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Analysis of Human Activities in Smart Home Using Abnormal Activity Recognition Algorithm (AAR) and Visualization Techniques

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Abstract

In Industry 4.0, Internet of Things(IOT) plays an major role in latest technologies. Smart sensors in IOT are used in many environments such as harsh environment, smart homes, remote sensing area and in many applications. Especially in smart home environment, elder people living are assisted using sensors helps us to recognize the activities of human behaviour. Currently many research works are focusing on machine learning and Artificial Intelligence for activity recognition in IOT and still there are pros and cons in applying such algorithms. An anomaly activity in smart home environment is something that indicates the change in the occurrence of event or change in the human behaviour. The Isolated Forest Algorithm(IFA) is one of the outlier detection algorithm that identify anomalies using score values of selected features of data set and thus used to predicts the behaviour of human activities. In this paper, we implemented Abnormal Activity Recognition(AAR) used to detect anomalies on sensor data set of home appliances usage in smart home . The performance metrics is computed for each and every activities with the predicted values of IFA and AAR where the recall and precision and accuracy for every activities varies from 98% to 100%. This paper also focused on visualization techniques helps us to detect the anomaly activities and also various analysis are done such as activity distribution of dataset, grouping the activity values in bins, evaluation of each activity distribution, correlation between any two activities and frequency of activities in terms of exponential and Gaussian distributions.

Keywords- IFA, AAR,IOT,Activity Recognition,Visualization

Introduction

In smart home environment, sensors datasets are used to capture the user activities and behaviour and thus the human behavior analysis can be done with the help of techniques used in machine learning algorithm. Activity recognition of elderly people is one of the key areas in research field and it is considered as the method of identifying the activities using sensor dataset of smart homes. The activities such as sleeping, eating, cooking, watching TV can be captured with the use of smart home sensor dataset. In our proposed system, consists of two modules, in the first module the activities are recognized with the use of sensors that monitors the usage of home equipments. We introduced an algorithm Abnormal Activity Recognition(AAR) to recognize the abnormal activities with sensor data set [19] that consists of energy consumption values of smart home equipments. Its prediction accuracy of AAR is computed and compared with prediction accuracy of IFA Isolated Forest algorithm which is an outlier detection algorithm.

In the second module, our proposed system applies visualization techniques to analyze the human behavior and also used to identify the activity that does not happen. So it helps us to take necessary action to confirm that there is change in behavior or due to failure of that respective sensor. The challenges of applying different learning algorithms uses training dataset for learning process requires continuous supply of training data since the human behavior can vary time to time. So that it takes time for training period and testing period. Applying visualization technique, where at any time, with time dataset samples, the human behavior can be dynamically analyzed with two types of plots such as univariate and multivariate plots.

In [1] discovered the activities used to find the behaviour of patterns from the sensor dataset(CASAS) and shown the performance improvement in their activity recognition algorithm. It identifies the relationship between the discovered activity and online recognition of activity. In existing systems researchers focused on various type of classifying activities with the help of sensor data, where the sensors are placed on the human body known as wearable sensors or smart phone sensors. Activities are also monitored using RFID tags, motion sensors and video tapes. Many machine learning models such as Naïve Bayes, decision trees, KNNs used offline or static learning of activities and sometimes those algorithms causes imbalance of every class labeling of activities in training data set. In this approach Activity Discovery, greedy search is used to reduce the searching space of sensor event sequences and thus the new patterns are formed by compressing the sequence of patterns and these patterns are used to recognize the activity. Its accuracy varies from 60% to 85% for different datasets. In[2] presented an elaborative review of various available sensor datasets available for recognizing human activities and described about various sensor datasets, classification techniques that are suitable for activity recognition system that produces good results. It discussed about the different ways of data collection, types of sensors, types of activities, number of residents, characteristics of dataset and also includes different classification techniques, segmentation techniques for partitioning dataset, distribution of datasets for learning process, performance metrics and analysis of results. It includes various sensor dataset of indoor environment, smart home, Intelligent buildings, Ambient intelligence, Assisted living used for home activity recognition which yields best results. It explored detailed information of classification techniques, evaluation of segmentation, feature representation, F-measure accuracy of every activity classification techniques that are applied in various sensor datasets such as VanKasteren and CASAS. The accuracy of various classification algorithms lies between 92.6% to 100%.

In this paper, section 2 describes related papers, section 3 about Abnormal Activity Recognition algorithm. Section 4 tells about performance metrics of AAR. Section 5 presented about visualization techniques used in analysis of human activities in smart home dataset. Section 6 gives conclusion.

