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ABSTRACT: Big data collected by the smart devices has been used to preserve human activity patterns to improve people's health, as much money is being invested in digital transformation to provide a healthier ecosystem for humans. The recognition of human action and the determination of human qualities are two tasks that require fine-grained classification. Indeed, small and unobtrusive objects and features often have to be discovered to distinguish their classes. Using Bayesian network needs to deal with strong assumption in data clusters, data scarcity in likelihood approach and continuous features is needed for the information. To meet this challenge, we propose a novel neural convolution network that mitigates mid-level image patches sufficient to resolve the intricacies. In particular, we train a newly designed CNN (deep pattern) that learns to discriminate patch groups. There are two innovative aspects. On the one hand, we pay attention to contextual information in an original way. On the other hand, we leave a set of dedicated patches that we use through an iteration of feature learning and patch clustering. DBSCAN clustering method was used to analyze the space-time patterns, and topic modeling was used to derive the associated semantic geographic patterns. The similarities between the spatiotemporal clusters of human activities were calculated to build a network that ultimately represents human activity patterns. Our simulation standard-level Big Data Mining CNN gets pervious results on these datasets without the need for annotating parts and poses using the proposed clustering method.

***Keywords*:** *Smart device, fine-grained classification, Bayesian network , DBSCAN ,Patch clustering*.

1. INTRODUCTION

To handle the above-mentioned issue, the paper proposes frequent pattern mining and prediction model to measure and analyze energy usage changes observed in the household behavior. The data from smart meters are observed in the quantum/data portion of 24 hours, and the results are preserved across subsequent mining activities. Frequent pattern tree for mining the entire set for pattern recognition is observed based on the comparison between k-means clustering algorithm and DBSCAN clustering algorithm to identify the appliance-to- appliance cooperative from incremental mining of energy consumption data.

This is not only used to determine activity routines, but also, used for detecting sudden changes of human activities when utilized by health care application, that is required for attention of a health provider. The signal is detected by the mobile telephone. Once the signal is detected, it is used for frequent pattern mining, cluster analysis, and prediction to measure and analyze changes in energy consumption caused by the behavior of the occupants. Since the destinies of man can be identified above all in everyday life, we recognize abnormal activities on these discoveries, which point to the difficulties of people to provide themselves. We propose a mountain model for human activity patterns based on the use of Smart Homes. The model that uses FP growth for pattern recognition and Fuzzy C, clustering algorithms, can be appliance and appliance consumption data. This is not only important to determine activity routines, but also when used by a health application to detect sudden changes in human activities observed by a health

care provider. We use ANN for activity prediction based on the individual and multiple use of devices. For healthcare applications that integrate certain activities based on historical data for patients.

The paper presents a newly designed CNN to extract such information by identifying informative image patches. The idea of focusing on patches or parts definitely is not new in computer vision, also not when it comes to human actions or attributes that a good solution to human action classification can be achieved without trying to obtain perfect pose estimation and without using body part detectors. Indeed, an alternative is to capture discriminative image patches. Mining such patches for the cases of actions and attributes is the very topic of this paper. After deriving some initial discriminative patch clusters for each category of action or attribute, our deep pattern CNN puts them into an iterative process that further optimizes the discriminative power of these clusters. Our experiments show that we obtain better performance for action and attribute recognition than top scoring, patch-based alternatives for object and scene classification. The latter do not seem to generalize well to the action and attribute case because these tasks need more fine-grained mid-level visual elements to make discrimination between similar classes.

2. LITERATURE REVIEW

In [1] authors Jing Liao, Lina Stankovic and Vladimir Stankovic in the paper **"Detecting Household Activity Patterns from Smart Meter Data"** proposed that there is a tough addiction on electrical appliances for domestic routines, here we propose an Non-intrusive appliance load monitoring (NALM) algorithm for identify domestic activities for smart meter aggregate data. We differentiate two types of behavior: Type I behavior are those that can be acknowledged using only smart meter data and Type II behavior are recognized by combining smart meter data with basic environmental sensing (temperature and humidity). By analyzing the both behaviour, we start by disaggregating the entire power produced down to individual electrical appliances.Then, we build an indicative activity model to reason four domestic behavior using the Dempster-Shafer theory of proof. To validate Non-intrusive appliance load monitoring (NALM) algorithms, we collect the environmental data of real energy in house hold during the period of months.Here we conclude that it is probable to notice four tested domestic daily behavior with high accuracy based on the aggregate energy usage.

