University of Kasdi Merbah, Ouargla
Faculty of New Information and Communication Technologies
Department of Computer Science and Information Technology

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Presented by:
HEMTI Maroua
TAMISSA Samiha

***Title*:**

An activity recognition based approach for energy efficiency in smart home

On:

Before the jury:

Dr. LAALLAM Fatima Zohra	Supervisor	UKM Ouargla
DEGHA Houssem Eddine	Second Supervisor	UKM Ouargla
Mr.	President	UKM Ouargla
Mr.	Examiner	UKM Ouargla

Academic Year: 2017 – 2018

Dedication:

May Allah have mercy on him and help him to complete this research. Who gave me all that he had until I fulfilled his hopes, to the one who was pushing me forward to achieve the desired, to the man who possessed humanity with all strength, to the one who took care of the sacrifices of a great soul translated in his sanctification of science, to my first school in life, My heart extended to God in his age; to whom I gave all the tenderness and tenderness of her liver, to the patience of all things, which sheltered me in the care of her, and she was in my adversity, and her plea to me was success. She followed me step by step in my work. In my face is the spring of tenderness my mother is the most precious angel on the heart and eye I also dedicate my best efforts to my dear teacher Dr LAALLAM Fatima Zohra and her son, DEGHA Houssem Eddine, who whenever the road is darkened in front of me. I resorted to him, and he turned to me, and whenever he gave me despair, he planted in me the hope of moving forward. Whenever I asked for knowledge, he provided me with it. Whenever I asked for a quantity of his precious time, he gave it to me despite his many responsibilities. To all the professors of the technology department for media and communication; To all who believe that the seeds of success change are in ourselves and in that Before we were in other things ... God said: ”God does not change what people do until they change what they themselves” .... verse 11 of Thunder To all these students, this work was given by Tamissa Samiha and Hemti Maroua

Thanks and gratitude:

The Messenger of Allaah (peace and blessings of Allaah be upon him) said: ”Whoever does not thank people does not thank God.” The Messenger of Allaah (peace and blessings of Allaah be upon him) believed in his kindness and thanks for his kindness and gratitude and we see that there is no god but God alone. And we see that our master and prophet Muhammad Abdo and his Messenger, who prayed for His mercy and blessings upon him and his family and his companions and peace. After thanking God Almighty for his support to us in order to complete this humble research, I extend my sincere thanks to the dear parents who have guided me and encouraged me to continue the march of science and success, and to complete myuniversity studies and research. I would also like to thank my honorable colleague for supervising a research note from Inside and outside the college, and especially the male student in the third, informing me that the letters of this note will not suffice to give him his great patience and his invaluable scientific guidance; which contributed greatly to the completion and completion of this work. I also express my thanks and appreciation to all Who helped me from near or far on Completion and completion of this work. ”O Lord, encourage me to thank your grace, which you have bestowed on me and on my father, and that I do good to please him and bring me to your mercy in your righteous worshipers”

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General Introduction:

The world has become a smart town quickly in the recent last years, where technology has evolved through its innovations and developments. human live has become in complete comfort through the devices that implement its functions and ensure its safety, including an endless range of smart home technology, Smart room temperature, as well as smart refrig-erators etc. The experience of a smart home may be a unique experience that everyone wants, but these are just plans for the future and are not currently fully present. Although many types of technology are available today, many of our things can be controlled automatically and via remote controls. Comfort and convenience are not the only advantages of such smart systems, as they contribute to reducing the cost of energy consumption and environmental conservation. Some systems, for example, shut down the heating system once the last person leaves the house. In terms of energy consumption, electricity is the heart of the latter. From the high consump-tion of excessive use and the lack of supervision and indifference, so we have to protect and rationalize in consumption, and rationalize the use of electricity . We reduce electricity bills and save money. We need to develop technical solutions that make the user spend his results with the lowestconsumer power. The lamps and devices work and extinguishes through thesensitivity of the human movement. It is the most comprehensive technology can be applied to the activities

Chapter 1:

Introduction:

Smart House is one of the latest developments in the world as it has become automated in the form of the mechanism of the Internet and remote control by the buttons and has passed the last several studies are in the teaching machine and the recognition of human activity and other aspects and all this to get to what it is now, but this Does not mean that it has reached the highest level of progress, but is still in the search to find a solution to other obstacles encountered, including the high proportion of the costs of electricity, how can we find a technology that we have reached the optimum consumption and economy of electricity.

Definition of smart home :

A Smart Home is one that provides its home owners comfort, security, energy efficiency (low operating costs) and convenience at all times, regardless of whether anyone is home. Smart Home" is the term commonly used to de ne a residence that has appliances, lighting, heating, air conditioning, TVs, computers, entertainment audio video systems, security, and camera systems that are capable of communicating with one another and can be controlled remotely by a time schedule, from any room in the home, as well as remotely from any location in the world by phone or internet. Installation of smart products give the home and its occupants various benefits — the same benefits that technology and personal computing have brought to us over the past 30 years — convenience and savings of time, money and energy. Most homes do not have these appliances and systems built into them, therefore the most common and The technical model of the SMART HOME is shown in . In a SMART HOME, the SMART circuit constitutes a Master sever with cloud capability with the up link interfaces on DEL, PON/WIFI on one side and other need-based plug-gable service modules on the home side. The service modules can bevariety of modules based on any short-range technologies like WIFI, ZIGBee, etc.affordable approach is for the home owner to retro t smart products into their own finished home.[1]

Figure 1.1: caracteristiques of smart home

Smartnet:

The technical model of the SMART HOME is shown in . In a SMART HOME, the SMART circuit constitutes a Master sever with cloud capability with the uplink interfaces on DSL, PON/WIFI on one side and other need-based pluggable service modules on the home side

The service modules can bevariety of modules based on any short-range technologies like WIFI, ZIGBee, etc.[2]

Figure 1.2: Conceptual SMART HOME model

Smart home technology:

Smart home technology, also known as home automation, provides homeowners security, comfort, convenience and energy efficiency by allowing them to control smart devices, oftenby a smart home app on their smart phone or other networked device. A part of the internet of things (IoT), smart home systems and devices often operate together, sharing consumer usage data among themselves and automating actions based on the homeowners' preferences. Nearly

Figure 1.3: example of smart home

every aspect of life where technology has entered the domestic space (light bulbs, dish-washers and so on) has seen the introduction of a smart home alternative:

•Smart TVs connect to the internet to access content through applications, such as on-demand video and music. Some smart TVs also include voice or gesture recognition. .

Figure 1.4: Example of Smart TVs

• In addition to being able to be controlled remotely and customized, smart lighting systems, such as Hue from Philips Lighting Holding B.V., can detect when occupants are in the room Smart thermostats, such as Nest from Nest Labs Inc., come with integrated Wi-Fi, al-lowing users to schedule, monitor and remotely control home temperatures. These devices also

learn homeowners' behaviors and automatically modify settings to provide residents with max-imum comfort and e ciency. Smart thermostats can also report energy use and remind users to change lters, among other things. and adjust lighting as needed. Smart light bulbs can also regulate themselves based on daylight availability.[3]

Figure 1.5: Smart light bulbs

. • Smart thermostats, such as Nest from Nest Labs Inc., come with integrated Wi-Fi, al-lowing users to schedule, monitor and remotely control home temperatures. These devices also learn homeowners' behaviors and automatically modify settings to provide residents with max-imum comfort and e ciency. Smart thermostats can also report energy use and remind users to change lters, among other things. Using smart locks and garage-door openers, users can grant or deny access to visitors. Smart locks can also detect when residents are near and unlobck the doors for them.With smart security cameras, residents can monitor their homes when they are away or on vacation. Smart motion sensors are also able to identify the difference between residents, visi-tors, pets and burglars, and can notify authorities if suspicious behavior is detected. . .

Using smart locks and garage-door openers, users can grant or deny access to visitors. Smart locks can also detect when residents are near and unlobck the doors for them.With smart security cameras, residents can monitor their homes when they are away or on vacation. Smart motion sensors are also able to identify the difference between residents, visi- tors, pets and burglars, and can notify authorities if suspicious behavior is detected. [3]

Figure 1.6: Smart thermostats

• Using smart locks and garage-door openers, users can grant or deny access to visitors. Smart locks can also detect when residents are near and unlobck the doors for thWith smart security cameras, residents can monitor their homes when they are away or on vacation. Smart motion sensors are also able to identify the difference between residents, visi-

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Figure 1.7: Using smart locks and garage-door openers

• With smart security cameras, residents can monitor their homes when they are away or on vacation. Smart motion sensors are also able to identify the difference between residents, visitors, pets and burglars, and can notify authorities if suspicious behavior is detected. . .

Figure 1.8: With smart security cameras

• Householdsystem monitors may,for example, sense an electric surge and turn o appliances or sense water failures or freezing pipes and turn o the water so there isn't a flood in your basement.

Figure 1.9: Household system monitors may

Characteristics of Smart Homes:

Smart home appliances come with self-learning skills whereby they can learn the home owner's schedules and adjust as needed. Smart homes enabled with lighting control allow homeowners to reduce electricity use and thus benefit from energy-related cost savings. Some home automation systems alert the home owner if any motion is detected in the home while away, and some can call the re department in case of any imminent situations. Once these smart appliances have been connected, we have an example of what we call Internet of Things (IoT) technology. Smart homes can feature systems that are wireless or hardwired. Wireless systems are cost-friendly and easier to install while hardwired systems are seen as more reliable and are typically harder to hack. While hardwired systems are also more expensive than wireless options, installing a hardwired system can increase the resale value of a home. Installing wireless home automation with features such as smart lighting, climate control and security can cost a household a couple thousand dollars. Meanwhile, luxury and hardwired options can cost homeowners tens of thousands of dollars. [4]

Figure 1.10: Characteristics of smart homes

68 million homes in Europe and North America will be smart by 2019:

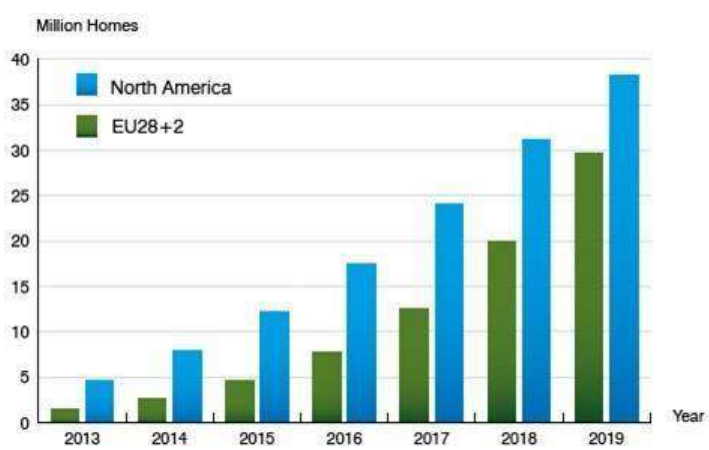

Figure 1.11: 68 million homes in Europe and North America will be smart by 2019

-In 2013 we find in north America 4.8 million home and 2 million home in EU28+2

-In 2014 we find in north America 7 million home and 3 million home in EU28+2

-In 2015 we find in north America 12 million home and 4.9 million home in EU28+2

-In 2016 we find in north America 17 million home and 7.8 million home in EU28+2

-In 2017 we find in north America 24 million home and 12 million home in EU28+2

-In 2018 we find in north America 31 million home and 20 million home in EU28+2

-In 2019 we find in north America 37 million home and 30 million home in EU28+2

Total number of smart homes (Europe and North America 2013–2019)[5]

Smart home and electrical energy :

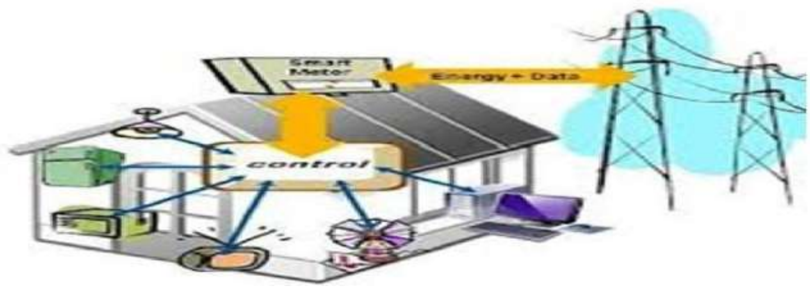

Figure 1.12: Smart Home and electrical energy

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Electricity generation is generating a lot of exciting debates: should we continue to exploit nuclear energy? What about ”green” sources like wind?