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1. Related Papers

In [3] presented a combined structure of sensor data associated with items usage for periodic activities using latent dirichlet allocation(LDA) that recognized the regular activities and interaction in smart home environment. It consists of two components namely the content description and ontology. The content description shows the context of items usage for specific activities and ontology component consists of concepts knowledge base , data, rules to support the activity recognition. The average precision, recall and F-score for kasteren datasets are 88.1%, 95% and 91% and for Ordonez datasets 84%, 94% and 88% respectively. In [4] proposed a system for tracking the activities of individual and multi residents of smart home environment. It applied classification algorithms that integrated the label combination using decision tree for solving the everyday activities of multi residents. This algorithm is used to predict the resident is male or female based on the activities and accuracy of prediction of activity in home A and home B are 97% and 99% respectively. In[5] sensor data were generated for smart home as a real world data sets using simulation of human behavior modeling and thus generated a daily routine activities sequentially with help of constraint based planning. 50% of activities of real data set is oriented towards the activities of simulated dataset. The drawback of this simulation is that it cannot generate parallel and interleaved activities. In [6] presented a review of existing technologies, devices used, algorithms implemented, analysis methods and various challenges of living activities of older people in smart home.

In [7]proposed a model to recognize activities using extensive short span memory deep learning algorithm. This model used to collect data from smart phone accelerometer in the laboratory and train the data to predict activities of smart home using deep learning. In [8] described about the dataset generated by CASAS and challenges were discussed about generation and distribution of data. It has been discussed about CASAS dataset, complete activity sensor dataset, activity dataset with errors, interleaving activities of dataset, multiple resident activity datasets, challenges faced in clarity, annotating and generating required data. It seems to be that many researchers used CASAS datasets for evaluation of technology improvement. In[9] reviewed on how the AI functions are clustered and applied on smart homes. The different way of integrating function leads to different products such as one AI function involves voice recognition, two AI function combines voice recognition with prediction making and it may also combined with image recognition activity with activity recognition to form a smart home products. Those products were utilized in energy management, health care, personal robot, security intelligent interaction and environment system in smart homes. It also revealed about relationship between literatures and products. In [10] used public dataset and applied 1D-CNN(Convolutional Neural Networks). The result performance of Convolutional NN, LSTM and probabilistic models for activity recognition algorithms are compared and shown the average accuracy of NN and LSTM are more or less same. It also discussed about classification of approaches in smart home activity recognition algorithm. These approaches include data driver and knowledge driver in which data driver deals with statistical and probabilistic models for learning from datasets whereas knowledge driver deals with knowledge about domain to create activities models and finalize with static model.

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In [11]described about how the unsupervised learning algorithm with cloud-based service are used in doing behavioral analysis of smart homes that includes outlier detection techniques, comparing the patterns of any two activities at different time, finding recurrent patterns involved in more than one activities. It provide univariate and multivariate analysis of smart home activities and thus help to assist activities of older people. In[12] described about the energy management in smart homes and provided possible solutions for the challenges faced by the people living in smart homes to reduce the power consumption and minimizing the amount of electricity bill.

In [13] identified and predicted the people who are suffering from dementia living in smart home using recurrent neural networks. It includes clustering analysis to detect the abnormal behavior of elderly people activities. Graphical representation is used to detect the changes in the behavior of their activities and it is suitable for the smart home with only discrete sensors. In [14] applied visualization methodologies on CASAS dataset to identify the behavior patterns of smart homes. The visualization methodologies includes graphic interface for collection of data from various sensors and application of machine learning algorithms to analyze the behavioral patterns. The visualizing application includes visualization interface, frequent count of every sensor triggers, activity graph and power usage graph. In [15] used ARAS datasets consists of multiple residents in multiple smart homes. The implementation of system consists of selection and deployment of sensors, collection of data, targeted activities and its location, distribution of every activity duration of real datasets with multiple residents in different homes.

In[16] applied vertical format data mining algorithm on sensor ids rather sensor values to generate frequent patterns of sensor epochs that helps to locate sensor failure or change in the occurrences of the event. In[17] classified data mining algorithms used for generating association rules on sensor data to calculate the missing sensor values and predicting the change in the events.In[18] identified the sensor fault or change in the activity in IOT data set using Frequent count activity matrix and its execution time is very less in centimilliseconds. In[20] discussed about the selection of suitable outlier detection algorithm for the various applications of IOT sensor data set. Also the author presented about the challenges facing in detecting anomalies, outlier and sensor faults in the applications of IOT. It clearly gives idea about the basic differences between the application and process of IOT and WSN, strategies adapted for detection of sensor failure and identification, multiple agents used for learning process.

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3.Proposed work

Our proposed work implemented an algorithm called Abnormal Activity Recognition(AAR) for recognizing abnormal activity of people living in smart homes. The proposed work used Smart Home Appliances energy data set [16] that consists of 15 activities based on usage of Appliances attached to sensors as shown in Table 1. AAR algorithm is applied on every column of dataset that indicates activities based on usage of appliances to identify the anomalies of dataset. The anomalies in this dataset are the representation of abnormal behavior in the home activities. Also preprocessing is done on the data columns to increase the performance of existing systems.

The accuracy is computed by comparing the anomalies generated by AAR and IFA. This AAR is applied only for non binary sensor value and to compute accuracy, it calls IFA and result produced . Then the result of both AAR and IFA are compared to calculate the performance metrics.

