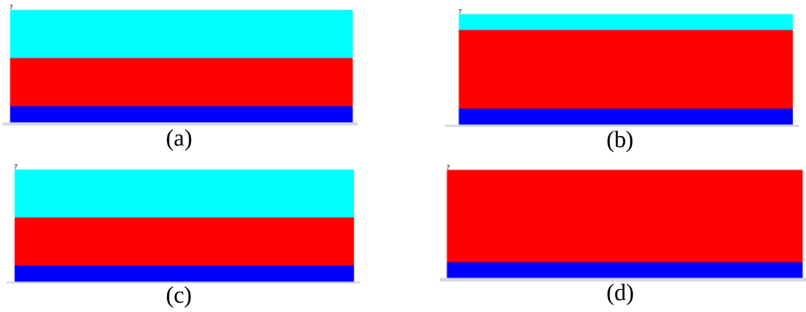


Figure 3: Result of Numeric to Binary Filter for our data set. (Only four attributes are shown in (a), (b), (c) and (d)).

3.3 Cluster Analysis

It is important to healthcare applications to define the relationships between time and appliances. It helps in monitoring the daily activities of the patient's on timely basis. We utilized cluster analysis to mention the appliance usage on timely basis. For suppose if the patient is watching television in particular time for whole day i.e. (00:00 – 23:59) and this activity will be monitored by the time of the day in three slots (i.e. morning, afternoon and evening). The relationship between the appliance and time on based on the gathered information via smart meter. For our work we have sensor instead of using smart meter. The recorded data is stored in data base and we can integrate them as a group of products so that the patient is using in particular time. Suppose if patient is using washing machine and micro oven at a time in the morning between 07:00 – 08:00 then, those dual data items come under a group and creates a cluster. When we upload a recent activity, there performed incremental clustering and then the clusters are formed accordingly and the corresponding clusters are shown in Figure 4. Eventually we combine the identified patterns and the relationship between time and appliances and is given to machine learning model known as Bayesian Network model to forecast the activities. In the table 'L' denotes 'LOW' and 'O' denotes 'OVER'

Attribute	**Full Data (7.0)**	**0 (6.0)**	**1 (1.0)**
DATE	5/20/2018	5/20/2018	5/20/2018
SHIFT	Evening	Evening	Morning
NO.OFMINUTES	60	60	60
WASHING MACHINE	0.1429	0	1
BOWL WASHER	0.1429	0	1
THREAD MILL	0.2857	0.1667	1
YOGA MAT	0.1429	0	1
MICROWAVE OVEN	0.2857	0.3333	0
NESPRESSO	0.1429	0.1667	0
TV	0.1429	0	1
LAPTOP	0.5714	0.5	1
WORK	L	L	O

FOOD	L	L	L
WORKOUT	L	L	O
REST	L	L	O

Figure 4: Summary of Cluster analysis

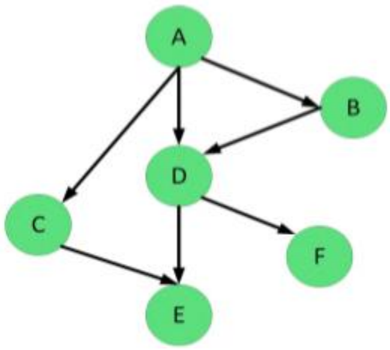


Figure 5: Bayesian network with '6' nodes.

As described in the previous section BN is a graph which has nodes and edges. Node represents random variables and edges represent probabilistic dependencies. We considered this model because of its main feature "causality". We have shown a sample Bayesian network model with '6' nodes in Figure 5.