In these debates, there is still little question of consumption: each producer and distributor strives to predict consumption, as precisely as possible, by exploiting very complicated mathematical calculations such as ”neural systems”. These systems take into account the weather, school holidays, the consumption pro le reported by the heavy consumer industries, and the habits of residential consumers.

The balancing act of producers and distributors is to satisfy at any time the need, the consumption pro le, according to the available sources, notably:

wind or photovoltaic electricity, which suffers from a major defect: like the sun or the wind, it is neither stable nor guaranteed, it is just predictable to a certain extent;

nuclear or thermal electricity (excluding gas and diesel), predictable and stable, does not absorb peak consumption the gas turbine: the ultimate: it starts in a few seconds to provide extra in case of ”peak” consumption.

If the proportion of green electricity increases, the equilibrist will be much more difficult, unless it is given a new lever: to be able to instantly influence the consumption of electricity,

If the proportion of green electricity increases, the equilibrist will be much more difficult, unless it is given a new lever: to be able to instantly influence the consumption of electricity, not just to predict it, or to influence it overall as with the two-hour meters.

And this is where the connected objects of a smart home can play a role! Imagine:

- a smart washing machine or dryer, whose electricity distributor could delay start / suspend activity in the event of a peak;
- an electric car that, in charge, would temporarily restore energy to the grid, provided that its owner has indicated when he will use it (or an exceptional use, such as a departure in the middle of the night);
- A vacuum cleaner or electric heater that would go into low power during peak consumption;
- the heating of sanitary water during periods of depression.

But would you be willing to give up a fraction of the comfort of an electricity always available at will?[6]

Some means used to reduce electricity consumption:

Bsection Smart Wall Socket:

General smart wall socket, wall water heater, air conditioner socket, with remote control function, built-in remote control code library, through mobile can remote control of water heater and air conditioner switch, temperature regulation and other functions. .

Smart bulb lamp:

The bulb is equipped with an intelligent chip which is connected to the intelligent gateway through the WiFi, and does not need special wiring when in use. It supports remote control, adjustment and status synchronization of the mobile phone, and can be set on time to open. We may have only learned to embrace the smart home in 2017, but 2018 is shaping up to be the

Figure 1.13: General smart wall socket

year we nally take our technology to the next level — and let it do all the heavy lifting in our homes. Regardless of whether you've just dabbled or full-on decked out your home, ahead you'll nd the products that we're quickly nding we can't live without and highly recommend you try out for yourself. From vacuums to thermostats to lighting and more, it's clear that the sky's the limit when it comes to the many, many tasks you can delegate to your digital assistant. Be sure to check back in here often, as we'll be updating this list as more devices are released over the coming year. We may have only learned to embrace the smart home in 2017, but 2018 is shaping up to be the year we finally take our technology to the next level — and let it do all the heavy lifting in our homes. Regardless of whether you've just dabbled or full-on decked out your home, ahead you'll find the products that we're quickly finding we can't live without and highly recommend you try out for yourself. From vacuums to thermostats to lighting and more, it's clear that the sky's the limit when it comes to the many, many tasks you can delegate to your digital assistant. Be sure to check back in here often, as we'll be updating this list as more devices are released over the coming year. .

Figure 1.14: Smart bulb lamp

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We may have only learned to embrace the smart home in 2017, but 2018 is shaping up to be the year we finally take our technology to the next level — and let it do all the heavy lifting in our homes. Regardless of whether you've just dabbled or full-on decked out your home, ahead you'll find the products that we're quickly finding we can't live without and highly recommend you try out for yourself. From vacuums to thermostats to lighting and more, it's clear that the sky's the limit when it comes to the many, many tasks you can delegate to your digital assistant. Be sure to check back in here often, as we'll be updating this list as more devices are released over the coming year.[8]

Figure 1.15: how can saving energy in our home

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Activity recognition :

Activity recognition The goal of activity recognition is to recognize common human activities in real life settings. Accurate activity recognition is challenging because human activity is complex and highly diverse. Several probability-based algorithms have been used to build activity 2 models. The Hidden Markov Model and the Conditional Random Field are among the most popular modeling techniques. We describe these two techniques in the context of an eating activity example.

[9]

Type of activity recognition:

Sensor-based, single-user activity recognition:

Sensor-based activity recognition integrates the emerging area of sensor networks with novel data mining and machine learning techniques to model a wide range of human activities.[1][2] Mobile devices (e.g. smart phones) provide sufficient sensor data and calculation power to enable physical activity recognition to provide an estimation of the energy consumption during everyday life. Sensor-based activity recognition researchers believe that by empowering ubiquitous computers and sensors to monitor the behavior of agents (under consent), these computers will be better suited to act on our behalf .Sensor-based activity recognition is a challenging task due to the inherent noisy nature of the input. Thus, statistical modeling has been the main thrust in this direction in layers, where the recognition at several intermediate levels is conducted and connected. At the lowest level where the sensor data are collected, statistical learning concerns how to find the detailed locations of agents from the received signal data. At an intermediate level, statistical inference may be concerned about how to recognize individuals' activities from the inferred location sequences and environmental conditions at the lower levels. Furthermore, at the highest level a major concern is to find out the overall goal or subgoals of an agent from the activity sequences through a mixture of logical and statistical reasoning. Scientific conferences where activity recognition work from wearable and environmental often appears are ISWC and UbiComp.[10]

Levels of sensor-based activity recognition:

Sensor-based activity recognition is a challenging task due to the inherent noisy nature of the input. Thus, statistical modeling has been the main thrust in this direction in layers, where the recognition at several intermediate levels is conducted and connected. At the lowest level where the sensor data are collected, statistical learning concerns how to find the detailed locations of agents from the received signal data. At an intermediate level, statistical inference maybe concerned about how to recognize individuals' activities from the inferred location sequences and environmental conditions at the lower levels. Furthermore, at the highest level a major concern is to find out the overall goal or subgoals of an agent from the activity sequences through a mixture of logical and statistical reasoning. Scientific conferences where activity recognition work from wearable and environmental often appears are ISWC and UbiComp.[10]

Sensor-based, multi-user activity recognition:

Recognizing activities for multiple users using on-body sensors first appeared in the work by ORL using active badge systems in the early 90's. Other sensor technology such as acceleration sensors were used for identifying group activity patterns during office scenarios. Activities of Multiple Users in intelligent environments are addressed in Gu et al. In this work, they investigate the fundamental problem of recognizing activities for multiple users from sensor readings in a home environment, and propose a novel pattern mining approach torecognize both single-user and multi-user activities in a unified solution.[10]

Sensor-based group activity recognition:

Recognition of group activities is fundamentally different from single, or multi-user activity recognition in that the goal is to recognize the behavior of the group as an entity, ratherthan the activities of the individual members within it. Group behavior is emergent in nature, meaning that the properties of the behavior of the group are fundamentally different then the properties of the behavior of the individuals within it, or any sum of that behavior. The main challenges are in modeling the behavior of the individual group members, as well as the roles of the individual within the group dynamic and their relationship to emergent behavior of the group in parallel. Challenges which must still be addressed include quantification of the behavior and roles of individuals who join the group, integration of explicit models for role description into inference algorithms, and scalability evaluations for very large groups and crowds. Group activity recognition has applications for crowd management and response in emergency situations, as well as for social networking and Quantified Self applications.
[10]

Sensors used in activity recognition:

Vision –based activity recognition:

It is a very important and challenging problem to track and understand the behavior of agents through videos taken by various cameras. The primary technique employed is computer vision. Vision-based activity recognition has found many applications such as human-computer interaction, user interface design, robot learning, and surveillance, among others. Scientific conferences where vision based activity recognition work often appears are ICCV and CVPR.[11]

Levels of vision-based activity recognition:

In vision-based activity recognition, the computational process is often divided into four steps, namely human detection, human tracking, human activity recognition and then a high-level activity evaluation.[11]

Automatic gait recognition:

One way to identify specific people is by how they walk. Gait-recognition software can be used to record a person's gait or gait feature pro le in a database for the purpose of recognizing that person later, even if they are wearing a disguise.[11]

Wi-Fi-based activity recognition :

When activity recognition is performed indoors and in cities using the widely available Wi-Fi signals and 802.11 access points, there is much noise and uncertainty. These uncertainties are modeled using a dynamic Bayesian network model by Yin et al. A multiple goal model that can reason about user's interleaving goals is presented by Chai and Yang, where a deterministic state transition model is applied. A better model that models the concurrent and interleaving activities in a probabilistic approach is proposed by Hu and Yang. A user action discovery model is presented by Yin et al. where the Wi-Fi signals are segmented to produce possible actions. A fundamental problem in Wi-Fi-based activity recognition is to estimate the user locations. Two important issues are how to reduce the human labelling e ort and how to cope with the changing signal pro les when the environment changes. Yin et al. dealt with the second issue by transferring the labelled knowledge between time periods. Chai and Yang proposed a hidden Markov model-based method to extend labelled knowledge byleveraging the unlabelled user traces. J. Pan et al. propose to perform location estimation through online co-localization, and S. Pan et al. proposed to apply multi-view learning for migrating the labelled data to a new time period.[11]

Types of activities recognized by state-of-the-art HAR system:

Group activities ambulation :

Walking, running, sitting, standing still, lying, climbing stairs, descending stairs, riding escalator, and riding elevator. Transportation Riding a bus, cycling, and driving.[12]

Phone usage :

Text messaging, making a call. Daily activities Eating, drinking, working at the PC, watching TV, reading, brushing teeth, stretching, scrubbing, and vacuuming.[12]

Exercise/fitness:

Rowing, lifting weights, spinning, Nordic walking, and doing push ups.[12]

Military:

Crawling, kneeling, situation assessment, and opening a door.[12]

Upper body:

Chewing, speaking, swallowing, sighing, and moving the head.
[12]

Activity recognition methods:

In Section II, we have seen that, to enable the recognition of human activities, raw data have to rst pass through the process of feature extraction. Then, the recognition model is built from the set of feature instances by means of machine learning techniques. Once the model is trained, unseen instances (i.e., time windows) can be evaluated in the recognition model, yielding a prediction on the performedactivity. Next, the most noticeable approaches in feature extraction and learning will be covered.[13]

Feature extraction :

Human activities are performed during relatively long periods of time (in the order of seconds or minutes) compared to the sensors' sampling rate (which can be up to 250 Hz). Besides, a single sample on a specific time instant (e.g., the Y-axis acceleration is 2.5g or the heart rate is 130 bpm) does not provide sufficient information to describe the performed activity. Thus, activities need to be recognized in a time window basis rather than in a sample basis. Now, the question is: how do we compare two given time windows? It would be nearly impossible for the signals to be exactly identical, even if they come from the same subject performing the same activity. This is the main motivation for applying feature extraction (FE) methodologies to each time window: ltering relevant information and obtaining quantitative measures that allow signals to be compared. In general, two approaches have been proposed to extract features from time series data: statistical and structural . Statistical methods, such as the Fourier transform and the Wavelet transform, use quantitative characteristics of the data to extract features, whereas structural approaches take into account the interrelationship among data. The criterion to choose either of these methods is certainly subject to the nature of the given signal. Each instance in the processed dataset corresponds to the feature vector extracted from all the signals within a time window. Most of the approaches surveyed in this paper adhere to this mapping. Next, we will cover the most common FE techniques for each of the measured attributes, i.e.,acceleration, environmental signals, and vital signs. GPS data are not considered in this section since they are mostly used to compute the speed , or include some knowledge about the place where the activity is being performed .