Sl.no	Activities based on usage	Sl.no	Activities based on usage
1	Watching Television	9	Usage of Hairdryer
2	Working on Laptop	10	Operating chimney
3	Usage of Washing Machine	11	Usage of Heater
4	Usage of Fan	12	Usage of Dishwasher
5	Usage of Refrigerator	13	Watching Home theater
6	Usage of AC	14	Usage of Kettle
7	Tredmiller walking	15	Usage of Ironbox
8	Microwave cooking		----

Table 1. List of activities based on usage of Home Appliances usage

3.1 DETECTING ANOMALIES USING ABNORMAL ACTIVITY RECOGNITION(AAR) ALGORITHM

The Abnormal Activity Recognition algorithm (AAR)identified number of anomalies in activity wise which indicates changes in the activities of human behaviour. The steps of AAR algorithm is shown in Table 2.

Input: *Sensor data set,*
Output:*Anomalies generated by IFA and AAR*
1. Importing library functions in python
2. Reading the sample data using dataframe from .csv data set.
3. Find the frequent count of each activity A_i.
4. Predict the number of anomalies (Predicted_anomalies)using Isolated Forest Algorithm(IFA) for each activity A_i . column value
5. compute the anomalies for each activity A_i, using Abnormal Activity Recognition algorithm by the following steps
a. Set FC_threshold_value,OL_threshold_value,Anomaly_count=0//Frequent count threshold value, Outlier threshold value
b. Remove the zeros from the activity A_i .column value //Data preprocessing steps
c. Remove the duplicate values from the activity A_i .column value and find the 'n' unique values of Activity Ai and store in the array U and corresponding frequent value in the array F
d. Sort the unique values (U)of Activity Ai in ascending order
e. for i varies from 1 to n
for j varies from i+1 to n
Compare(U_i,U_j) s to find the difference'D'
*If D>=OL_threshold_value and U_i . (F_i)<FC_threshold _value then display("**abnormal** "),*
Anomaly_count=Anomaly_count ++
*Else display("**normal**")*
6. Performance metrics report is generated with the predicted values of AAR and IFA
7. step 3 – 7 is repeated for every Activity A_i to predict the anomalies of every activity.
8. stop

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The step1 in Table 2. AAR algorithm imports required python library functions numpy,

Table 2. Abnormal Activity Recognition (AAR) algorithm

The step2 … umn Ai is computed. For illustration we have considered the activity "Laptop usage" and calculated the predicted anomalies that indicates that it is an abnormal activity.

The step4 IFA constructs the model for and fit the model for the activity A_i and calculates the score values and thus predict anomalies of the activity A_i. The Isolated Forest Algorithm differs from other outlier detection algorithm, in such a way that it clearly detects anomalies and also this algorithm evolved from decision tree concept. It creates the partition in tree by arbitrarily selection an attribute or feature. The random split value or then selected between the minimum and maximum of the selected attribute.

Outlier can be defined as the values that are different from regular or normal observations and also they are less frequent. In IFA, a score is computed to detected the anomalies and it is defined as:

$$Score(o_i,m) = 2^{-E(h(o))/c(m)}$$

Where $h(o_i)$ is path length of observation o_i, c(m)is the average path length of unsuccessful search in BST(binary search tree),'m' are the number of external nodes in the decision tree and path length is the observations passing through no. of edges in the tree from roof to terminal node.

$$Score(o) = \begin{cases} -1 & \text{indicates anomalies} \\ =1 & \text{indicates normal observations} \\ \sim 0.5 & \text{it is neither normal nor anomalies} \end{cases}$$

Thus the anomalies predicted by IFA for the activity "Laptop usage" are shown in the following Table 2. It is found that two anomalies indicating that usage of laptop is found more on two dates '2/2/17' and '4/2/17'.

```
Number in data in samples 48
Total number of Laptop usage activities happened: 9
Laptop usage percentage 18.75
Report showing Record index,Date, Starting Time(ST), Ending time(ET) of the Activity "Using Laptop"
Index       Date      ST      ET   Laptop
   8   2/2/2017  14:00  15:00   4.1236
   9   2/2/2017  15:00  16:00   2.3654
  15   2/2/2017  21:00  22:00   2.3021
  16   2/2/2017  22:00  23:00   6.7563
  32   3/2/2017  14:00  15:00   4.1236
  33   3/2/2017  15:00  16:00   2.3654
  39   3/2/2017  21:00  22:00   2.3021
  40   3/2/2017  22:00  23:00   3.4562
  44   4/2/2017   2:00   3:00   6.7345
Result of IFA:
Index      Date      ST      ET    Laptop      scores (IFA) anomaly(IFA)
16      2/2/2017  21:00  22:00      6.7563    -0.069193      -1
44      3/2/2017  21:00  22:00      6.7345     -0.069193      -1

Result of AAR:
Index  Date      ST      ET            Laptop     anomaly(AAR)
16   2/2/2017  21:00  22:00          6.7563         Abnormal
44   3/2/2017  21:00  22:00          6.7345         Abnormal
Number of outliers found :2

Result of AAR showing both normal and abnormal Observations:
Index       Date      ST      ET  anomaly/normal
8      2/2/2017  14:00  15:00        1
9      2/2/2017  15:00  16:00        1
15     2/2/2017  21:00  22:00        1
16     2/2/2017  22:00  23:00       -1
32     3/2/2017  14:00  15:00        1
33     3/2/2017  15:00  16:00        1
39     3/2/2017  21:00  22:00        1
40     3/2/2017  22:00  23:00        1
44     4/2/2017   2:00   3:00       -1
```