In [2]authors Abdulsalam Yassine, Ali Asghar Nazari Shirehjini, And Shervin Shirmohammadi in the paper "**Smart Meters Big Data: Game Theoretic Model for Fair Data Sharing in Deregulated Smart Grids"** propose a game theoretic mechanism that balances between valuable uses of data and individuals' privacy in deregulated smart grids. Smart meters big data has large societal importance that can be achieved by mechanisms that balance between consumers privacy and the benefit of sharing data.

we presented a mechanism for sharing power consumption data in deregulated smart grids and also the concept of Activities in Daily Living as a means of data categorization and to help the data aggregator and the consumers to identify privacy risk values we assume that participants increase their cost linearly with the privacy risk value or with the anonymization level.

These assumptions may require a more detailed modeling and user based studies to reflect reality. The concepts of "smart grid" and "smart meter " detected a significant gap between the knowledge of consumers and that they should have to take advantage of the new smart energy initiatives.

In [3]authors Qin Ni, Ana Belén García Hernando and Iván Pau de la Cruz in the paper "**The Elderly's Independent Living in Smart Homes: A Characterization of Activities and Sensing Infrastructure Survey to Facilitate Services Development**" propose a classification of the main activities considered in smart home scenarios which are targeted to older people's independent living, as well as their characterization and formalized context representation. Smart Home (SH) has gained a lot of attention for the terms of enhanced quality of life within the home. SH technologies may help to enhance quality of life, make longer independent living and reduce caregivers' necessary time and healthcare costs in general, without losing the safety that a continuous and unobtrusive monitoring provides. This is what is sometimes known as Ambient Assisted Living (AAL). AAL technologies

and tools in terms of smart homes,assistive robotics, e-textile and wearable sensors, also exploring healthcare applications that focus on activity recognition algorithms and context modeling. They also use machine learning algorithms and statistical techniques to infer relevant information from the correspondence between the accelerometer and the electro myo gram (EMG)sensors measurements. The UML models show advantages in capturing information about the static structure and dynamic behaviour of a system, but have limitations in providing precise semantics and supporting reasoning on human behaviours.

In [4]authors Mohammad Arif Ul Alam, Nirmalya Roy, Michelle Petruska and Andrea Zemp in the paper **"Smart-Energy Group Anomaly Based Behavioral Abnormality Detection"** propose a data analytic approach that helps detect energy usage anomalies corresponding to the behavioral abnormality of the residents .It relies on detecting everyday appliances usage from smart meter and smart plug data traces in regular activity days and then learning the unique time segment group of each appliance's energy consumption. Nonintrusive load monitoring (NILM) research domain has been confined into the detection of types of appliances people have and their behavioral patterns through energy profiling and disaggregation. We apply other alternative methods such as GLDA, GMM and the K-Nearest Neighbor (KNN) algorithms that have been used successfully for collective anomaly detection for long time. it is possible to determine when prevention is necessary for an individual at risk.

In [5]authors M. Shamim Hossain in this paper **"Cloud-Supported Cyber–Physical Localization Framework for Patients Monitoring"** has drawn a great deal of interest from academia and industry. CCPSs facilitate the seamless integration of devices in the physical world (e.g., sensors, cameras, microphones, speakers, and GPS devices) with cyberspace. This enables a collection of emerging applications or systems such as patient or health monitoring, which require patient locations to be tracked. These systems integrate a large number of physical devices such as sensors with localization technologies (e.g., GPS and wireless local area networks) to generate, sense, analyze, and share huge quantities of medical and user-location data for complex processing. It presented an iPhone based localization system for healthcare applications, whereby Wi-Fi signals and ZigBee RFID are used for localization. In their approach, the iPhone's position is first identified from the received Wi-Fi signal using a fingerprinting algorithm. Users' mobility can be examined from mobile-phone location sensing mechanisms and cloud computing technologies for reliable localization. It introduced range-free localization algorithms for mobile clouds. It has benefits and limitations with regard to accuracy, ubiquity, and flexibility. A hybrid patient tracking localization technique is proposed to overcome this issue.

In [6]authors Kaustav Basu, Vincent Debusschere, Seddik Bacha in this paper "**Appliance Usage Prediction Using a Time Series Based Classification Approach"** proposed a model tries to formalize such an approach using a time-series based multi-label classifier which takes into account correlation between different appliances among other factors.