[13]

Learning:

In recent years, the prominent development of sensing devices (e.g., accelerometers, cameras, GPS, etc.) has facilitated the process of collecting attributes related to the individuals and their surroundings. However, most applications require much more than simply gathering measurements from variables of interest. In fact, additional challenges for enabling context awareness involveknowledge discovery since the raw data (e.g., acceleration signals or electrocardiogram) provided by the sensors are often useless. For this purpose, HAR systems make use of machine learning tools, which are helpful to build patterns to describe, analyze, and predict data. In a machine learning context, patterns are to be discovered from a set of given examples or observations denominated instances. Such input set is called training set. In our specific case, each instance is a feature vector extracted from signals within a time window. The examples in the training set may or may not be labeled, i.e., associated to a known class (e.g., walking, running, etc.). In some cases, labeling data is not feasible because it may require an expert to manually examine the examples and assign a label based upon their experience. This process is usually tedious, expensive, and time consuming in many data mining applications . There exist two learning approaches, namely supervised and unsupervised learning, which deal with labeled and unlabeled data, respectively. Since a human activity recognition system should return a label such as walking, sitting, running, etc., most HAR systems work in a supervised fashion. Indeed, it might be very hard to discriminate activities in a completely unsupervised context. Some other systems work in a semi supervised fashion allowing part of the data to be unlabeled. [13]

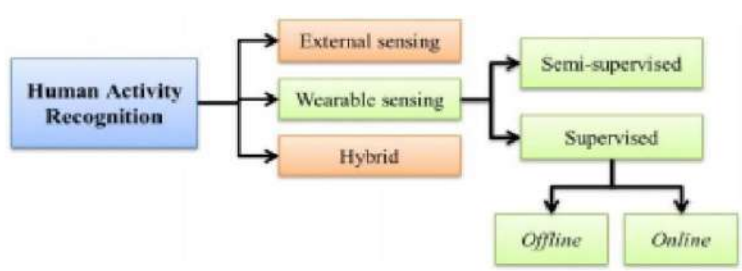

Figure 1.16: Taxonomy of Human Activity Recognition Systems

Activity recognition process :

Thereare many different methodsfor retrieving activity information from rawsensor data in the literature. However, the main steps can be categorized as preprocessing, segmentation, feature extraction, dimensionality reduction and classification .[14]

Preprocessing and signal representation :

Due to the nature of inertial sensors, the acquired sensor data should first pass a pre-processing phase. Almost always, high frequency noise in acceleration data needs to be removed. Therefore, non-linear, low-pass median , Laplacian , and Gaussian lters can be employed for removal of high-frequency noise. In some cases gravitational acceleration has to be extracted from accelerometer data in order to analyze only useful dynamic acceleration. For this purpose, high-pass lters can be used to distinguish body acceleration from gravitational acceleration . Representation of raw data while preserving useful information is the key to efficient and effective solutions and it a ects the overall performance and computation time of activity recognition systems. Steps for activity recognition process. [14]

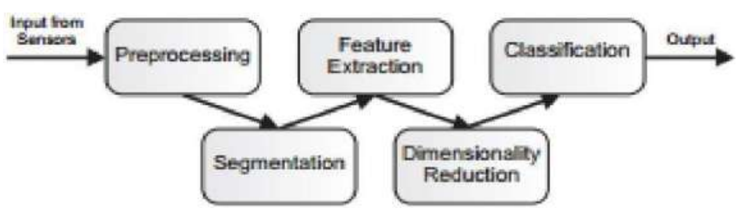

Figure 1.17: Steps for activity recognition process

Segmentation:

Retrieving important and useful information from continuous stream of sensor data is a di cult issue for continuous activity and motion recognition . For this purpose, several segmentation methods for time series data have been proposed.

[14]

Feature extraction :

In general, features can be defined as the abstractions of raw data and the purpose of feature extraction is to find the main characteristics of a data segment that accurately represent the original data . In other words, the transformation of large input data into a reduced representation set of features, which can also be referred as feature vector, is called feature extraction. The feature vector includes important cues for distinguishing various activities and features are then used as inputs to classification algorithms . Table 1 presents the most widely used features and their applications.[14]

Dimensionality reduction :

The goal of dimensionality reduction methods is to increase accuracy and reduce computational e ort. If less features are involved in the classification process, less computational e ort and memory are needed to perform the classification. In other words, if the dimensionality of a feature set is too high, some features might be irrelevant and do not even provide useful information for classi cation, and computation is slow and training is difficult as well . Two general forms of dimensionality reduction exist: feature selection and feature transform.[14]

Classification and recognition:

The selected or reduced features that create feature sets are used as inputs for the classification and recognition methods.

[14]

Conclusion :

Homes of the future may very well come with smart home features built in, considering the rate at which these technologies are being developed and integrated into our everyday lives. Still, some people may want to install and further customize home automation devices themselves. Home automation technology seeks to reduce your stress by ensuring your home is secure even when you are far away. It is also meant to reduce the amount of e ort you put every day into running your household so you can focus more on yourself and the people inside of it. Imagine if your home could automatically save you money, time and e ort. With many of these already established and acSmart home systems will only continue to evolveand become more advanced. These days, the range of options available for purchase are constantly expanding, so that you are not limited to one size, color or shape. Many gadgets and systems are designed to either blend in with surroundings or even stand out as a statement piece. So while smart home systems may take some time to understand and master, they will, and already are, making life easiertively iThese devices do more than just simplify your life. Many are designed to sync up to other devices and systems so that your home automation system can continue to evolve as households progress. Thus, these technologies may also increase the real estate value of your home. proving systems, these ambitions are possible.

Chapter 2

RELATED WORKs

Introduction:

Detection of human activities is a set of techniques that can be used in wide range of applications, including smart homes and healthcare. In this chapter we have put together some ideas and methods that others have used to know about human activity and how to get it. We also dealt with some of the most important characteristics on which each of them relied on to arrive at an approved result, as was the case for each of them in a study.

2.1 Ontology-based activity recognition in intelligent pervasive environments

Activity recognition is the process whereby an actor's behavior and his/her situated environment are monitored and analysed to infer the undergoing activity(ies). It comprises many different tasks, namely activity modeling, behavior and environment monitoring, data processing and pattern recognition. To perform activity recognition ,it is therefore necessary to (1) create computational activity models in a way that allows software systems/agents to conduct reasoning and manipulation. (2) monitor and capture a user's behavior along with the state change of the environment. (3) process perceived information through aggregation and fusion to generate a high-level abstraction of context or situation. (4) decide which activity recognition algorithm to use, and finally (5) carry out pattern recognition to determine the performed activity.

2.2.1 Activity recognition approaches :

Monitoring an actor's behavior along with changes in the environment is a critical task in activity recognition. This monitoring process is responsible for capturing relevant contextual information for activity recognition systems to infer an actor's activity. In terms of the way and data type of these monitoring facilities, there are currently two main activity recognition approaches; vision-based activity recognition and sensor-based activity recognition.

2.3 Vision-based activity recognition:

uses visual sensing facilities, e.g., camera-based surveillance systems, to monitor an actor's behavior and its environment changes . it exploits computer vision techniques to analyse visual observations for pattern recognition. Vision based activity recognition has been a research focus for a long period of time due to its important role in areas such as human-computer interaction, user interface design, robot learning and surveillance. Researchers have used a wide variety of modalities, such as single camera, stereo and infra-red, to capture activity contexts. In addition, they have investigated a number of application scenarios, e.g., single actor or group tracking and recognition. The typical computational process of vision-based activity recognition is usually composed of four steps, namely object (or human) detection, behavior tracking, activity recognition and finally a high-level activity evaluation.

wSensor-based activity recognition :

exploits the emerging sensor network technologies to monitor an actor's behaviour along with their environment. The sensor data which are collected are usually analysed using data mining and machine learning techniques to build activity models and perform further means of pattern recognition. In this approach, sensors can be attached to either an actor under observation or objects that constitute the environment. Sensors attached to humans, i.e., wearable sensors often use inertial measurement units (e.g. accelerometers, gyroscopes, magnetometers), vital sign processing devices (heart rate, temperature) andRFID tags to gather an actor's behavioural information. Activity recognition based on wearable sensors has been extensively used in the recognition of human physical movements (Bao , 2004; Huynh, 2008; Patterson, 2005; Lee 2002; Parkka , 2006). Activities such as walking, running, sitting down/up, climbing or physical exercises, aregenerally characterisedbyadistinct, often periodic, motionpattern. Thewearable sensor based approach is effective and also relatively inexpensive for data acquisition and activity recognition for certain types of human activities, mainly human physical movements.

Activity recognition algorithms:

Activity recognition algorithms can be broadly divided into two major strands. The first one is based on machine learning techniques, including both supervised and unsupervised learning methods, which primarily use probabilistic and statistical reasoning. Supervised learning requires the use of labelled data upon which an algorithm is trained. Following training the algorithm is then able to classify unknown data. The general procedure using a supervised learning algorithm for activity recognition includes several steps, namely, (1) to acquire sensor data representative of activities, including labelled annotations of what an actor does and when, (2) to determine the input data features and its representation, (3) to aggregate data from multiple data sources and transform them into the application-dependent features, e.g., through data fusion, noise elimination, dimension reduction and data normalization, (4) to divide the data into a training set and a test set, (5) to train the recognition algorithm on the training set,

(6) to test the classification performance of the trained algorithm on the test set, and finally

(7) to apply the algorithm in the context of activity recognition.

An ontology-based approach to activity recognition in ADL:

Activity ontologies are the explicit representation of a hierarchy of activities that consists of activity types and their relationships in a problem domain. Activities in activity ontologies are modeled not only based on objects, environmental elements and events but also the interrelationships between them, such as is-a or part-of relations. This allows an assistive system/agent to take advantage of semantic reasoning directly to infer activities rather than using the traditional probabilistic methods. Ontological activity recognition is closer to the logical approach in nature. It uses a logic based markup language, e.g. OWL or RDF (OWL, 2003) for specifying activities, and their descriptors and relationships. The major strength of ontology-based activity recognition is that the explicit commonly shared specification of terms and relationships for all relevant entities, e.g., objects, environment elements and events, facilitates interoperability, reusability and portability of the models between different systems and application domains. We conceive a system architecture for the realisation of the proposed ontology-centred approach. Central to the architecture is the ontological modelling and representation of SH domain knowledge (refer to the components in the right-hand column). This provides Context and ADL Ontologies as conceptual knowledge models and User Profiles and Situa- tions as knowledge entities in corresponding repositories. The context ontologies are used to semantically describe contextual entities, e.g., objects, events and environmental elements. The generated semantic contexts, i.e. Situations are used by the ADL Recognition component for activity recognition. The ADL ontologies are used, on the one hand, to create ADL instances for an inhabitant in terms of their ADL profiles, and on the other hand, to serve as a generic ADL model for activity recognition. In addition, archived data in these repositories can be mined for advanced features such as learning, high-level long-term trend recognition as well as automatic model creation. The components in the left hand column denote the physical environment, sensors, devices and assistive services in a SH. The sensors monitor an inhabitant's

ADL and use their observations, together with context ontologies, to generate semantic contexts. Assistive Services receive instructions from the ADL Recognition component and further act on the environment and/or the inhabitant through various actuators. Activity recognition is performed through a description logic based reasoned (the components in the middle column). The reasoned takes as inputs the semantic descriptions of a situation and performs reasoning against the ADL ontologies to provide incremental progressive activity recognition. To support fine-grained activity recognition, concrete sensor observations will be bound with context models to create an activity's description. By reasoning the descriptions against an inhabitant's personal ADL profile, specific personalized activities can be recognized . As most ADLs in the context of ambient assisted living are daily routines with abundant common sense patterns and heuristics from medical observations and psychological behavioral studies (James, 2008) (WHO), it is reasonable and straightforward to construct an ontological activity model using a description language. This avoids problems suffered by probabilistic algorithms such as the lack of large amounts of observation data, inflexibility, i.e. each activity model needs to be computationally learned, and reusability, i.e. one person's activity model may be different from others. Using ontological modeling the creation of user activity profiles is equivalent to creating activity instances in terms of a user's preferences and styles of performing ADLs. Hence it is relatively straightforward to undertake and is also scalable to a large number of users and activities in comparison with traditional approaches.

