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Mining Human Activity Patterns from Smart Home Big Data for Healthcare Applications

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Abstract- During a time where there is a solid reliance on electrical apparatuses for residential schedules, this paper proposes a calculation for distinguishing residential exercises from non-nosy shrewd meter total information. It recognizes exercise of human activities pattern and predict its effect on human health. For the two kinds of exercises, it begins by disaggregating the add up to control utilization down to individual electrical machines. At that point, fabricate a characteristic action model to reason four residential exercises utilizing the Dempster-Shafer hypothesis of confirm. To approve our calculations, utilize genuine vitality and ecological information gathered in a genuine UK family unit over a time of three months, benchmarked on a period stamped log of exercises. The outcomes demonstrate that it is conceivable to distinguish four tried household day by day exercises with high exactness based on the total vitality use.

Keywords-– smart meter, NALM, smart home, big data, healthcare application, SMM, ADL.

I. INTRODUCTION

Recognizable proof of everyday residential exercises in light of remote checking has applications in numerous areas, such as, social insurance and elderly care [1]. Thus, residential movement acknowledgment investigate is increasing expanded premium, particularly because of current patterns to move social insurance from healing facilities to patients' homes and encourage free living. Be that as it may, conceivable applications go a long ways past human services. For instance, perceiving exercises of everyday life can likewise be utilized to help home robotization and vitality investment funds in shrewd homes/structures.

This paper contend that numerous vital exercises of everyday life can be recognized utilizing vitality screens just, i.e., shrewd meter information. By 2020 all UK homes will be outfitted with a savvy meter [3], with comparable patterns in other created nations. Instinctively, so as to perceive a movement utilizing savvy meters, it is important to distinguish turning on and off of electric machines. Be that as it may, shrewd meters that have been, or will be, introduced in normal homes measure just total power utilization, that is, the aggregate power utilization of the entire house. Consequently, the initial move towards action acknowledgment is to disaggregate savvy meter readings down to singular apparatuses. Non-intrusive appliance load monitoring checking (NALM) [4] alludes to algorithmic techniques to disaggregate add up to vitality use. Numerous NALM systems have been proposed (see [5] for a current audit) that apply diverse directed or unsupervised machine learning and flag handling instruments, to show apparatus task, extricate electrical highlights, and perform characterization. In this paper, it utilize keen meter information and plan a novel residential movement acknowledgment framework utilizing NALM and Dempster-Shafer (D-S) hypothesis of proof [6], [7].The key oddity of our work contrasted with the above investigations lies in the particular idea of accessible sensor information (total power readings) which presents another sort of vulnerability into the model, because of the mistake of current NALM calculations.

To begin with, the information assembled from a test home is pre-prepared to detach key highlights that will be utilized to recognize the electrical machine utilization designs [13]. At that point, the information is sustained to a machine learning- based calculation that performs NALM took after by the D-S hypothesis of proof [6] to segregate the residential exercises, from vitality readings, time data and ecological information.

The paper is progress as follows. Section II illustrates the literature review. Section III defines the problem definition. Section IV discuss about the proposed approach, Section V concludes the work and future scope is presented.

II. LITERATURE STUDIES

These days there has been a developing pattern in using smart home technologies keeping in mind the end goal to identify human movement designs for social insurance applications. The principle point is to learn and find human practices with a specific end goal to anticipate the human exercises inside smart homes that can help in recognizing medical problems.

Paper 1: Detecting Household Activity Patterns from Smart Meter Data

In the paper, Detecting Household Activity Patterns from Smart Meter Data[4] a calculation is proposed for distinguishing local exercises from the total information gathered by the smart meter. There are two kinds of exercises: Type I exercises are those that can be distinguished by the smart meter information and Type II exercises can be recognized from the smart meter information and natural detecting (temperature and humidity).For distinguishing the individual activities, y disaggregate the aggregate power use down to individual electrical machines. At that point, a movement demonstrate is made to reason the local activities. This thinking is finished with the assistance of Dempster- Shafer theory of evidence. The hypothesis expresses that we can consolidate confirm from various sources and touch base at a level of conviction that considers all the accessible confirmation. Distinguishing proof of local exercises inside a shrewd home has numerous applications for instance, medicinal services what's more, elderly care. In any case, different applications go a long ways past human services. For example, support home automation and energy savings in smart homes.