4. Results & Discussion

This section covers our experimental study and the results of our proposed work. Our software system is capable of storing huge amount of data base and can also be applied big data frame work for getting better performance and computations. The patients are able to register through the network and the details are stored in cloud or any other information repository. A list of doctors of different categories is maintained in our database, for example to give precautions or remedy for various diseases. Once the doctor accepted the request from the patient a connection is established between the patient and doctor and are able to exchange the messages in online. Along with this, the doctor is now able to monitor the daily activities done by the patient in the smart home through our software system. For example, the doctor can send a warning message or a general message to the patient to give precautions to the patient once he observed the activity by the patient, this is done by the sensor device over IoT. But in our work, the patient can upload his daily activities from his login/family login. This information can now transferred to the doctor and patients are able to get the suggestions from the doctor in online. We used our algorithm for extracting the frequent patterns/ associations from the captured data from the patient at the doctor side. As in our work, we used to upload a data file or binary information by the patient to give input for our algorithm, but we can getter better user satisfaction once the data is collected automatically be the smart meter or sensor data using IoT. The input for the algorithm is shown in Figure 8, the details uploaded by four patients along with their log information. These activities are captured with the time duration of 60 minutes in three slots, i.e. morning, afternoon, evening. We can add few more security mechanisms to enter the confidential information from the user side to avoid the misusage. There exists several appliances in the smart home, we considered '8' appliances in our work and binary data set is shown in Figure 6. For example WM denotes Washing Machine, TV denotes Television and LT denotes Laptop. There exists only two states for each appliance, whether the appliance is in use (True) or not in use (False). For example, True indicates the appliance is ON, False indicates the appliance is OFF. Figure 8 shows the details of three patients along with their regular activities at three regular intervals. The time span may be different for each user. We have consider few attributes such as ID, Name, Email, Mobile, Age, Gender, and Disease for each user. The activities of the patient are shown in Figure 7 and the clustered data is shown in Figure 8. The cluster results may vary once, the data has been uploaded by the patient, since the activities of the patient of the other time slot may be different with the current clustering result. The result is shown in Figure 10. We also shown the list of work out, work, rest and the food consumed by the patient in Figure 11. The terms L,A,O are Low, Average, Over respectively in Figure 9.

WM	BW	TM	YM	MO	NES	TV	LT
0	0	0	0	1	0	0	1
1	1	1	1	0	0	1	1
0	0	0	0	0	0	0	1
0	0	0	0	0	1	0	1
0	0	0	0	1	0	0	1
0	0	0	0	0	0	0	1
0	0	1	0	0	0	0	0

Figure 6: Activities of the patient with unique appliances

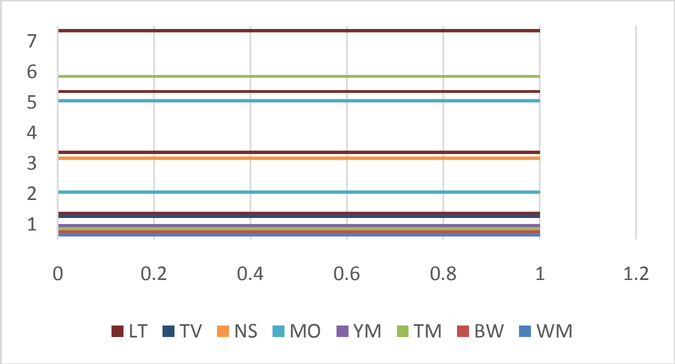


Figure 7: Activities of the patient at different time slots

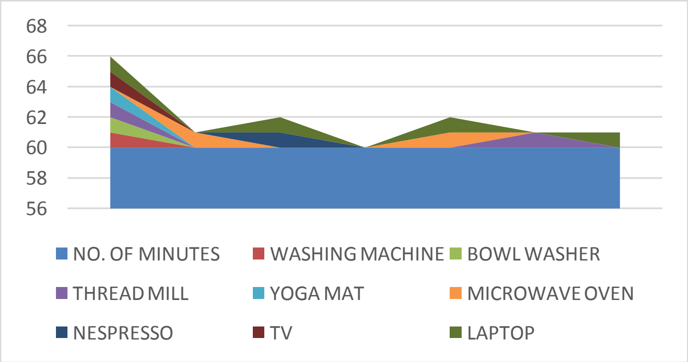
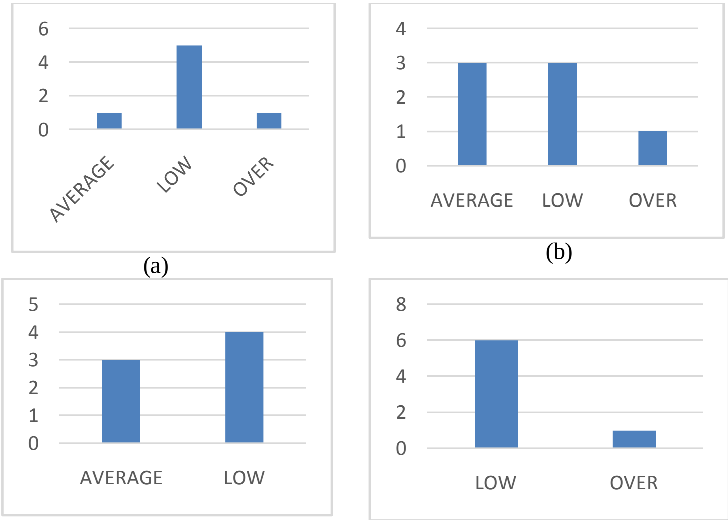