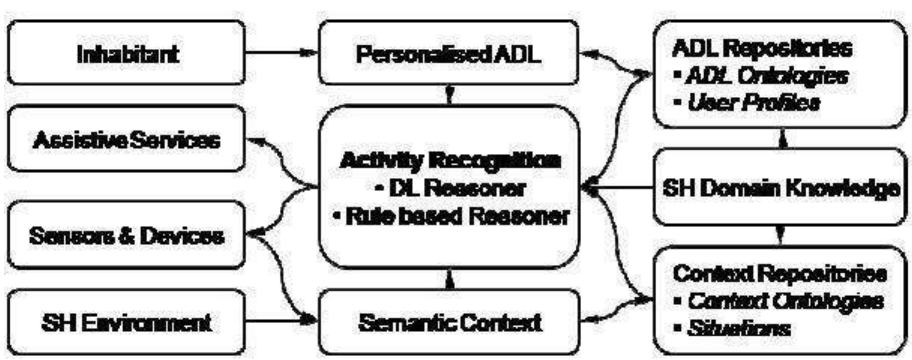

Figure 2.1: The system architecture

Ontological activity modeling :

Ontological modeling is the process to (1) explicitly specify key concepts and the relationships among them for a problem domain and (2) build a hierarchical structure to encode the concepts and their interrelations using the commonly shared terms in the problem domain. The resulting ontologies are essentially shared knowledge models that enhance the capabilities of automated processing and the level of automation by allowing machines or agents to interpret data/information and reason against ontological context, thus enabling knowledge based intelligent decision support. In addition, ontologies facilitate interoperability and integration in terms of the shared structure and terminology. These features make ontological modeling increasingly popular for SH to provide automatic cognitive assistance. ADLs may be viewed, in simplistic terms as the things we normally undertake in daily living such as self-care, leisure activities and eating/drinking to name but a few. They have some general characteristics. Firstly, they can be conceptualized at different levels of granularity. For example, Grooming can be considered to be comprised of sub-activities Washing, Brushing and Applying Make-up. There are usually a "is a" and "part of" relationship between a primitive and composite ADL. Secondly, ADLs are usually performed in specific circumstances, i.e. in a specific environment with specific objects for specific purposes. For example, people go to bed in a bedroom at a specific time for example around 8pm for a child or around 11pm for an adult; meals are made in kitchen with a cooker and may occur three times a day. This may be viewed as common sense domain knowledge and heuristics. Thirdly, people have different lifestyles, habits or abilities. ADLs may be carried out with variations in one or another way. For example, a drink could be a white coffee, black coffee, a tea or a specific type of tea. As such ADLs can be categorized as generalized ADLs applicable to all and specialized ADLs with subtlety between individuals. Obviously a computational ADL model should be able to capture and encode these relationships and variations so that software agents can derive and use them for reasoning as humans. We believe that ontological modeling is the most suitable approach to ADL modeling in terms of the SH's nature, characteristics and its application scenarios. We have developed a conceptual activity model as shown in 2.2 . Apart from the name and textual description, an activity can be described by a number of properties that relate an activity to other physical objects and conceptual entities. As can be seen from 2.2, properties like time, location and actor represent the context within which the activity takes place. Properties such as conditions and effects represent the causal and/or functional relations that are used for inference during activity level reasoning. Subclass and superclass properties denote the type and interrelationship between activities. Given the diversity of ADLs this conceptual model will serve as a base model and can be extended to cover ADLs at multiple levels of abstraction.

Figure 2.2: The conceptual activity model

A Knowledge-Driven Approach to Activity Recognition in Smart Homes

Ontologtcal modelling for the SH domain:

Ontological modeling is the process to explicitly specify key concepts and their properties for a problem domain. These concepts are organized in a hierarchical structure in terms of their shared properties to form super-class and sub-class relations. For example, MakeTea is a sub-class of MakeHotDrink. Properties establish the interrelations between concepts. For instance, hasDrinkType is a property of the MakeHotDrink activity that links the DrinkType concept (e.g., tea, coffee, chocolate) to the MakeHotDrink concept. Both concepts and properties are modeled using the commonly shared terms in the problem community. The resulting ontologies are essentially knowledge models able to encode and represent domain knowledge and heuristics. This avoids the manual class labeling, pre-processing and training processes in the traditional

approaches to activity recognition. In addition, ontologies allow software agents to interpret data and reason against ontological contexts, thus enhancing the capabilities of automated data interpretation and inference.

Ontological context modeling :

SH inhabitants perform ADLs in a diversity of temporal, spatial, environmental contexts. Spatial contexts relate to location information and surrounding entities such as rooms, household furniture and appliances .Event contexts contain background activities and dynamic state changes of appliances and devices. Example events could be the state changes of doors, windows, lights, alarms, a cooker and taps. Environmental contexts are composed of environmental information such as temperature, humidity and general weather conditions. Temporal contexts indicate the time and/or duration. There is a high correlation between ADLs and contexts. For example, a cooking ADL happens in the kitchen with a cooker turned on. A grooming ADL takes place in the bathroom in the morning. Contextual information is usually captured through various sensors. Each sensor monitors and reflects one facet of a situation. Based on this observation our context modeling is centered on ontological sensor modeling. As can be viewed from the generic conceptual model in 2.3, sensors are inherently linked to a number of physical and conceptual entities such as objects, locations and states. For example, a contact sensor is attached to a teapot in the second cupboard to the left of the sink in the kitchen. By explicitly capturing and encoding such domain knowledge in a sensor model it is possible to infer the corresponding objects and location from the activation of the sensor. This implies that an inhabitant performs an activity in the inferred location with the inferred object.

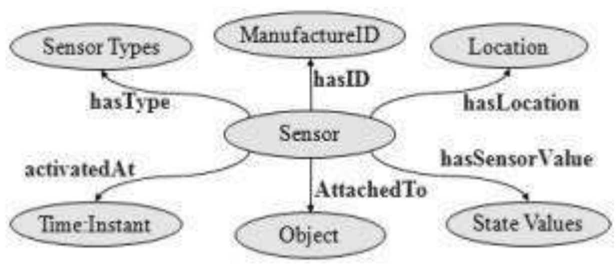

Figure 2.3: The generic conceptual sensor mode

2.7 Multiview activity recognition in smart homes with spatio-temporal features

The overall hierarchical activity recognition system :

Asthewhole activityrecognitionsystem,weuseahierarchicalapproach toclassifyuser activities with visual analysis in a two-level process. Different types of activities are often represented by different image features, hence attempting to classify all activities with a single approach would be ineffective. In 2.5, activities are represented by coarse and fine levels. The coarse activity level includes the classes of standing, sitting and lying, which relate to the pose of the user. Adding global motion information and face detection, more attributes are added to standing and sitting to discriminate walking and watching in the second level. The fine activity level also consists of activities involving movement such as cutting, eating, reading, etc. We applysuch a hierarchical approach because the first-level activities are discriminated based on pose, while the second-level activities are classified based on motion features. In the first level, activity is coarsely classified into standing ,sitting and lying with temporal conditional random field (CRF), throughemployingaset offeaturesconsisting of theheight oftheuser(through 3Dtracking) and the aspect ratio of the user's bounding box. Details of the process and performance evaluation can be found in [19]. Based on the result of the coarse level, the activity is further classified at the fine-level based on spatio-temporal features [20]. A codebook of size N is constructed with Kmeans clustering on a random subset of all the extracted spatio-temporal features of the training dataset. Each feature is assigned to the closest cluster in Euclidean distance. The video sequences are segmented into episodes with duration of t seconds. Bag-of-features (BoF) are collected for every episode, therefore each episode has the histogram of spatiotemporal features as its feature vector. We use discriminative learning with SVM. The activities in the second level and their semantic location contexts are shown in Table I. Note that we have others as an activity category. This is because our sequences are not specifically designed for the defined activity types. There are many observations where the activities are in transition phase or the person is simply doing some activities at random which are not within our defined categories. This is also a challenge for our activity recognition algorithm, since due to the fact that others includes many different motions, the feature space for others is complex.

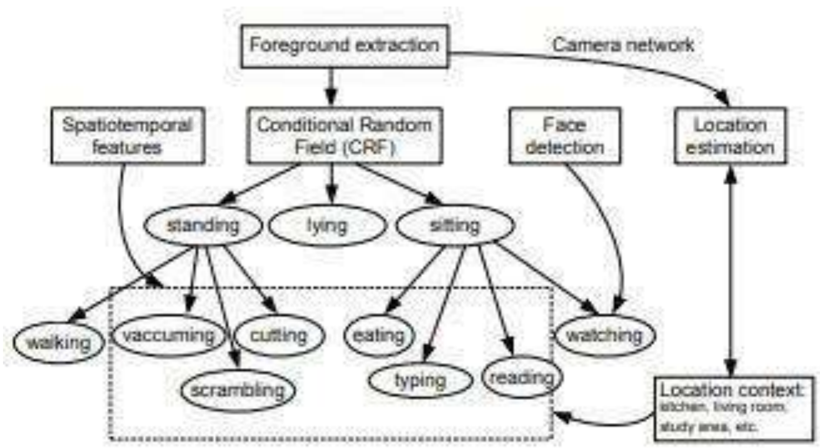

Figure 2.4: Hierarchical activity analysis.

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location	Activity
kitchen	cutting,scrambling,vacuming,others
dining table	eating,vacuming,others
living room	wwatching,reading,vacuming,others
study room	typing,reading,vacuming,others

Table 2.1: ACTIVITY CLASSES OF THE SECOND LEVEL AND THEIR SEMANTIC LOCATION CONTEXT.

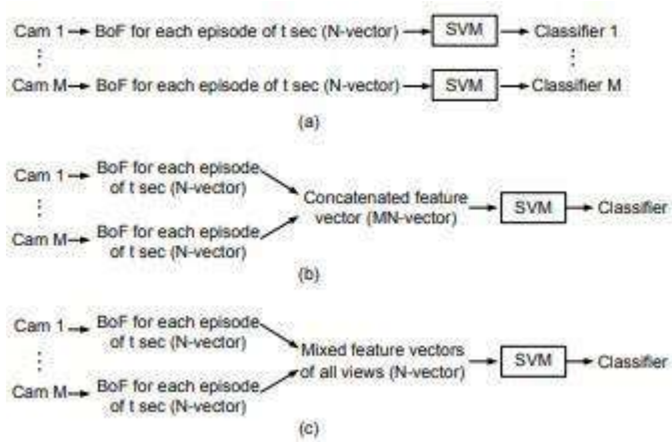


Figure 2.5: Comparison of the three fusion methods. (a) best-view fusion, (b) combined-view fusion, (c) mixed-view fusion. BoF refers to bag-of-features.

Multiview activity recognition with spatio-temporal features:

we describe the three fusion methods for the second level activity recognition of 2.5: best-view fusion ,combined view fusion and mixed-view fusion . Best-view and mixed-view fusion belong to decision-level fusion, while combined-view fusion belongs to feature-level fusion. Comparison of the fusion process .

Best-view fusion:

The training process is done independently for each camera, and each camera has its own activity classifier. The set of activities for each camera differs depending on what activities are observable n its field of view. In our experiments, since the cameras' deployment and the room layout do not change, the viewpoint of activities for each camera does not vary much. During recognition phase, the fusion process chooses the best-view camera. For each episode of t seconds, the best-view camera m is chosen and the activity classification result of camera m is determined as the person's activity.

Combined-view fusion:

This is a feature-fusion approach similar to [8], [15]. For each episode, the bags of features from all cameras are concatenated sequentially to make a single feature vector for classification. For example, the feature vectors from cameras are q1; q2; : : : ; q M, each of them is N-vector (codebook size is N). Then the concatenated feature vector is Q = (q1; q2; : : : ; q M), with length of MN 2.7. Vector Q is used for the SVM classifier. This fusion method is straightforward and it has the advantage of having more information (all the features from all cameras) for classification.