The objective is to construct a model able to predict the appliance usage in housing which helps the system to arrange energy production and consumption and to decide which appliance will be used at each hour. The proposed model uses an iterative learning approach and tries to take into account all the possible information based on consumption data, time of the event and meteorological informations. The approaches range from using methodologies such as similar day, expert knowledge and linear and non linear learning algorithms. It gives details of implementation of neural networks in the domain of energy load forecasting and [lO] proposed a SVM model to predict daily load demand for a month. Another is to modify an existing single-label algorithm directly for the purpose of multi-label classification.

In [7]authors Kaustav Basua, Lamis Hawaraha, Nicoleta Arghira, Hussein Joumaaa, Stephane Ploixa in this paper **"A prediction system for home appliance usage"** has a novel about Power management in homes and offices requires appliance usage prediction when the future user requests are not available .This improve learning algorithms with expert knowledge and proposes a general model using a knowledge driven approach to predict if a particular appliance will start during a

given hour or not .It is tested over the IRISE data and using different machine learning algorithms. The approaches range using methodologies such as similar day, expert knowledge and linear and nonlinear learning algorithms. The tested classifier algorithms were also introduced. These classifiers are used in order to choose the best one (which gives best accuracy) for each service in a house.

In [8]authors Yi-Cheng Chen, Hsiu-Chieh Hung, Bing-Yang Chiang, Sheng-Yuan Peng, Peng-Jun Chen in this paper **"Incrementally Mining Usage Correlations among Appliances in Smart Homes"** propose a great advent of sensor technology, residents can collect household appliance usage data easily. However, in general, usage data are generated progressively; visualizing how appliances are used from huge amount of data is challenging. Thus, an algorithm is needed to incrementally discover appliance usage patterns. Prior studies on usage pattern discovery are mainly focused on mining patterns while ignoring the incremental maintenance of mined results. In this paper, a novel method, Dynamic Correlation Miner (DCMiner), is developed to incrementally capture and maintain the usage correlations among appliances in a smart home environment. Furthermore, several optimization techniques are proposed to effectively reduce the search space. Experimental results indicate that the proposed method is efficient in execution time and possesses great scalability. Subsequent application of DCMiner on a real dataset also demonstrates its practicability.

In [9]authors Jiawei Han, Jian Pei, Yiwen Yin in this paper "**Mining Frequent Patterns without Candidate Generation: A Frequent-Pattern Tree Approach**" propose a novel frequent-pattern tree (FP-tree) structure, a large database is compressed into a condensed, smaller data structure, FP-tree which avoids costly, repeated database scans. The Apriori heuristic achieves good performance gained by (possibly significantly) reducing the size of candidate sets. However, in such situations with a large number of frequent patterns, or quite minimum support thresholds, an Apriori-like algorithm may suffer from the following two nontrivial costs: It is costly to handle a huge number of candidate sets. It is boring to repeatedly scan the database and check a large set of candidates by pattern matching, which is particularly true for mining long patterns . The benefits of FP-growth over Apriori becomes clear when the dataset contains an abundant number of mixtures of short and long frequent patterns.

In [10]authors Shailendra Singh, Abdulsalam Yassine, Shervin Shirmohammadi in this paper **"Incremental Mining of Frequent Power Consumption Patterns from Smart Meters Big Data**" propose incremental mining of frequent power consumption patterns from smart meters big data. The benefits of pattern growth strategy and mine in quantum of 24 hour period. i.e. frequent patterns are extracted from data comprising of appliance usage tuples for 24 hours period, in a progressive manner. Apriori algorithm with candidate generation approach suffers from two problems, it generates a large number of candidate sets and repeatedly searches through the entire database to find support for an item set.

Similarly, it use incremental sequential mining technique to discover correlation patterns among appliances, and proposes a new algorithm offering reduction in memory with improved performance .It reduces the memory requirement on the cost of marginal increase in processing time, whereas former approach reduces processing time but requires more memory.

3. PROBLEM STATEMENTS

In the data mining model for human activity patterns based on the use of Smart Homes. The model that uses FP growth for pattern recognition and Fuzzy C, clustering algorithms can be appliance and appliance consumption data. This is not only important to determine activity routines, but also, when used by a health care application, to detect sudden changes in human activities observed by a health care provider. We use an ANN for activity predictions based on individual and multiple use of devices. For healthcare applications that integrate certain activities on the basis of historical data for patients. There is a need to analyze temporal energy consumption patterns at the device level, which are directly related to human activities.