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In step 5 the AAR algorithm preprocess the Activity column A_i value in order to remove the zeros of the activity column. Then it computes the frequent count of each unique value and stored in the F_i array. The duplicate values are removed to create an array of unique values U of A_i and sorted in ascending order. Using nested looping, the difference between the unique values are found and if the values is greater than the outlier threshold value and the if the corresponding frequent count is lesser than frequent count threshold value then the respective value with date, starting time and ending time are displayed indicating it is anomaly. The total number of anomaly is found by incrementing the anomaly counter and it is shown in the Table 2. Similarly anomalies are computed for each and every activities using AAR algorithm. The result shows the output of IFA and AAR indicating abnormal and normal values of Activity "Laptop Usage". The score normal activity is 1 and abnormal is -1.

3.2 PERFORMANCE METRICS

Our algorithm AAR is applied on the dataset[19] of home appliances usage(total 21day s) and determined the normal and abnormal behaviour of each and every activity that is impleme nted in python using sklearn.metrics, sklearn.ensemble, importing numpy, pandas, matplotlib fu nctions. To compare the performance of AAR, the metrics are computed using predicted anomali es of AAR and predicted anomalies of IFA. The performance metrics includes confusion matrix, Accuracy scores, precision, recall , f1-score and support value. For each activity the confusion m atrix and report were generated using the True Positive, True Negative, False Positive, False Neg ative of normal and abnormal behaviour. The following performance report is generated for the a ctivity "Usage of Laptop". The report in Table 4 shows the confusion matrix indicates '6' abnor mal and '15' normal activities happened for 21 days. The result of AAR is compared with the pr edicted values of IFA and shows that accuracy, recall, precision and f1-score of AAR are 100% and the execution time of AAR is 0.1secs less when compared with IFA.

```
Performance Metric Report:
Confusion Matrix:
[[6 0]
 [0 15]]
accuracy score is 1.0
Performance metrics report of normal and abnormal behaviour
             precision    recall   f1-score     support

         -1       1.00      1.00      1.00         6
          1       1.00      1.00      1.00        15

avg / total       1.00      1.00      1.00        21
```

4. Analyzing the human behaviour activities using data visualization techniques

Data visualization is one of the techniques which is used along with machine learning algorithm that help us to understand the statistics of data. This technique helps us to work with various analysis such as activity distribution of dataset, grouping the activity values in bins,

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evaluation of each activity distribution, correlation between any two activities. This technique uses two types of plots known as univariate and multivariate plots. The univariate plots are used for analyzing each attribute of dataset separately and it includes histogram, density plots, boxplots. The multivariate plots helps to understand the relationships between the attributes of dataset. It includes correlation matrix plot and scatter matrix plot.

In our proposed system, visualization techniques is applied on a window frame of smart home dataset to do various analysis such as frequent activities, correlation between any two activities, to discover the usage of all appliances using python programming. The figure(1) represents histogram for each activities to identify the distribution of activities of smart home dataset. Also used to detect the outliers that represents change in the behavior of human activities.