Mixed-view fusion:

In this fusion method, a single activity classifier is obtained on the BoF of episodes (t seconds) irrespective of camera views 2.7. For each episode, when the number of spatio-temporal features is above a threshold meaning there is significant motion, the BoF of this episode will be used for activity classification. This approach gives a general activity model which does not depend on the camera field of view and the camera network setup. Therefore it is transferrable to the other environments.

	cam 1	cam 2	cam 3	cam 4	cam 5
cutting	0	9032	0	0	0
scrambling	0	9042	0	0	0
eating	0	11397	11414	0	0
reading	3082	0	5176	10484	0
cumputer	4640	0	0	0	0
vacuming	0	9052	0	0	17942
others	5130	9022	18160	8909	17902

Table 2.2: NUMBER OF FRAMES FOR EACH ACTIVITY FROM EACH CAMERA

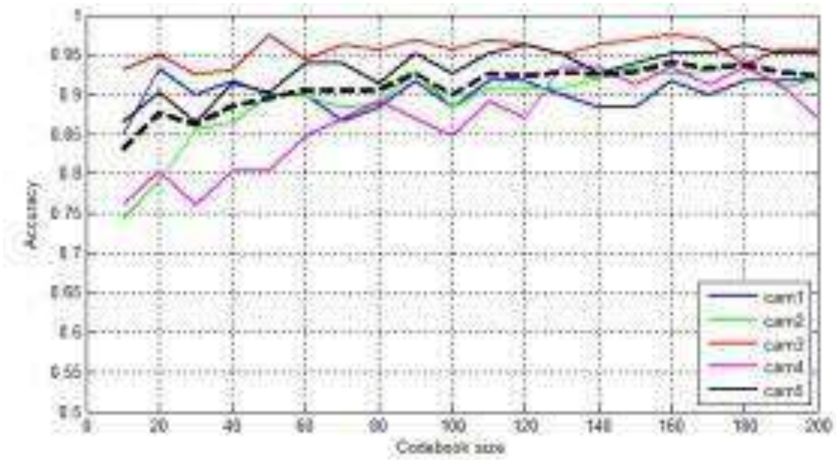


Figure 2.6: (a)Accuracy w.r.t. the code book size

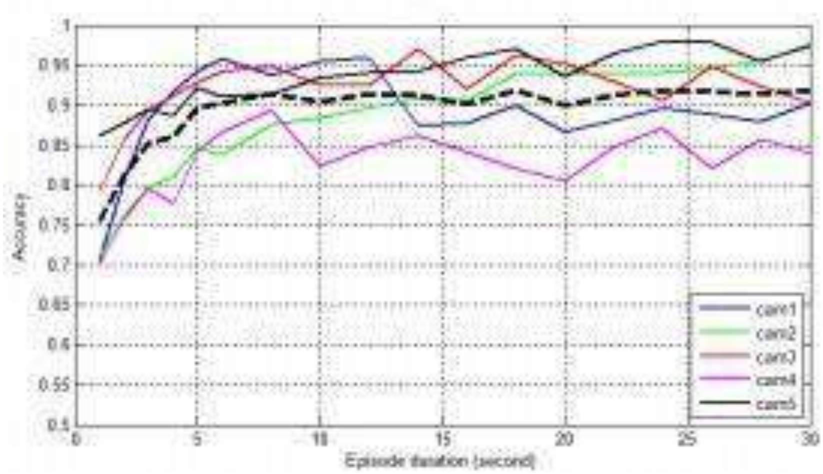


Figure 2.7: (b)Performance curve of best-view fusion. (a) Accuracy w.r.t. the codebook size. (b) Accuracy w.r.t. the episode duration. The black dashed line represents average accuracy of all cameras

A Survey on human activity recognition using wearable sensor

General structuer of HAR systems:

Similar to other machine learning applications, activity recognition requires two stages, i.e., training and testing (also called evaluation). illustrates the common phases involved in these two processes. The training stage initially requires a time series dataset of measured attributes from individuals performing each activity. The time series are split into time windows to apply feature extraction thereby filtering relevant information in the raw signals. Later, learning methods are used to generate an activity recognition model from the dataset of extracted features. Likewise, for testing, data are collected during a time window, which is used to extract features. Such feature set is evaluated in the priorly trained learning model, generating a predicted activity label .We have also identified a generic data acquisition architecture for HAR systems. In the first place, wearable sensors are attached to the person's body to measure attributes of interest such as motion [17],location [18], temperature [19], ECG [20], among others. These sensors should communicate with an integration device (ID), which can be a cellphone [21], [22], a PDA [19], a laptop [20], [23], or a customized embedded system [24], [25]. The main purpose of the ID is to preprocess the data received from the sensors and, in some cases, send them to an application server for real time monitoring, visualization, and/or analysis [20], [26]. The communication protocol might be UDP/IP or TCP/IP, according to the desired level of reliability. Notice that all of these components are not necessarily implemented in every HAR system. In [27]–[29], the data are collected offline, so there is neither communication nor server processing. Other systems incorporate sensors within the ID [30]–[32], or carry out the inference process directly on it [31], [33]. The presented architecture is rather general and the systems surveyed in this paper are particular instances of it.

Design issues :

We have distinguished seven main issues pertaining to human activity recognition, namely, (1) selection of attributes and sensors, (2) obtrusiveness, (3) data collection protocol, (4) recognition performance, (5) energy consumption, (6) processing, and (7) flexibility. The main aspects and solutions related to each one of them are analyzed next. the systems surveyed .

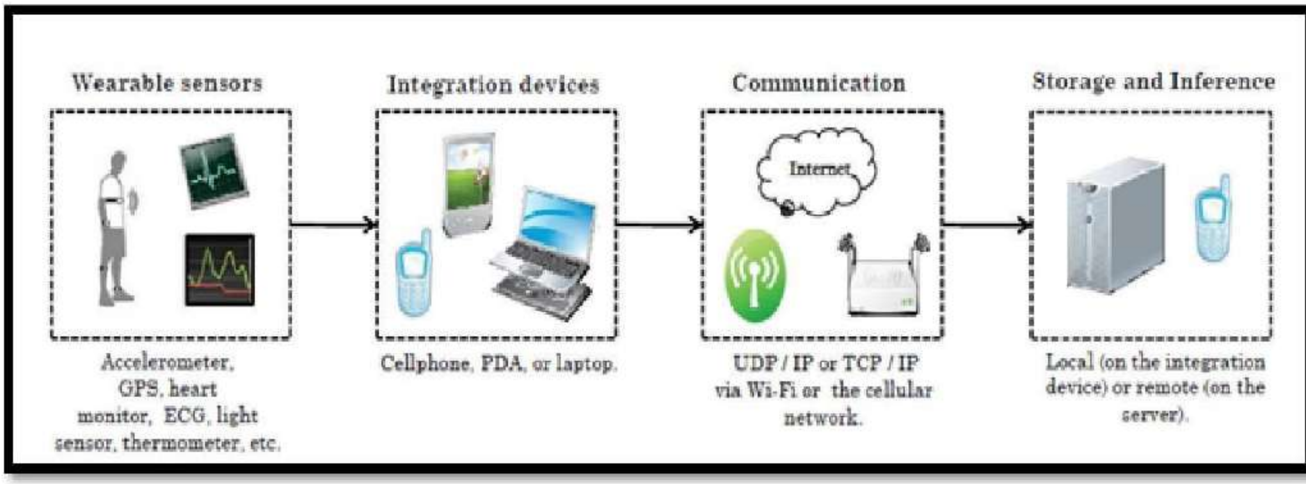


Figure 2.8: Generic data acquisition architecture for Human Activity Recognition

Activity Recognition method :

we have seen that, to enable the recognition of human activities, raw data have to first pass through the process of feature extraction. Then, the recognition model is built from the set of feature instances by means of machine learning techniques. Once the model is trained, unseen instances (i.e., time windows) can be evaluated in the recognition model, yielding a prediction on the performed activity. Next, the most noticeable approaches in feature extraction and learning will be covered.

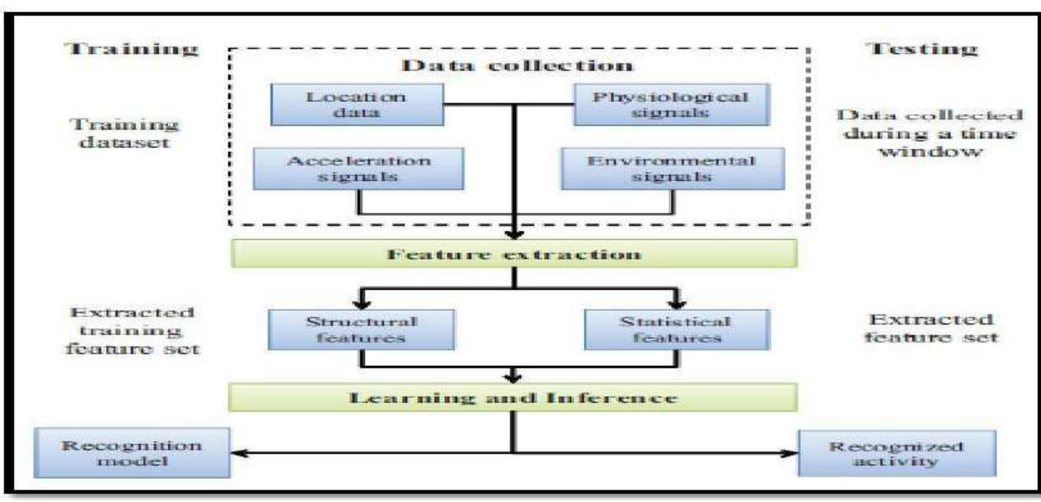


Figure 2.9: General data flow for training and testing HAR systems based on wearable sensors

Conclusion:

In conclusion, we note that each of the above is based on its own method of data collection and case study and they follow different approaches in learning about activity but most of them follow the steps in case study that monitor the behavior of a person by specific means and then collect Processing these data and defining the pattern of activity using specific structures.

Chapter 3

Conception and implementation:

3.1 Introduction:

The goal of our system is to reduce the consumption of electricity by identifying the activity of persons in the house and monitor the devices to measure the temperature, the humidity , the presence of people etc. This program relies on building a database containing the statistics of the devices in the house and their cases (operating or extinguished) and monitoring the temperature and humidity sensors then put them in the form of compatible groups based on the activities located in the base algorithm k-means and then we classies the new extension to the near by group create an algorithm knn. All the previous steps taken by this program in order to reach the goal, which is to compare the state of change devices introduced devices located in the center of the assembly of each group and in the latter is the result of the removal of devices that must be stopped when the activity happened .

Architecture of our work:

Before we started our work, we drew up a blueprint explaining the steps we have taken to build our system and to reach the desired results as shown in the following figure. .

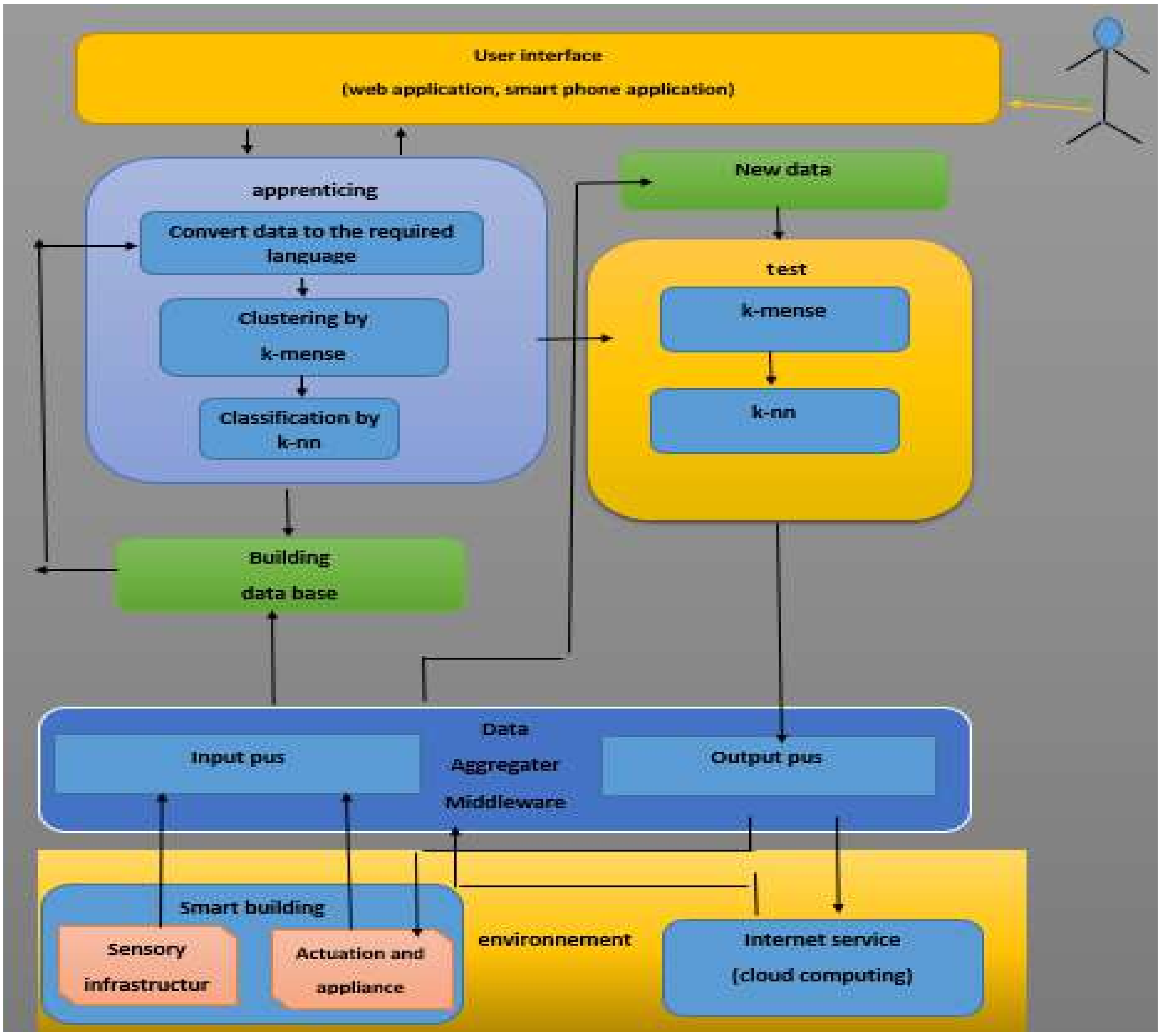


Figure 3.1: conception of our system

Explanation of the system architecture:

1-The environment :is the headquarters of the study, which is divided into two parts:

-smart building(smart home): witch contain sensor ,device ,actors

-internet service(cloud computing)

2- input pus: all data witch are contain in smart building

3- building data set: is contains the equipment used in the study with the values of their changes according to time, in addition to the human activity at every moment

4- apprenticing : We taught the program based on the database and using a specific algorithm 5-test: We tested the program by giving new data and comparing it with the results obtained in the step that precedes it Output pus : Represent the results obtained in the study

3.1.1 Algorithms used in our project:

We chose two algorithm for did our work and we tray to make relation between them which are k-means and-K Nearest Neighbors(k-nn):

K-means Clustering :

Is an algorithm to collect a number of data from a data center to the properties and attributes of this data. The assembly process is performed by reducing the distances between the data and the cluster center. This algorithm is carried out through the following steps: 1- Calculate the coordinates of the assembly centers

2- Calculate the course between all data and assembly centers.