Paper 2: Detecting Activities of Daily Living with Smart Meters

Detecting activities of daily living with smart meters [2] is an examination work in which smart meters are utilized to give data energy utilization of building and to identify the use of machines. This encourages the more established individuals to remain longer independent in their homes by recognizing their action and their conduct models to guarantee their healthy level. This paper can be utilized to analyze smart meter information to screen human behavior in single home. There are two methodologies centered by this paper. They are Semi Markov Model (SMM) and Influence based method. The Semi-Markov-Model (SMM) is used to analyze and detect individual habits to find unique structures representing habits. If the most possible executed activity (PADL) is evaluated then it can infer the currently executed activity (ADL) of the inhabitant. The impulse based technique is utilized for the location of ADLs by investigating all parallel ADLs. Both methodologies depend on smart meter occasions which help to recognize which home appliances was exchanged. In this way, this paper will likewise give an outline of well known strategies to recognize the occasions on power utilization information.

Paper 3: Smart meter profiling for health applications

C. Chalmers et.al proposed Smart meter profiling for health applications [5] in which the smart meters are utilized to screen power utilization and perceive sudden changes in the conduct of people inside smart homes. Its applications come in the field of following people experiencing Alzheimer's disease, Parkinson's disease and clinical gloom(depression). This spotlights on information grouping procedures which identify irregularities in conduct by breaking down individual energy usage pattern. Here the foundation is named as Advanced Metering Infrastructure (AMI). This is the AMI in which there is a smart home furnished with smart gadgets like smart meter gas, smart meter power and there is a smart meter that gathers information from all the smart gadgets. The smart meter information is exchanged to Data and Communications Company (DCC)) by means of a Wide Area Network (WAN) module which goes about as a correspondence specialist organization between smart homes and clients.

Paper 4: The Elderly's Independent Living in Smart Homes: A Characterization of Activities and Sensing Infrastructure Survey to Facilitate Services Development

Q.N i.A.B.G.Hernando et.al proposed The Elderly's independent living in smart homes a characterization of exercises and detecting infrastructure overview to encourage administrations improvement [3] that includes the recognition of human exercises inside brilliant homes as per the health observing of a quickly maturing population in developed nations. This is the engineering taken from the paper Elderly's free living in smart homes: a characterization of exercises and detecting framework study proposed by Q.Ni.A.B.G .Hernando et.al to encourage administrations improvement. Such a living is named as Ambient Assisted Living (AAL). The action based AAL comprises of three phases: Raw information procurement, Sensor data processing and getting the hang of/thinking via caregivers. In raw information procurement stage, the client profile which comprises of points of interest of client like age and area learning like things inside smart home are put away in database. There are different sensors like audio/video, ecological and wearable sensors inside the smart home that gathers information and this sensor information are likewise put away in the database. Next stage is sensor information preparing in which the information from the database is taken and changed into a setting formalized representation. Presently this information is preprocessed with a specific end goal to remove noise. The preprocessed information is partitioned to parcel the information into gatherings of information having similar properties. The sectioned information will experience dimensionality decrease in which the dimension of the data are decreased with the end goal that it is changed into a frame proper for mining. At that point a activity modeling happens in the smart home. Advance these activities are learnt by the caregivers/specialists through the UI of the health care applications keeping in mind the end goal to distinguish medical issues of people inside the smart homes.