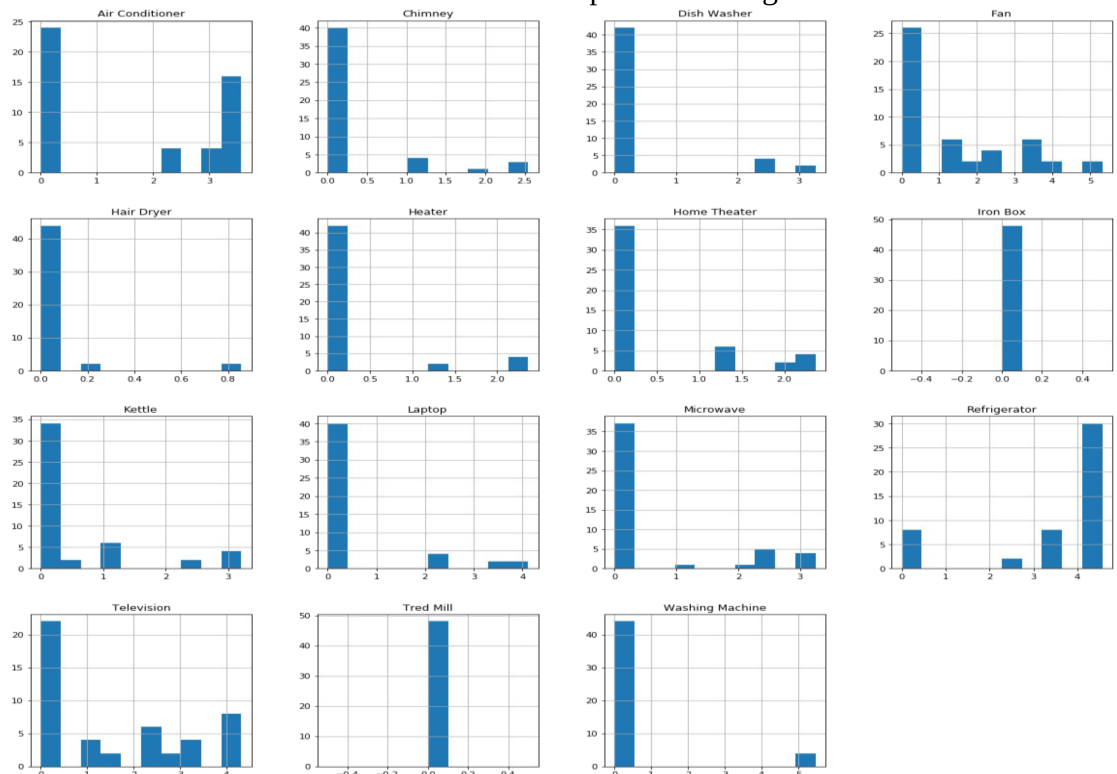

Fig 1. Histograms showing the Activity frequency distributions and outliers of

From the fig(1) we can observe outliers that has less frequent usage and has distinct values, which involve chimneys, dishwasher, hairdryer, kettles, laptop, microwaves that help us to predict the change in the activities. From the fig(1), the activity tredmill shows no values and it has to be confirmed that is it is due to sensor failure or no activity is performed. The histograms created for smart home dataset sample shows the frequent count distribution of all activities. Similarly density plots can be drawn to represent the distribution of activities with respect to frequent count.

The figure(2) shows the activity performance with the usage of the appliances. From the figure 2 It is discovered that the activities involved refrigerator, Watching Television, usage of Air conditioner are frequently happened when compared with other activities.

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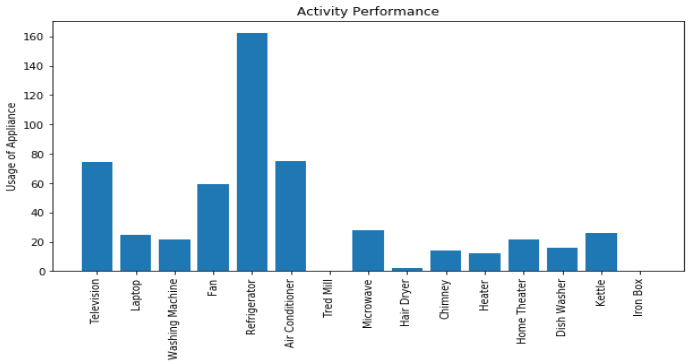

Fig2. Comparison of all activities

The figure(3) represents box and whisker plots which is an another technique to assess the attribute or activity distribution. It represents a box starting from 25% to 75% distribution of data having same value and the middle line of the box represents median or 50% of data has same value. The bottom line and top line of the box in the whisker plot represents the minimum and maximum value of each Activity.