3- Data collection and organization in groups based on the lowest distances between the center and data points.

Perform steps 1 - 3 until the stability is achieved The performance of this algorithm depends on the initial positions of the Centroid centers, and it is recommended that this algorithm be implemented several times with different positions each time than before.

k-nearest neighbors algorithm :

k- Nearest Neighbors is one of the Predictive Modeling algorithms. It does not need to learn complex mathematical equations, but only needs to be available in Dataset data. This algorithm is carried out through the following steps:

1. Determine the value of the variable k, which expresses the number of neighbors

2. We calculate the distance between the new example and the examples in the dataset

3 - we arrange examples to get the neighbors depending on the least distance calculated in the

previous step and take them the number of adjacent k

4 - we define the class for the neighbors

5 - The most common class of neighbors is the expected class for this example

Environment of development:

WEKA machine learning:

The WEKA system is not so much a single program as a collection of interdependent programs bound together by a common user interface. Typically these modules fall into three categories: data set processing, machine learning schemes, and output processing. The processing of data sets involves extracting information about a data set for the user, splitting data sets into test and training sets, filtering out features in the data not required by the user, and translating the data set into a form suitable for a machine learning scheme to work with. Machine learning schemes are implementations of machine learning algorithms and typically take a converted data set and produce some output, normally a rule set. Output processing modules are concerned with taking the output from a machine learning scheme performing some task with it, such as evaluating a rule set against a test file or displaying the output in a window for the user. .

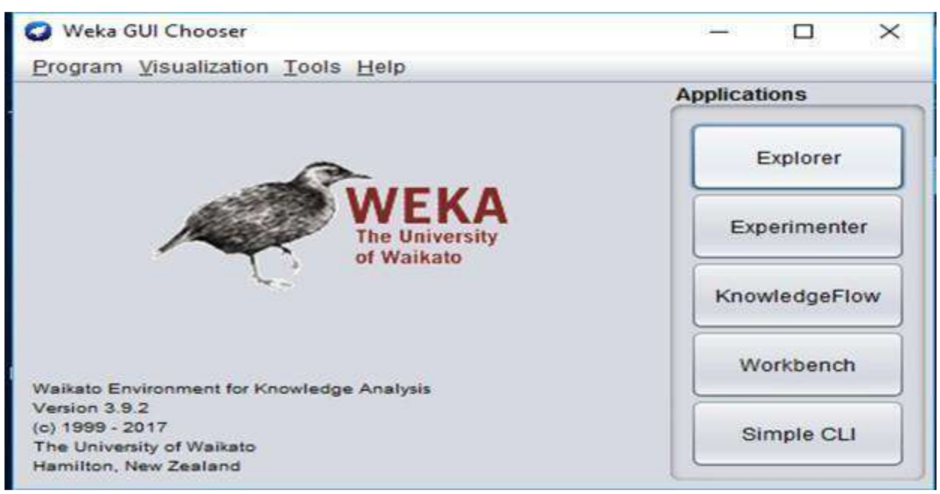


Figure 3.2: weka program

This image represents a set of points, which is the result of the application the weka assembly

algorithm on our database to determine the expected result and each color determined one cluster.

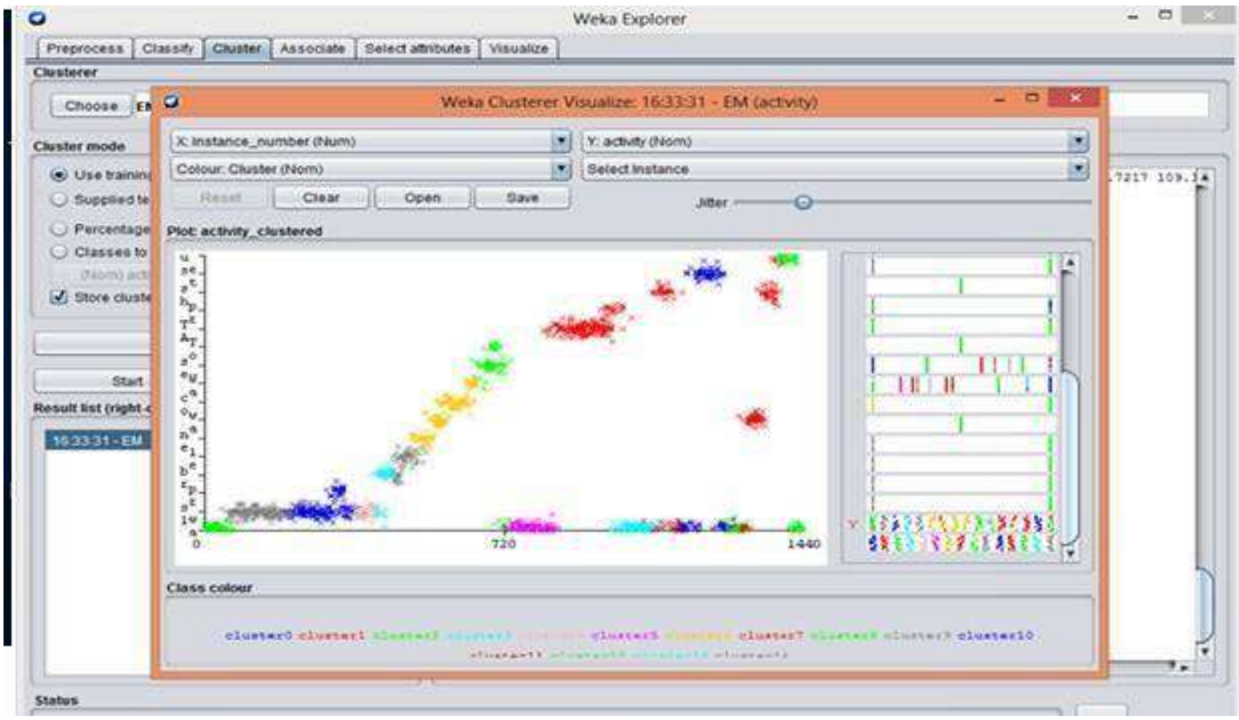


Figure 3.3: example of clustering in weka program

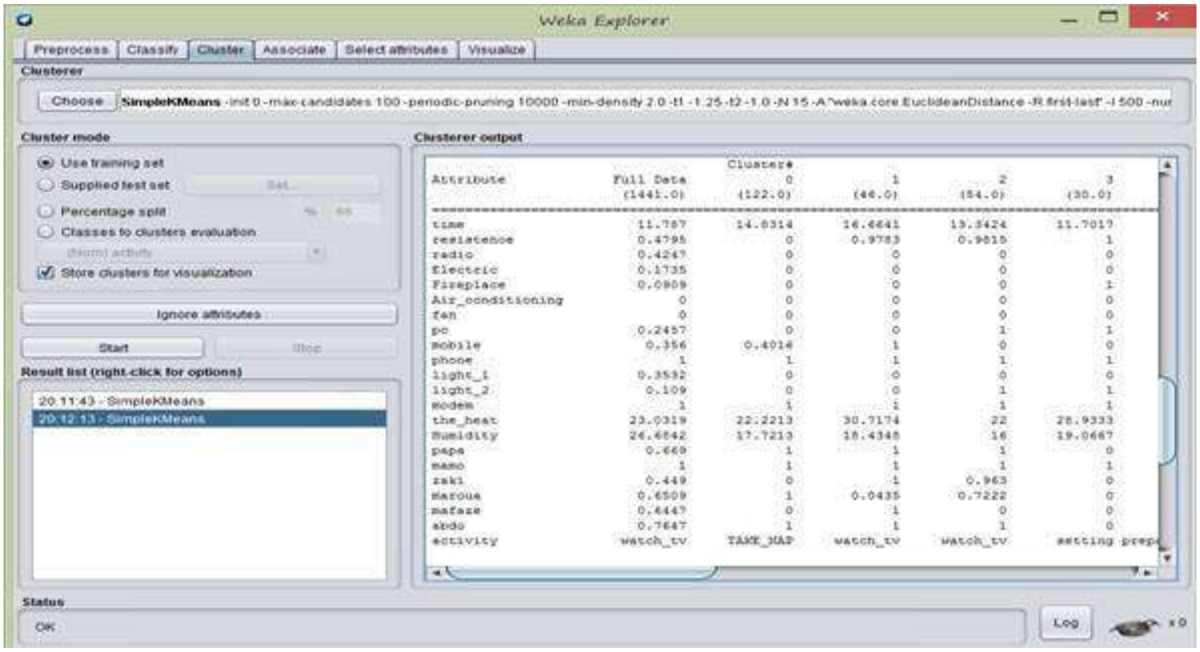


Figure 3.4: example of clustering in weka program

JAVA Eclipse:

Eclipse is a free, Java-based development platform known for its plug-ins that allow developers to develop and test code written in other programming languages. Eclipse is released under the terms of the Eclipse Public License. .

Figure 3.5: JAVA eclipse

Sequence diagram and Data set:

sequence diagram :