Paper 5: Smart energy group anomaly based behavioral

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Abnormality detection

In this paper, Smart energy group anomaly based behavioral abnormality detection [6] manages An information explanatory approach and therefore recognize behavioral anomaly of residents. Here the smart meter is utilized to identify regular appliances usage. This work takes after a various leveled probabilistic model. In hierarchical probabilistic model, observations are grouped into m clusters. The model is utilized for anomaly detection discovery which distinguishes the behavioral inconsistencies over an arrangement of energy sourse data point. The hierarchical form of analysis and association helps in the comprehension of multi parameter issues and furthermore assumes a vital part in developing computational methodologies.

III. PROPOSED SYSTEM

A. Data Preparation
B. Extracting Frequent Patterns Of Human Activities
C. Clustering Analysis: Incremental K-Means
D. Bayesian Networks For Activity Prediction

ALGORITHM 1: Incremental Frequent Pattern Mining

Require: Transaction database (*DB*), Frequent pattern discovered database (*FP_DB*)

Ensure: Incremental discovery of frequent patterns, stored in frequent patterns discovered database (*FP_DB*)

1: **for all** Transaction data slice *db*24 in quanta of 24 hours in database *DB* **do** {Data is processed in slices of 24 hour period}
2: Determine database size *Database_Sizedb*24 for data slice/quantum *db*24.
3: Mine Frequent patterns in *FP_DBdb*24 using extended FP-growth approach
4: **for all** Frequent Pattern *FP* in *FP_DBdb*24 **do**
5: Search a frequent pattern *FP* in *FP_DB*
6: **if** Frequent Pattern found **then**
7: Update frequent pattern in *FP_DB*
8: **else**
9: Add a new Frequent Pattern to *FP_DB*
10: **end if**
11: **end for**
12: For all Frequent Patterns in Database *FP_DB* increment *Database Size* by *Database_Sizedb*24 13: **end for**

IV. PROBLEM STATEMENT

Problem being solved: Healthcare issue and also reduces over consumption of energy.

The use of energy data from smart meters installed at homes to unveil important activities of inhabitants and also the daily unhealthy activities performed by the user in the house by frequently monitoring them.

V. EXISTING SYSTEM WORKING OF

ALGORITHM

K-Means clustering intends to partition *n* objects into *k* clusters in which each object belongs to the cluster with the nearest mean. This method produces exactly *k* different clusters of greatest possible distinction. The best number of clusters *k* leading to the greatest separation (distance) is not known as a priori and must be computed from the data. The objective of K-Means clustering is to minimize total intra-cluster variance, or, the squared error function:

1. Clusters the data into *k* groups where *k* is predefined.

Stringcluster[]={"-12600","-5400","1800","9000","16200","23400","30600","37800","45000","52200","59400","66300"};

2. Select *k* points at random as cluster centers. int temp= 100000;

int index=0;
for (int i = 0; i <l.size(); i++) { String s1=l.get(i).toString();
String s[]=s1.split(" "); String dataset=s[2];

3. Assign objects to their closest cluster center according to the *Euclidean distance* function.

String apnames[]={"bedroomlamp1","dishwasher","freez1","hairdriyer","katle","kitechanlight","laptop","toster","tv","washingmc"};

4. Calculate the centroid or mean of all objects in each cluster.

index=0;
//temp=66600; temp= 665

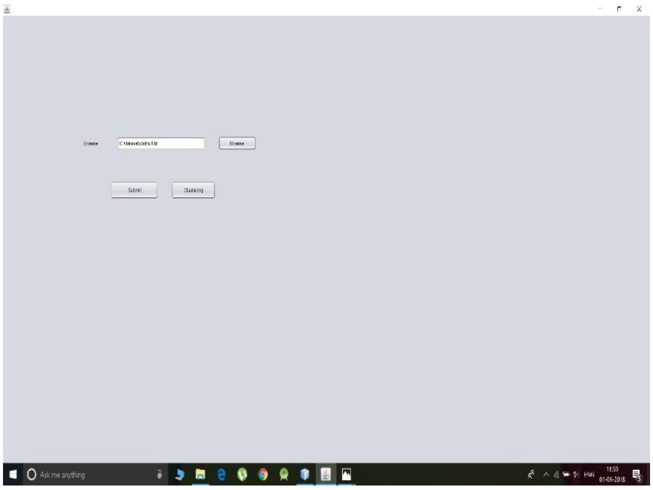
5. Repeat steps 2, 3 and 4 until the same points are assigned to each cluster in consecutive rounds.