4. PROPOSED SYSTEM

A sequence of steps includes carrying out the work for detecting the human activity patterns. This work helps to identify a model that analyses the human activity patterns of smart homes residents for the health prediction. To implement the model, we collect the smart home data and apply pattern CNN classification algorithms and apply DBSCAN clustering algorithms. The obtained result set is used to generate a trained neural network, for classifying human activity patterns to predict abnormalities in the behavior of the smart home residents. The obtained result set is used to generate a trained dataset, for classifying human activity patterns to predict abnormalities in the behavior of the smart home residents. First it starts by applying frequent pattern mining to discover appliance-to-appliance relations that is for understanding which appliances are functioning together. Then, this model uses cluster analysis DBscan clustering algorithms for deducing appliance-to-time associations. To learn such elements using a Deep Convolution Neural Network this also has a new architecture. The algorithm explores a huge number of candidate patches, covering human body parts as well as scene context.

4.1 MODULES DESCRIPTION

4.1.1 Data Preparation:

The dataset used in this study is a collection of smart meter data from five houses in the United Kingdom (UK). This data volume comprises 400 million raw data at a time resolution of 6 seconds. In the first phase of the cleaning process tailor-made processes were developed to remove noise from the data and to prepare it for the mining industry. After cleaning and preparation, the data set is reduced to 20 million. In addition, we developed a synthetic data set for the preliminary assessment of the model with over 1.2 million records. In the resulting ready to produce source data format comprising four devices from onehouse. Smart meter time series raw data, which is high-resolution data, is converted into a one-minute resolution load data; then translated into source data with 30 minute resolution, i.e. 24 × 2 = 48 readings per day per device, while start time and end time are recorded for each active device.

4.1.2 Extracting Frequent Patterns of Human Activities:

As stated above, the goal is to use human activity patterns from smart meter data such as television, cooking, computers, food and cleaning dishes or clothing "are usually regular routines. Our goal is to identify the patterns of these activities, so (eg patients with cognitive impairment) can send a timely warning to health care providers.

A 30-minute time interval is included in the source database for frequent pattern data mining The energy consumption of equipment (TV, oven and treadmill) depends on human activities like as leisure / relaxation time, food preparation and training. A simplified example describing possible relationships between the use of devices and activities. Extracting human activity patterns not only detects the individual device operation, but also the device-to-device connections; i.e. the activity patterns which are combined with one another, such as during the washing of clothes during training or television. The underlying concept of the model is based on a pattern growth or FP growth approach using the technique of deep initial division and conquest. However, this operation is normally performed offline, which may not be applicable to health care applications that require prompt decision-making. Therefore, we propose a new technique that exploits the advantages of the pattern growth strategy and expands it in order to achieve a gradual reduction of frequent patterns by mining within a 24-hour period; i.e., frequent patterns are extracted from data consisting of a device-used tuple for a 24-hour period in a progressive manner. Extensive details on the proposed incremental, frequent pattern decomposition can be found in our earlier work; For the sake of completeness, we briefly describe the preparations and provide the algorithm that describes the incremental decomposition process.

4.1.3 DBscan Clustering Algorithm:

The main impression of the DBSCAN algorithm is that, for each point of a cluster, the neighborhood of a given radius must contain a minimum number of points, that is, the density in the neighborhood must extinguish some predefined threshold. The Clustering procedure is based on the category of the points in the dataset as core points, border points and noise points and on the use of

density link among points (directly density reachable, density reachable, density-connected to form the clusters.

4.1.4 CNN Algorithm:

Our main insight is that the representation of image patches plays an important role in clustering. Assuming that the initial clustering is reasonable, in this block, we train a new CNN to improve the representation. The new CNN is trained so that given patch images, it predicts their cluster label. This is in contrast to the initial CNN that was learned to classify bounding box images to different action categories. We believe learning this fine-grained classification using discriminative patch cluster CNN results in a better representation for clustering. All of the networks have been trained using the caffe CNN training package with back-propagation. We use weights of the trained Network on Image Net dataset as initial weights and fine-tune our networks on specific datasets and with different properties according to the task. We set the learning rate of CNN training to 0.0001, the batch size to 100.