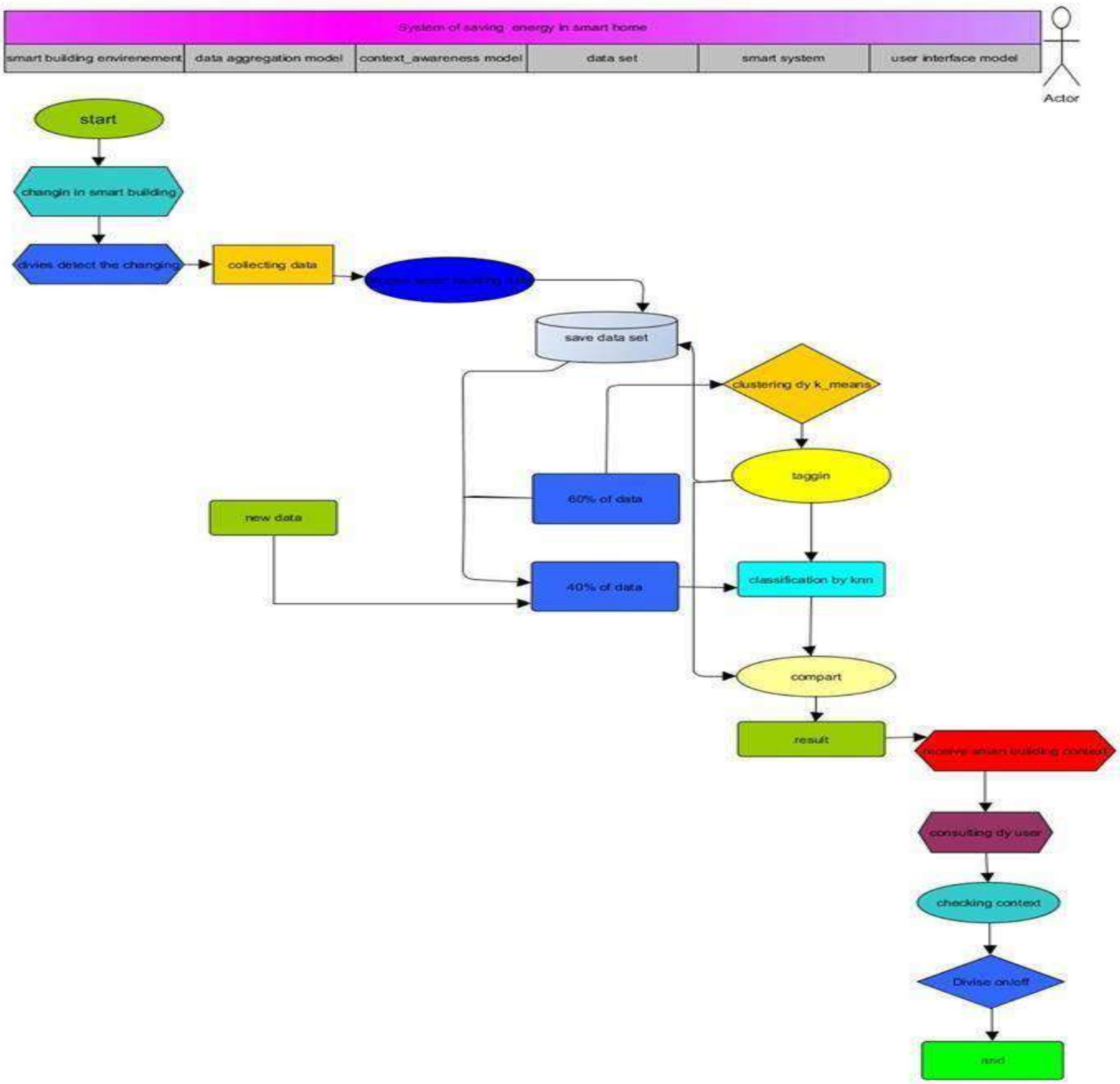


Figure 3.6: Sequence diagram

Explanation of the sequence diagram:

1 - the beginning of research and observation in the environment by sensors

2- Recording the expected changes in the studied environment

3. Data collection

4. Introduce them to the program

5. Save them as a database

6. Divide the database into two parts

7. Get 60 percent of the data

8. Pass 60 percent in the k-means assembly algorithm

9. Name each group

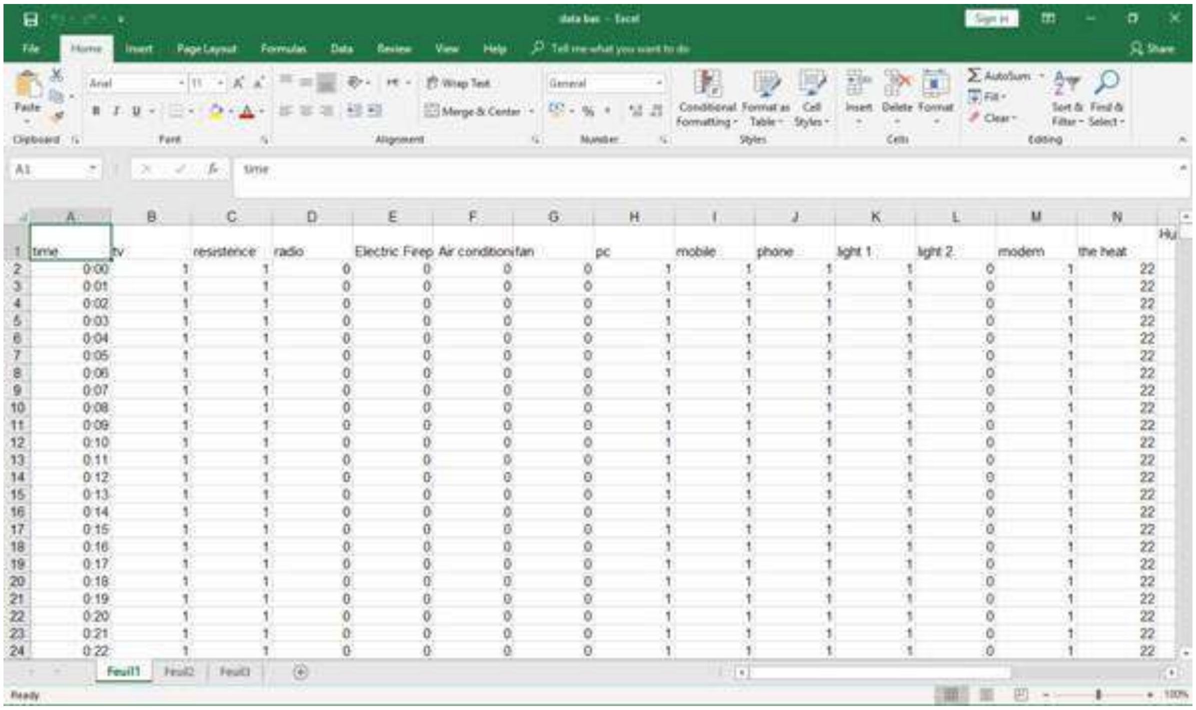
10 - We get 40 percent of the remaining data and use it in the algorithm of classification k-nn.

11 - then we make the relation between two result k-means and k-nn

12 - Then we get the equipment that must be extinguished because of the don't need for it in the current activity current activity

Data set :

The database is the statistics of the devices in the house which are (TV - resistance - pc - radio- fan -electric replace-air conditioning-mobile-phone-light1-light2-modem) in addition to the sensors (temperature and humidity) as well as people in the home (Mather-father and 4 children) as we mention the activities are happening at home. We have built this database by setting 0 for non-operating devices and 1 for devices operating with time change so we collected more than 1400 extension. .



time	tv	resistence	radio	Electric Firep	Air conditioni	fan	pc	mobile	phone	light 1	light 2	modem	the heat	Hu
0:00	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:01	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:02	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:03	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:04	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:05	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:06	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:07	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:08	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:09	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:10	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:11	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:12	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:13	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:14	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:15	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:16	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:17	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:18	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:19	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:20	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:21	1	1	0	0	0	0	1	1	1	1	0	1	22	
0:22	1	1	0	0	0	0	1	1	1	1	0	1	22	

Figure 3.7: Data set in excel

Implementation:

Implementation of algorithm k-means and k-nn in javaeclipse:

1- We put Library of weka.jar in our java project

2-We Convert excel file to extension .arff

3- We split our data set to two part 60 percent for training and 40 percent for testing

Method of k-means algorithm (Class of clustering):

We bring 60 of the database. We applied the K-means algorithm to apply the aggregation process by determining the number of groups that was equal to the activities in the database where the Kmeans process on the database was as follows:

-Randomly identify any point of the data planner and then apply the assembly process, depending on how to calculate the distance between distance points euclidian.

Our result in the latter was a group of gatherings and each gathering representing a particular activity with the coordinates of each gathering center

```java
package application;



import java.io.File;

import weka.clusterers.ClusterEvaluation;
import weka.clusterers.ClusterEvaluation;
import weka.clusterers.SimpleKMeans;
import weka.core.Instances;
import weka.core.converters.ArffSaver;
import weka.core.converters.ConverterUtils.DataSource;

public class Clustering {

    public static void main(String args[]) throws Exception{
        //load dataset
        String dataset = "data_train.arff";
        DataSource source = new DataSource(dataset);
        //get instances object
        Instances data = source.getDataSet();
        // new instance of clusterer
        SimpleKMeans model = new SimpleKMeans();//Simple EM (expectation maximisation)
        //number of clusters
        model.setNumClusters(20);
        //set distance function
        model.setDistanceFunction(new weka.core.ManhattanDistance());
        // build the clusterer
        model.buildClusterer(data);
        System.out.println(model);
```

Figure 3.8: clustering class

```
<terminated> Clustering (1) [Java Application] C:\Program Files\Java\jre1.8.0_172\bin\javaw.exe (Jul 3, 2018, 12:56:06 AM)
Initial starting points (random):

Cluster 0: 19.22,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,0,1,1,1,watch_tv
Cluster 1: 19.55,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier
Cluster 2: 19,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,0,0,1,1,watch_tv
Cluster 3: 15.25,0,0,0,0,0,0,0,1,1,0,0,1,22,18,1,1,0,1,0,1,TAKE_NAP
Cluster 4: 18.23,1,0,0,0,0,0,0,0,1,0,0,1,18,38,0,1,0,0,1,1,showering
Cluster 5: 14.25,0,0,0,0,0,0,0,0,1,0,0,1,22,18,1,1,0,1,0,1,TAKE_NAP
Cluster 6: 18.32,1,0,0,0,0,0,0,0,1,0,0,1,18,38,0,1,0,0,1,1,showering
Cluster 7: 17.08,1,0,0,0,0,0,0,1,1,0,0,1,31,18,1,1,1,0,1,1,watch_tv
Cluster 8: 20.3,1,1,0,0,0,0,1,0,1,1,0,1,18,38,0,1,0,1,1,1,etudier
Cluster 9: 22.5,1,1,0,0,0,0,0,1,1,1,0,1,22,25,1,1,0,1,1,1,use_pc
Cluster 10: 21.28,1,1,0,1,0,0,0,0,1,1,0,1,26,24,1,1,0,1,1,1,watch_tv
Cluster 11: 20.24,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,0,1,1,1,etudier
Cluster 12: 21.04,1,1,0,0,0,0,1,0,1,1,0,1,22,11,0,1,0,1,1,1,watch_tv
Cluster 13: 23,1,1,0,0,0,0,0,1,1,1,0,1,22,25,1,1,1,1,1,1,use_pc
Cluster 14: 17.2,1,0,0,0,0,0,0,1,1,0,0,1,18,38,1,1,0,0,1,1,watch_tv
Cluster 15: 19.16,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,0,1,1,1,watch_tv
Cluster 16: 19.11,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,0,1,1,1,watch_tv
Cluster 17: 19.24,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,0,1,1,1,watch_tv
Cluster 18: 17.38,1,0,0,0,0,0,0,1,1,0,0,1,18,38,1,1,0,0,1,0,watch_tv
Cluster 19: 16.14,0,0,0,0,0,0,0,1,1,0,0,1,31,18,1,1,0,1,1,1,prepared_tea

Missing values globally replaced with mean/mode

Final cluster centroids:
                              Cluster#
Attribute          Full Data        0         1         2         3         4         5         6         7         8         9        10
                     (576.0)    (8.0)    (30.0)    (19.0)    (49.0)    (18.0)    (49.0)    (16.0)    (44.0)    (27.0)    (34.0)    (59.0)
---------------------------------------------------------------------------------------------------------------------------------------
time                  19.115   19.215    19.515      18.5     15.38    18.155     14.49    18.325    16.525     20.43    22.425     21.56
resistence                 1        1         1         1         0         1         0         1         1         1         1         1
radio                      1        1         1         0         0         0         0         0         0         1         1         1
Electric                   0        0         0         0         0         0         0         0         0         0         0         0
Fireplace                  0        0         0         0         0         0         0         0         0         0         0         1
Air_conditioning           0        0         0         0         0         0         0         0         0         0         0         0
fan                        0        0         0         0         0         0         0         0         0         0         0         0
```