Figure 8: Cluster representation of the appliances

WORK	FOOD	WORKOUT	REST
O	L	O	O
L	A	L	L
L	A	L	A
L	L	L	L

L	A	L	A
L	L	A	L
L	L	L	A

Figure 9: Result of workload by the patient



(a) (b) (c) (d)

Figure 10: Analysis of the four resultant attributes

The statistics of the Naïve Bayes are shown in Table 1.The confusion Matrix is $\begin{bmatrix} 1 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 3 \end{bmatrix}$. The above matrix is classified as a, b, c i.e. a= OVER, b= LOW, c = AVERAGE respectively.

Table 1: Statistics of the Naïve Bayes

TP Rate	Precision	Recall	F-Measure	MCC	ROC	PRC
1.000	1.000	1.000	1.000	1.000	1.000	1.000
1.000	1.000	1.000	1.000	1.000	1.000	1.000
1.000	1.000	1.000	1.000	1.000	1.000	1.000
1.000	1.000	1.000	1.000	1.000	1.000	1.000

5. Conclusion

Healthcare services are considered as the most challenging aspects that must be needed to people with abnormal health. Data mining performs a crucial role on healthcare industries, especially in forecasting various types of diseases. The medical diagnosis is widely used during diseases forecasting. As conclusion there should not be any data mining method for risk resolving in healthcare data sets. We have to build a hybrid model which is supportive for resolving the mentioned issues. Initially we have recorded patient’s daily activities for a particular time at three regular intervals. Subsequently, we have applied the FP-growth for retrieving the association rules from log file. Eventually, we applied k-means clustering for the input along with Bayesian network model to forecast the patient’s health behavior and suggests precautions accordingly. It helps in getting high accuracy among classifiers which is very important in medical diagnosis by including the characteristics of data with care. For better improvement in forecasting along with the real time sensor meter information with the use of hybrid models is our future work.

References

[1] Aldrich, F.K., 2003. Smart Homes: Past, Present and Future. Inside the Smart Home. In: Harper, R. (ed.). Springer-Verlag, London, pp. 17–39.

[2] Hargreaves, T., Hauxwell-Baldwin, R., Wilson, C., Coleman, M., Kane, T., Stankovic, L., Stankovic, V., Liao, J., Hassan, T., Firth, S., 2015. Smart Homes, Control and Energy Management: How Do Smart Home Technologies Influence Control over Energy Use and Domestic Life? European Council for an Energy Efficient Economy (ECEEE) Summer Study on Buildings, Hyeres, France.

[3] H. Zheng, H. Wang, and N. Black, "Human activity detection in smart home environment with self-adaptive neural networks," in Proc. of IEEE International Conference on Networking, Sensing and Control, pp. 1505-1510, 2008.

[4] E.M. Tapia, S.S. Intille, and K. Larson, "Activity recognition in the home using simple and ubiquitous sensors," Proceeding of Pervasive, vol. LNCS 3001, Springer Berlin Heidelberg, pp.158–175, 2005.

[5] Rashidi, P.; Cook, D.J. Transferring Learned Activities in Smart Environments, In Proceedings of the International Conference on Intelligent Environments, Barcelona, Spain, 20–21 July 2009.

[6] Jakkula, V.R.; Cook, D.J. Using Temporal Relations in Smart Environment Data for Activity Prediction. In Proceedings of the International Conference on Machine Learning, Corvallis, OR, USA, 20–24 June 2007.