VI. MATHEMATICAL MODEL

Discovering appliance-to-time associations is vital to health applications that monitor patients' activity patterns on a daily basis. In this section, a clustering analysis mechanism is used to discover appliance usage time with respect to hour of day (00:00 - 23:59), time of day (Morning, Afternoon, Evening, Night), weekday, week and/or month of the year.

Appliance-to-time associations are underlying information in the smart meter time series data which include sufficiently close time-stamps, when relevant appliance has been recorded as active or operational. Using this data can group a class or cluster of appliances that are in operation simultaneously or overlapping. The size of the cluster that describes such associations is dined as the count of members in the cluster as well as its relative strength. Clustering analysis is the process of creating classes (or groups/segments (automatic segmentation) or partition where members must possess similarity with one another, but should be dissimilar from the members of the other clusters.

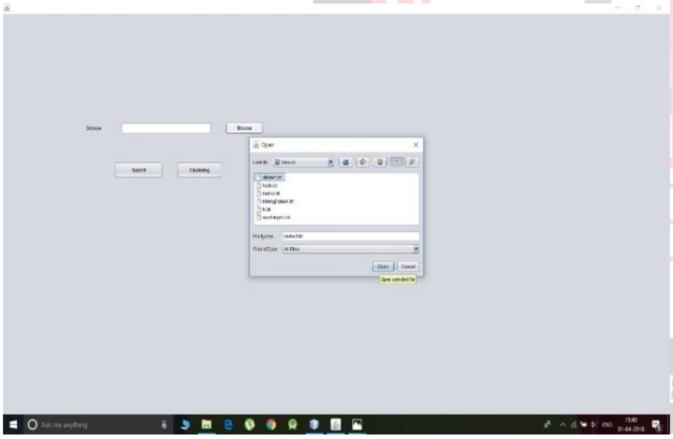
VII. DESIGN DETAILS



Partitional clustering distributes the data points from DB into k clusters, C1,C2, ….,Ck, having centroids c1, c2,…., ck such that DB C Ci , Ci ∩Cj = ø and ci ≠cj for(1 ≤ i, j ≤ k). An objective function based on Euclidean distance,

distance(x,y) $=\sqrt{\sum j(x_j - y_j)^2}$

It is used to measure the cohesion among data points, which reflects the quality of the cluster. This objective function is the sum of the squared error (SSE), SSE =Pki=1Pd2Ci distance(d; ci)2, and k-means algorithm seeks to minimize the SSE. And, make use of the silhouette score which is calculated based on the Euclidean distance to determine the optimal number of the clusters; i.e., k.



SYSTEM ARCHITECTURE

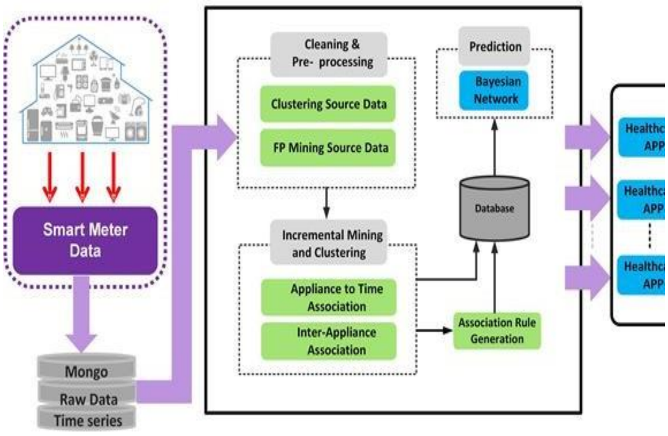


Fig. Mining Frequent Patterns and Activity Predictions for Healthcare Applications in Smart Homes