ADVANTAGES

- Training large amount of data sets.
- The output performance will depend upon the trained parameters and the data set relevant to the training.
- Objects on the boundaries between several classes are not forced to fully belong to one of the classes, but rather are assigned membership degrees between 0 and 1 indicating their partial membership.

SYSTEM ARCHITECTURE

The proposed system uses the use of everyday devices from smart meter and smart plug data to track regular activities and to experience unique time segment groups of the appliance's energy consumption. The study uses a hierarchical probabilistic model-based detection to infer anomalous abnormal behavior. We use ANN for activity predictions based on individual and multiple use of devices.

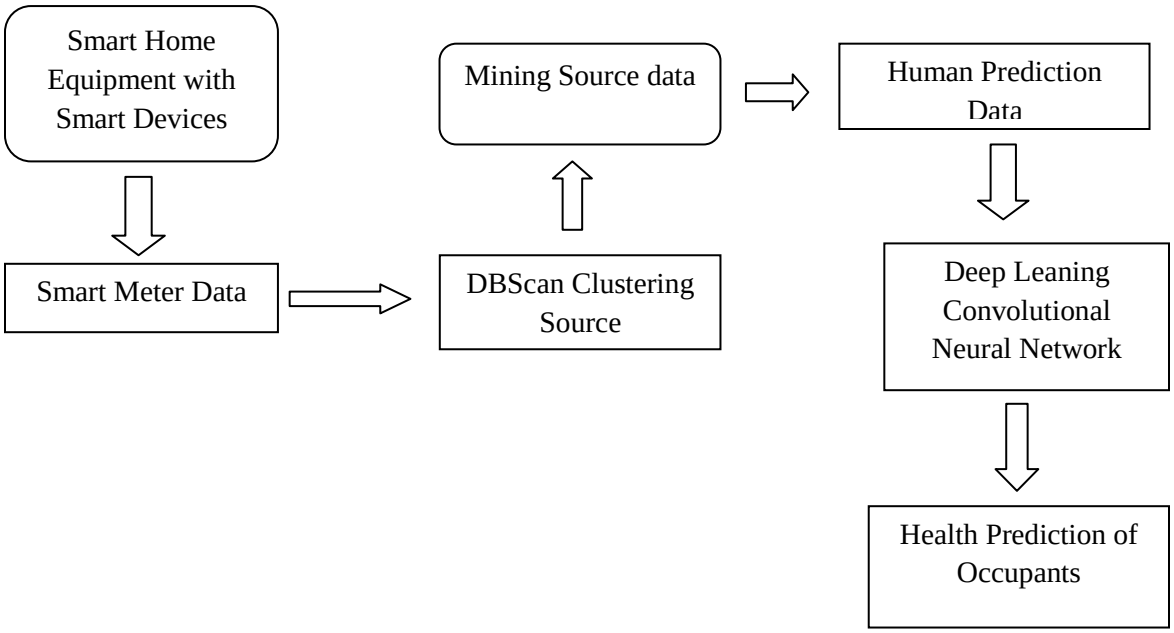

Figure 1: System Design

5. OUTPUT

A quality output is one, which meets the requirements of the end user and presents the information clearly. In any system results of processing are communicated to the users and to other system through outputs. In output design it is determined how the information is to be displaced for immediate need and also the hard copy output. It is the most important and direct source information to the user. Efficient and intelligent output design improves the system's relationship to help user decision-making.

1. Designing computer output should proceed in an organized, well thought out manner; the right output must be developed while ensuring that each output element is designed so that people will find the system can use easily and effectively. When analysis design computer output, they should Identify the specific output that is needed to meet the requirements.

2. Select methods for presenting information.

   3.Create document, report, or other formats that contain information produced by the system.

The output form of an information system should accomplish one or more of the following objectives.

- Convey information about past activities, current status or projections of the Future.
- Signal important events, opportunities, problems, or warnings.
- Trigger an action.
- Confirm an action.