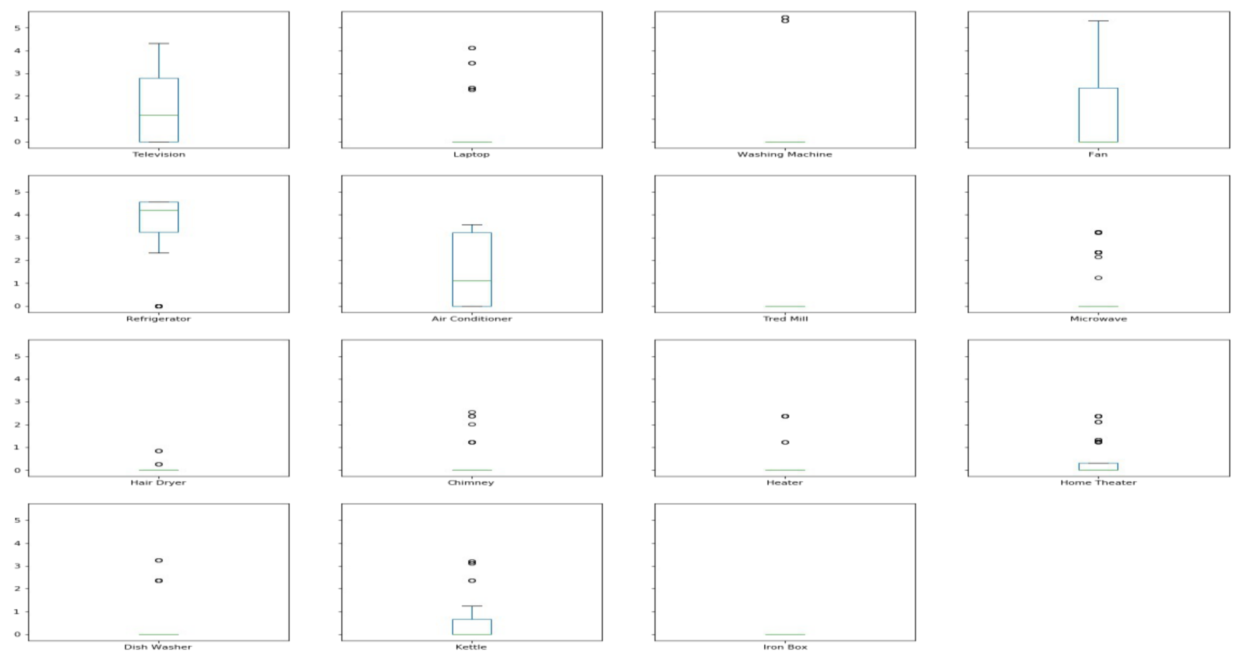

Fig 3.Whisker plots representing the number of outlier dots in

The fig(3)shows the number of outlier dots in each attributes that indicates the activities such as usage of chimneys, dishwasher, hairdryer, kettles, laptop, microwaves are found to be skewed nearer to the lesser value and may help us to predict the changes in the behaviour of activities .The outlier values are found to be 1.5 times more than the value of the middle data. The fig(3) shows clearly the outlier values, median values of all activities. If no box is generated it indicates that, no activities are performed involving the appliances 'tredmill', 'Iron box' or sensor attached with those appliances may get failed.

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The fig(4) shows correlation between any two activities and behaviour of smart home data, where the activities are closely correlated ,activities are independent. The correlation matrix is plotted using pearson correlation coefficient and shows the dependency between any two attributes.

Correlation Coefficient(A_i, A_j) =+1 Positive Correlation
= 0 No Dependency
= -1 Negative Correlation

The positive correlation indicates that the one value of attribute increases with another attribute value increases. The negative correlation indicates that the one value of attribute decreases with another attribute value increases.

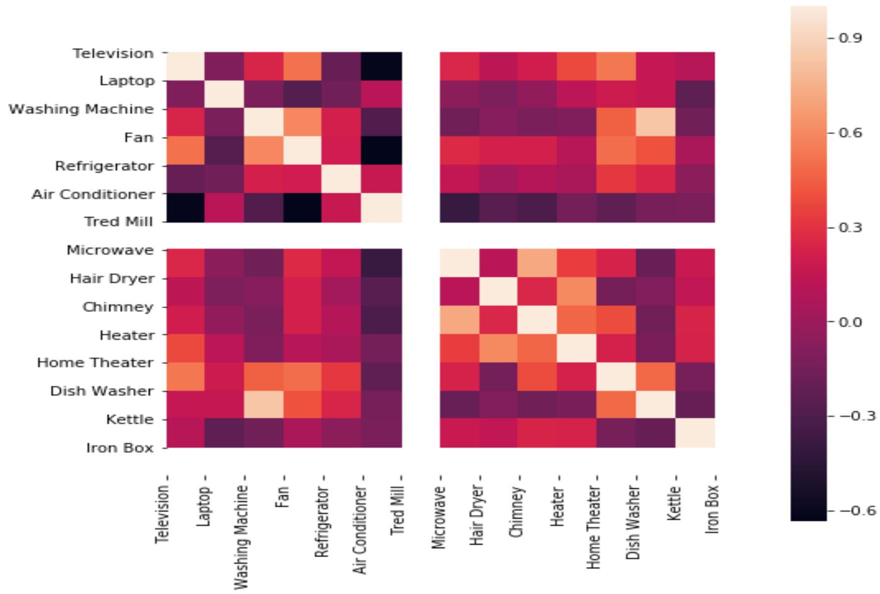

Fig 4. Correlation chart representing the correlation between all the Activities

The fig(4) shows degree of correlation between every pair of activities and correlation coefficient values lies between -1 to +1. The Table 4 shows the Correlation(activity1, activity2) and behaviour of the activities that are given based on the correlation coefficient values viewed from the fig(4). and each color shades indicates correlation coefficient of all pair of activities

Correlation (activity1,activity2)	**Correlation Coefficient value**	**Behaviour of Activities**
(laptop, television)	-ve	**Both of the activities performed independently**
washing, television	+ve	both activities are closely correlated
fan, television	+ve	both activities are closely correlated
AC, television	-ve	either one of the activities is performed
laptop, chimney	0	both activities are independent
laptop, microwave	0	both activities are independent

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Table 4. List of correlated activities observed from the correlated chart

Fig(5)represent the scatter matrix of smart home data set. This graph generates the significant relationship between any two activities whether they are closely related with each other or not.