[7] Riabov, A.; Liu, Z.; Wolf, L.; Yu, S.; Zhang, L. Clustering Algorithms for Content-Based Publication-Subscription Systems. In Proceedings of the 22nd International Conference on Distributed Computing Systems, Vienna, Austria, 2–5 July 2002; pp. 133–142.

[8] Li, C.; Biswas, G. Unsupervised Learning with Mixed Numeric and Nominal Data. IEEE Trans. Knowl. Data Eng. 2002, 4, 673–690.

[9] Alam, M.R.; Reaz, M.B.I.; Mohd Ali, M.A. SPEED: An Inhabitant Activity Prediction Algorithm for Smart Homes. IEEE Trans. Syst. Man Cybern. Part A Syst. Hum. 2011, 4, 985–990.

[10] Liao, L.; Fox, D.; Kautz, H. Location-Based Activity Recognition Using Relation Markov Network. In Proceedings of the International Joint Conference on Artificial Intelligence, Edinburgh, Scotland, 30 July–5 August 2005; pp. 773–778.

[11] Miskelly, F.G. Assistive Technology in Elderly Care. Age Ageing 2001, 6, 455–458.

[12]. Building Classification Models: ID3 and C4.5. Available online: http://www.cis.temple.edu/~ingargio/ci587/readings/id3-c45.html (accessed on 21 May 2015).

[13]. Weka 8: Data Mining Software in Java. Available online: http://www.cs.waikato.ac.nz/ml/weka/ (accessed on 08/04/2018).

[14] W. Haizhou and S. Mingzhou, ''Ckmeans.1d.dp: Optimal k-means clustering in one dimension by dynamic programming,''RJ. vol.3,no.2, pp. 29–33, 2011. [Online]. Available: http://journal.r-project.org/ archive/2011-2/RJournal_2011-2_Wang+Song.pdf

[15] J.-J. Yang, J. Li, J. Mulder, Y. Wang, S. Chen, H. Wu, Q. Wang, and H. Pan, "Emerging information technologies for enhanced healthcare," Comput. Ind., vol. 69, pp. 3–11, 2015.

[16] N. Wickramasinghe, S. K. Sharma, and J. N. D. Gupta, "Knowledge Management in Healthcare," vol. 63, pp. 5–18, 2005.

[17] U. Fayyad, G. Piatetsky-Shapiro, and P. Smyth, "From data mining to knowledge discovery in databases," AI Mag., pp. 37–54, 1996.

[18] B. Liu, Y. Xiao, L. Cao, Z. Hao, and F. Deng, "SVDD-based outlier detection on uncertain data," Knowl. Inf. Syst., vol. 34, no. 3, pp. 597–618, 2013.

[19] R. Veloso, F. Portela, M. F. Santos, Á. Silva, F. Rua, A. Abelha, and J. Machado, "A Clustering Approach for Predicting Readmissions in Intensive Medicine," Procedia Technol., vol. 16, pp. 1307–1316, 2014.

[20] N. Sharma and H. Om, "Data mining models for predicting oral cancer survivability," Netw. Model. Anal. Heal. Informatics Bioinforma., vol. 2, no. 4, pp. 285–295, 2013.

[21] K.-J. Wang, B. Makond, and K.-M. Wang, "An improved survivability prognosis of breast cancer by using sampling and feature selection technique to solve imbalanced patient classification data.," BMC Med. Inform. Decis. Mak., vol. 13, p. 124, 2013.

[22] H. M. Zolbanin, D. Delen, and A. Hassan Zadeh, “Predicting overall survivability in comorbidity of cancers: A data mining approach,” Decis. Support Syst., vol. 74, pp. 150–161, 2015.
[23] W.-C. Yeh, W.-W. Chang, and Y. Y. Chung, “A new hybrid approach for mining breast cancer pattern using discrete particle swarm optimization and statistical method,” Expert Syst. Appl., vol. 36, no. 4, pp. 8204–8211, 2009.
[24] S. W. Fei, “Diagnostic study on arrhythmia cordis based on particle swarm optimization-based support vector machine,” Expert Syst. Appl., vol. 37, no. 10, pp. 6748–6752, 2010.
[25] M. J. Abdi and D. Giveki, “Automatic detection of erythemato-squamous diseases using PSO-SVM based on association rules,” Eng. Appl. Artif. Intell., vol. 26, no. 1, pp. 603–608, 2013