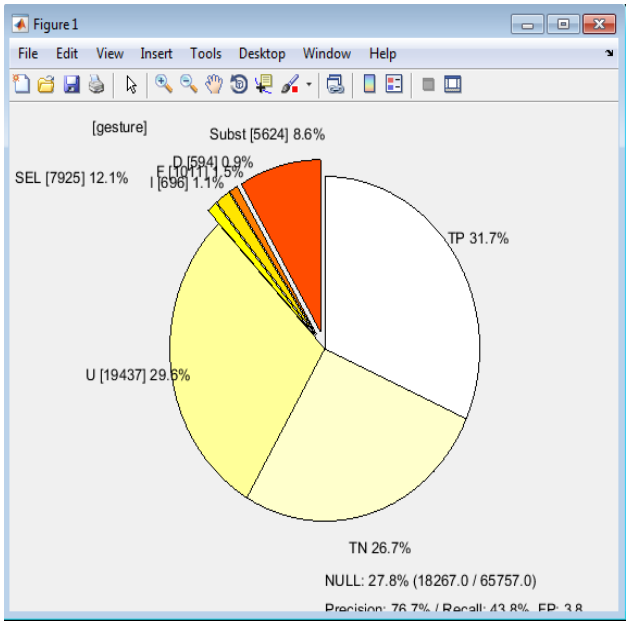

Figure 2: Pie Chart for actions in confusion matrix

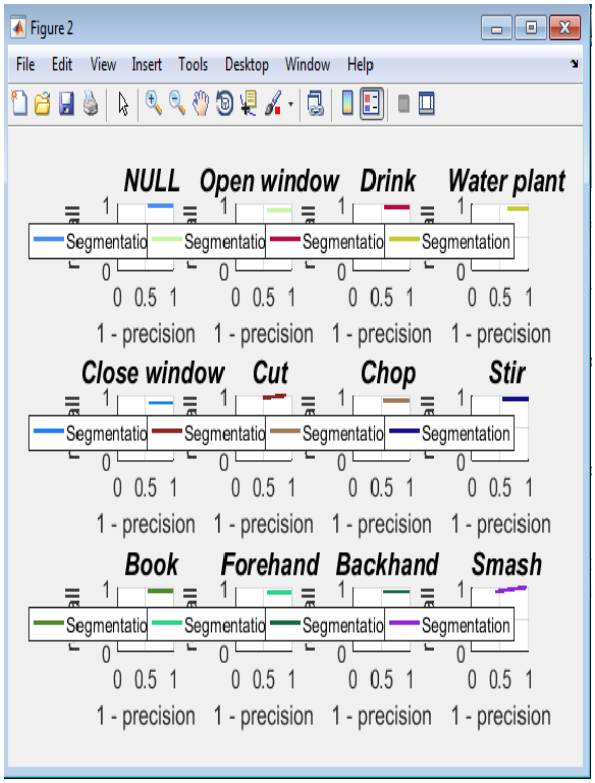

Figure 3: segmentation and precision values for human actions

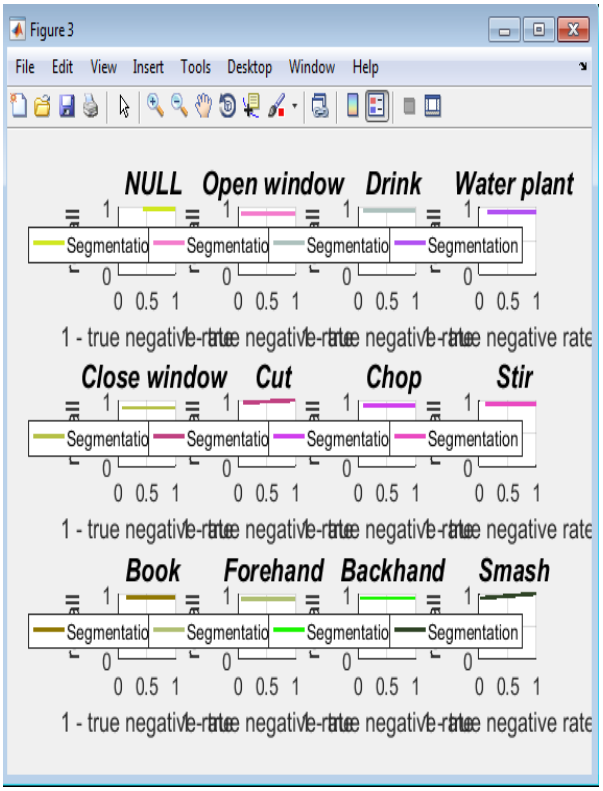

Figure 4: confusion matrix in which true negative rate achieved

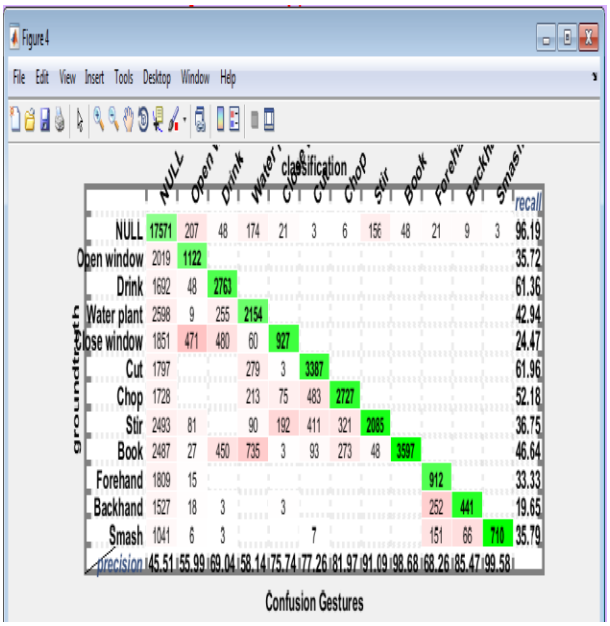

Figure 5: confusion matrix in which highest values achieved for particular actions like drink water, open window etc…

6. PERFORMANCE AND ANALYSIS

We presented a model for observing the human activity patterns from smart meter data and presented a model by comparing the with two most structured clustering techniques using smart meter data. Most of the human activities can be observed from appliance-to-appliance and appliance-to-time associations.

We presented a model by frequent pattern mining based on the clustering of the dataset and prediction model is presented based on the CNN classification. One-year geo-tagged tweets was processed and used to explore human activity patterns, we found that 68% of individuals live based on a specific activity pattern, while only 12% of individuals have a living style tend to be independent from the mass. In addition, we believe that through analyzing the network structure of connected activities involving individuals, communities and cities and the relationship between those networks, how the networks evolve from a micro scale to a macro scale could be simulated, which can better illustrate complex urban systems.