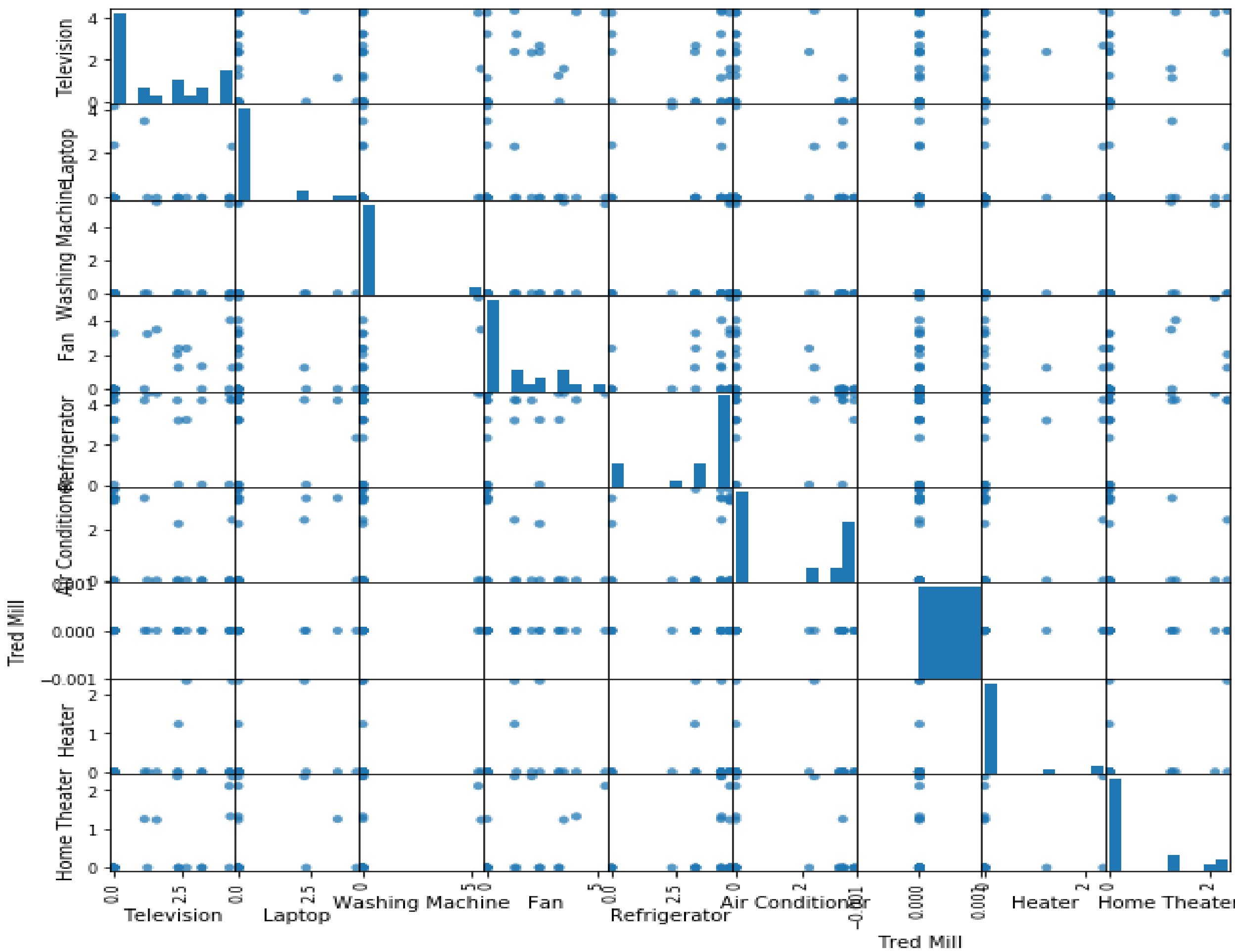

Fig 5. Scatter matrix plot showing relationship between any two activities

5. Conclusion

Recognizing Activities and detecting abnormal behaviour in activities are really important in IOT. In our paper Abnormal Activity Recognition algorithm is implemented in python to predict normal and abnormal activities. IFA using sklearn.ensemble is also implemented and predicted values of anomalies in both the algorithms are computed. Using sklearn.metrics, performance report is generated that includes precision, recall and accuracy score for each and every activities of sensor data set of home appliances usage. The execution time taken for IFA is 0.12267secs and AAR is 0.01994 secs for the sample of 48 data of particular Activity(A_i) and our proposed algorithm AAR performs better than Isolation Forest algorithm since in our algorithm data preprocessing is done to remove the zeros from the activity column values so that computing process takes place with few number of rows with unique values and hence reduce the execution time.