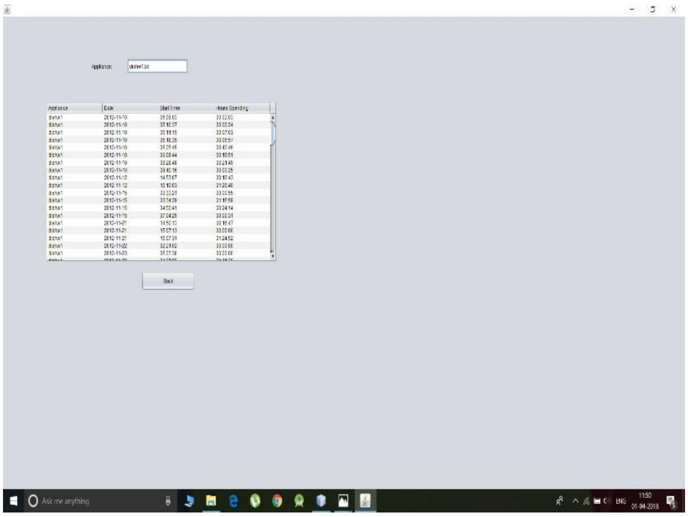
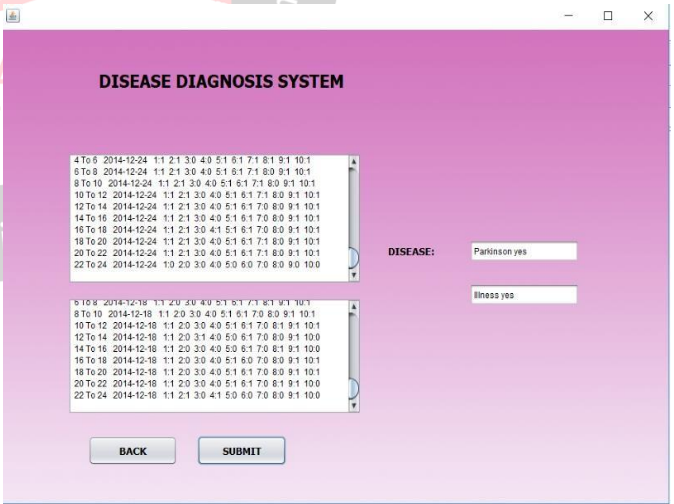


Figure represents the proposed model. It starts by cleaning and preparing the data and then applying frequent pattern mining for discovering appliance-to-appliance associations, i.e., determining which appliances are operating together. Then, it uses cluster analysis to determine appliance-to-time associations. With these two processes, the system is able to extract the pattern of appliance usage which is then used as input to the Bayesian network for short-term and long-term activities prediction. The output of the system is utilized by specific health care applications depending on the intended use. For example, a health care provider might only interests in knowing activities related to cognitive impairment where tracking the sequence of daily activities is crucial for reminding the patient when abnormal behaviour is detected. Next subsection explain such processes and briefly outlines the theoretical background.



VIII. CONCLUSION

In this paper a model for recognizing human activities patterns from low resolution smart meters data. Occupants' habits and behavior follow a pattern that could be used in health applications to track the wellbeing of individuals living alone or those with self-limiting conditions. Most of these activities can be learned from appliance-to-appliance and appliance-to-time associations. It presented incremental frequent mining and prediction model based on Bayesian network. In our current work, through experiments, it found that 24-hour period was optimal for data mining, but built the model to operate on any quantum of time. From the experiment results have demonstrated the applicability of the proposed model to correctly detect multiple appliance usage and make short and long-term prediction at high accuracy.

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