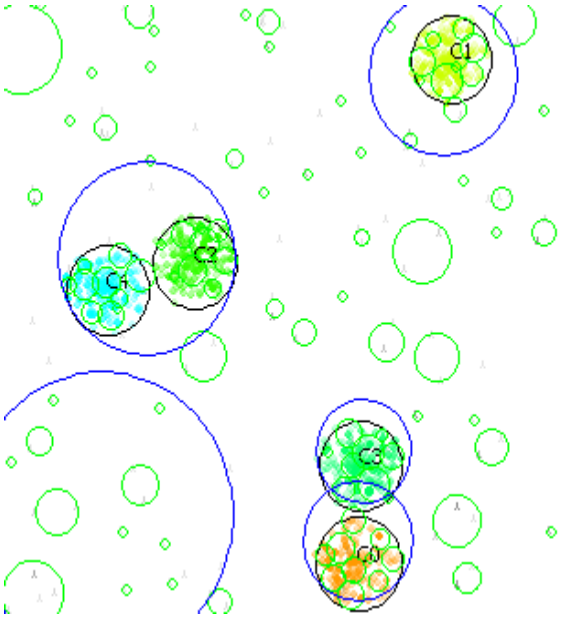

Figure 6: DBscan Clustering Plots

The results represent the associations for 3 homes and it depends on processing 35% of the dataset. It is easily observed from appliance interrelation,

behavior of inhabitant is observed, like to relax while preparing food.

7. CONCLUSION

Human activity patterns are important to understanding of how people live, work and play in cities and better designing of our cities. The purpose of this study was to understand human activity patterns not only from spatiotemporal dimensions but also with consideration of the related motivation inferred by semantic patterns. DBSCAN clustering method was used to analyze the spatiotemporal patterns, and topic modeling was used to infer the associated sematic patterns. The similarity between spatiotemporal clusters of human activities was computed, which was used to build up a network to finally represent human activity patterns. We proposed a novel framework to learn such elements using a Deep Convolutional Neural Network which also has a new architecture. The algorithm explores a huge number of candidate patches, covering human body parts as well as scene context. The results are good, both qualitatively and quantitatively, reaching the state-of-the-art, but without using any human pose or part annotations.

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