REFERENCES

1. Diane Cook, Fellow, IEEE, Narayanan Krishnan, Member, IEEE, and Parisa Rashidi, Member, IEEE,Activity Discovery and Activity Recognition-A New Partnership
2. EMIRO DE-LA-HOZ-FRANCO , PAOLA ARIZA-COLPAS , JAVIER MEDINA QUERO , AND MACARENA ESPINILLA Sensor-Based Datasets for Human Activity Recognition – A Systematic Review of Literature, volume 6, 2018, 2169-3536, IEEE.
3. Isibor Kennedy Ihianle, Usman Naeem , Syed Islam and Abdel-Rahman Tawi,A Hybrid Approach to Recognising Activities of Daily Living from Object Use in the Home Environment , Informatics 2018, 5, 6; doi:10.3390/informatics5010006, www.mdpi.com/journal/informatics
4. Raihani Mohamed, Thinagaran Perumal, Md Nasir Sulaiman, Norwati Mustapha, Syaifulnizam Abd. Manaf , Tracking and Recognizing the Activity of Multi Resident in Smart Home Environments, https://www.researchgate.net/publication/320281788 ,October 2018,e-ISSN: 2289-8131 Vol. 9 No. 2-11 39
5. Jennifer Renoux, Franziska Klügl, SIMULATING DAILY ACTIVITIES IN A SMART HOME FOR DATA GENERATION , 978-1-5386-657,2-5/18/$31.00 ©2018 IEEE 798
6. Rishabh Dev Manu, Sourav Kumar, Sanchit Snehashish, K.S. Rekha4 Smart Home Automation using IoT and Deep Learning, Volume: 06 Issue: 04 | Apr 2019 www.irjet.net p-ISSN: 2395-0072, e-ISSN: 2395-0056
7. D.J. Cook, M. Schmitter-Edgecombe, Aaron Crandall, Chad Sanders, and Brian Thomas, Collecting and Disseminating Smart Home Sensor Data in the CASAS Project,
8. Xiao Guo , Zhenjiang Shen , Yajing Zhang and Teng Wu, Review on the Application of Artificial Intelligence in Smart Homes, Smart Cities 2019, 2, 402–420; doi:10.3390/smartcities2030025 www.mdpi.com/journal/smartcities.
9. Xiao Guo , Zhenjiang Shen , Yajing Zhang and Teng Wu ,Review on the Application of Artificial Intelligence in Smart Homes , Smart Cities 2019, 2, 402–420; doi:10.3390/smartcities2030025 www.mdpi.com/journal/smartcities
10. Deepika Singh , Erinc Merdivan , Sten Hanke, Johannes Kropf , Matthieu Geist and Andreas Holzinger, Convolutional and Recurrent Neural Networks for Activity Recognition in Smart Environment, : https://www.researchgate.net/publication/320688135, Chapter · October 2017,
11. Niccolò Mora , Guido Matrella ,Paolo Ciampolini ,Cloud-Based Behavioral Monitoring in Smart Homes, Sensors 2018, 18, 1951; doi:10.3390/s18061951 www.mdpi.com/journal/sensors
12. K.Malathi, R.Kavitha, Recognition and classification of diabetic retinopathy utilizing digital fundus image with hybrid algorithms,International Journal of Engineering and Advanced Technology, 2019Kavitha, R., Nedunchelian, R., “Domain-specific Search engine optimization using healthcare ontology and a neural network backpropagation approach”, 2017, Research Journal of Biotechnology, Special Issue 2:157-166
13. Kavitha, G., Kavitha, R., “An analysis to improve throughput of high-power hubs in mobile ad hoc network” , 2016, Journal of Chemical and Pharmaceutical Sciences, Vol-9, Issue-2: 361-363

14. Kavitha, G., Kavitha, R., “Dipping interference to supplement throughput in MANET” , 2016, Journal of Chemical and Pharmaceutical Sciences, Vol-9, Issue-2: 357-360
15. R.M.Rani ,M.Pushpalatha ,Generation of Frequent sensor epochs using efficient Parallel Distributed mining algorithm in large IOT, Computer Communication, Volume 148, 15 December 2019, Pages 107-114, https://doi.org/10.1016/j.comcom,2019.19.006
16. R.M.Rani ,M.Pushpalatha ,Discovery of Knowledge Using Association Rules in Wireless Sensor Epocs-a Survey , International Journal of Engineering & Technology, 7 (4.10) (2018) 436-439, www.sciencepubco.com/index.php/IJET
17. R.M.Rani ,M.Pushpalatha , Detecting Change in Activity or Identifying Failure sensors in IOT Using Frequent Count Activity Matrix(FCAM) Algorithm, International Journal of Advanced Science and Technology, Vol. 29, No. 6, (2020), pp. 4804-4813.http://sersc.org/journals/index.php/IJAST/article/view/19403
18. https://archive.ics.uci.edu/ml/index.php,
19. Anuroop Gaddam, Tim Wilkin, Maia Angelova and Jyotheesh Gaddam, Detecting Sensor Faults, Anomalies and Outliers in the Internet of Things: A Survey on the Challenges and Solution, Electronics 2020, 9, 511; doi:10.3390/electronics9030511 www.mdpi.com/journal/electronics.