Figure 3.9: Result of class clustering

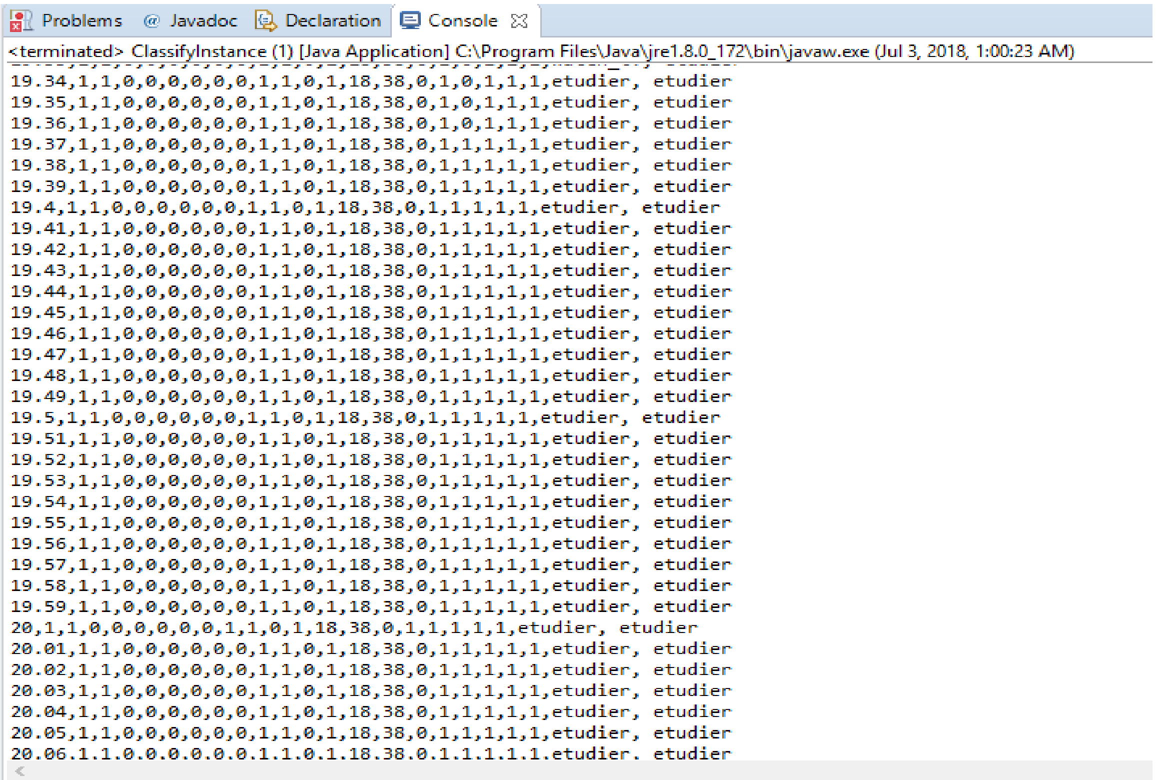
Method of k-nn algorithm(class of classification):

In this section, we downloaded the second part of the database of the experiment of the program (40 of the database). Here we did not specify the coefficient k, but it was randomized as it completed the work of this algorithm as follows:
-It classifies each point to the nearest point, depending on the distance euclidian calculation method (Each point is filled with a certain aspect) and so is the classification process.

```
package application;



import weka.core.Instance;
import weka.core.Instances;
import weka.core.converters.ArffSaver;
import weka.core.converters.ConverterUtils.DataSource;

import java.io.File;

import weka.classifiers.bayes.NaiveBayes;
//import weka.classifiers.functions.SMOreg;

public class ClassifyInstance{
    public static void main(String args[]) throws Exception{
                DataSource source = new DataSource("new.arff");
        Instances trainDataset = source.getDataSet();
        //set class index to the last attribute
        trainDataset.setClassIndex(trainDataset.numAttributes()-1);
        //get number of classes
        int numClasses = trainDataset.numClasses();
        //print out class values in the training dataset
        for(int i = 0; i < numClasses; i++){
            //get class string value using the class index
            String classValue = trainDataset.classAttribute().value(i);
            System.out.println("Class Value "+i+" is " + classValue);

        }
        //create and build the classifier
        NaiveBayes nb = new NaiveBayes();
        nb.buildClassifier(trainDataset);

        //load new dataset
        DataSource source1 = new DataSource("data_test.arff");
        Instances testDataset = source1.getDataSet();
        //set class index to the last attribute
        testDataset.setClassIndex(testDataset.numAttributes()-1);
```

Figure 3.10: class of classification

.



```
Problems  @ Javadoc  Declaration  Console
<terminated> ClassifyInstance (1) [Java Application] C:\Program Files\Java\jre1.8.0_172\bin\javaw.exe (Jul 3, 2018, 1:00:23 AM)
19.34,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,0,1,1,1,etudier, etudier
19.35,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,0,1,1,1,etudier, etudier
19.36,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,0,1,1,1,etudier, etudier
19.37,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.38,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.39,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.4,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.41,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.42,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.43,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.44,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.45,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.46,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.47,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.48,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.49,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.5,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.51,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.52,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.53,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.54,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.55,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.56,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.57,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.58,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
19.59,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
20,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
20.01,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
20.02,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
20.03,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
20.04,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
20.05,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
20.06,1,1,0,0,0,0,0,0,1,1,0,1,18,38,0,1,1,1,1,1,etudier, etudier
```

Figure 3.11: Result of class classification

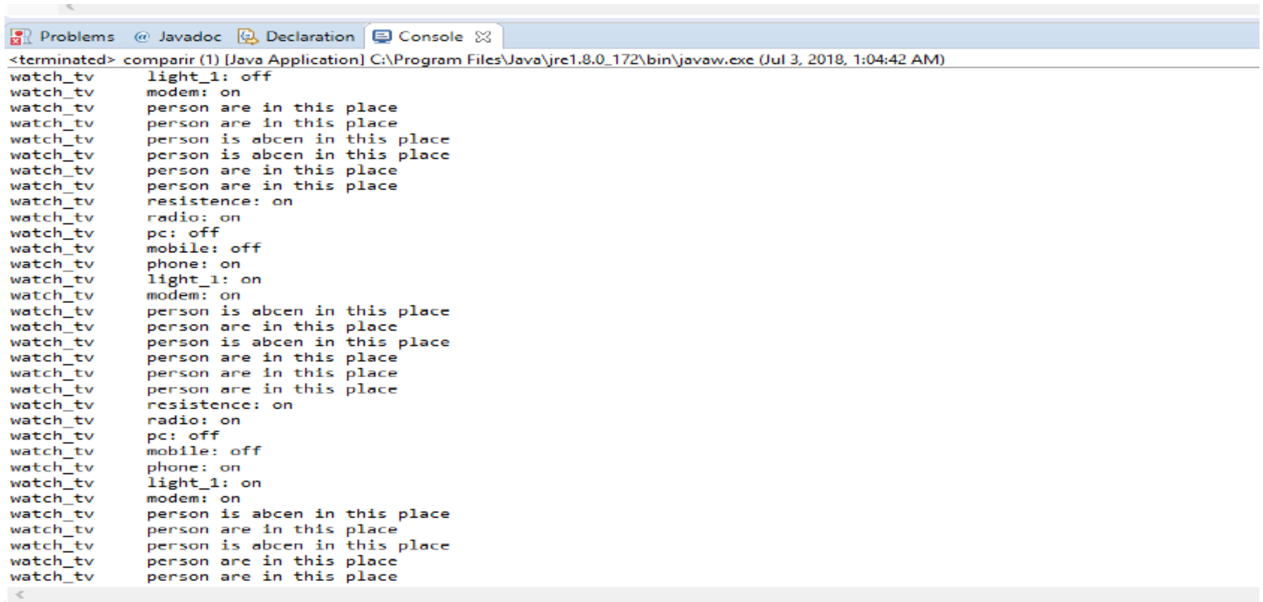
Result (class Compart) :

After selecting the above steps, we find the results of the classification that he has categorized Then we took out the group that fit the class we came to Finally, we came to the steps of comparing the state of the devices by comparing the machines in the result of the classification with the devices in the result of the clustering and shut down if they are only working in the first result (classification).

```java
package application;


import weka.classifiers.evaluation.output.prediction.Null;
import weka.core.Attribute;
import weka.core.Instances;
import weka.core.converters.ConverterUtils.DataSource;

import java.util.Vector;

import weka.classifiers.evaluation.output.prediction.Null;
import weka.core.Attribute;
import weka.core.Instances;
import weka.core.converters.ConverterUtils.DataSource;
public class comparir {
    Vector<String> vector;
    static Vector<String> vector1;
    Vector<String> vector2;

    public static void main(String[] args) throws Exception {
        // TODO Auto-generated method stub
        String dataset = "result.arff";
        DataSource source = new DataSource(dataset);
        String dataset1 = "new.arff";
        DataSource source1 = new DataSource(dataset1);
        Instances data = source.getDataSet();
        Instances data1 = source1.getDataSet();
        Vector vector =new Vector<Object>();
        vector.add("time");
        vector.add("resistence");
        vector.add("radio");
        vector.add("Electric");
        vector.add("Fireplace");
        vector.add("Air_conditioning");
        vector.add("fan");
        vector.add("pc");
        vector.add("mobile");
        vector.add("phone");
        vector.add("light_1");
```

Figure 3.12: class of compart

.



```
Problems  @ Javadoc  Declaration  Console
<terminated> comparir (1) [Java Application] C:\Program Files\Java\jre1.8.0_172\bin\javaw.exe (Jul 3, 2018, 1:04:42 AM)
watch_tv      light_1: off
watch_tv      modem: on
watch_tv      person are in this place
watch_tv      person are in this place
watch_tv      person is abcen in this place
watch_tv      person is abcen in this place
watch_tv      person are in this place
watch_tv      person are in this place
watch_tv      resistence: on
watch_tv      radio: on
watch_tv      pc: off
watch_tv      mobile: off
watch_tv      phone: on
watch_tv      light_1: on
watch_tv      modem: on
watch_tv      person is abcen in this place
watch_tv      person are in this place
watch_tv      person is abcen in this place
watch_tv      person are in this place
watch_tv      person are in this place
watch_tv      person are in this place
watch_tv      resistence: on
watch_tv      radio: on
watch_tv      pc: off
watch_tv      mobile: off
watch_tv      phone: on
watch_tv      light_1: on
watch_tv      modem: on
watch_tv      person is abcen in this place
watch_tv      person are in this place
watch_tv      person is abcen in this place
watch_tv      person are in this place
watch_tv      person are in this place
```

Figure 3.13: Result of class compart

We have developed our application in java eclipse environment by using JavaFX than We connected the program interface with source code as we Mentioned down.

2.4.3 Display of dataset(dataset-chart):

The first part text area we use it for visible our data set and the second part is chart which are represent our dataset before did opiration of Assembly.

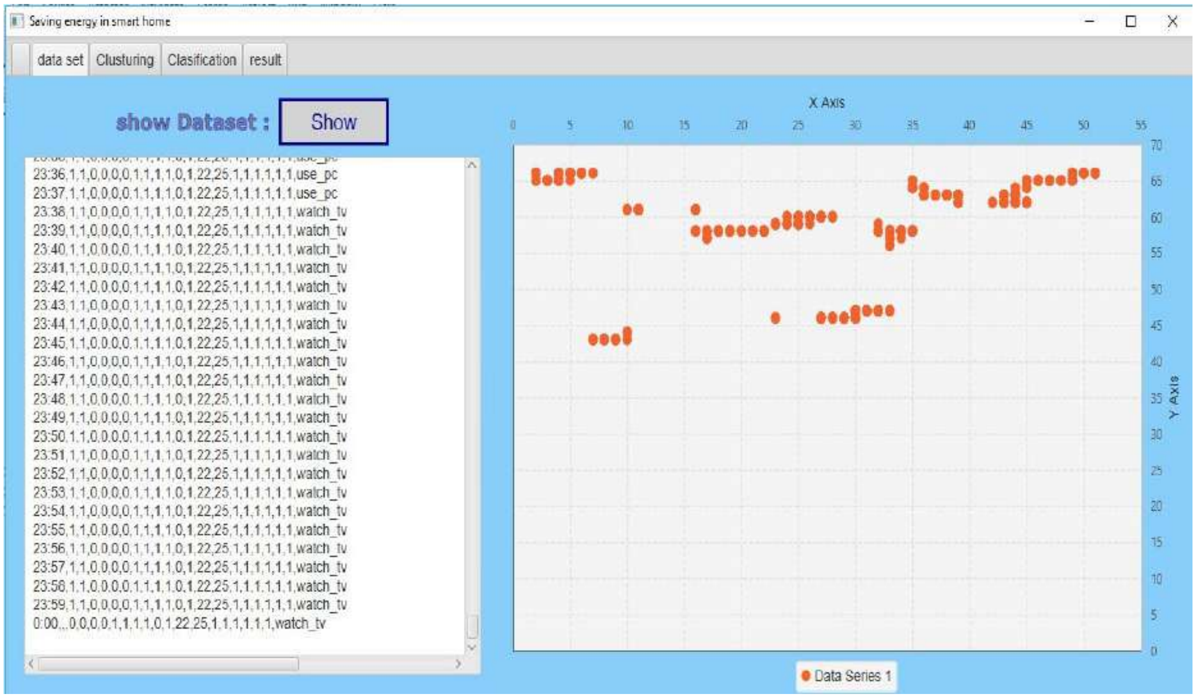


Figure 3.14: Data set in application

3.4.3 Display of clustering(dataset-chart):

In this interface, we use also text area for visible our cluster(assembly)and the chart which is in the second part represents the cluster of our data set . each cluster is represented with deferent form and color.

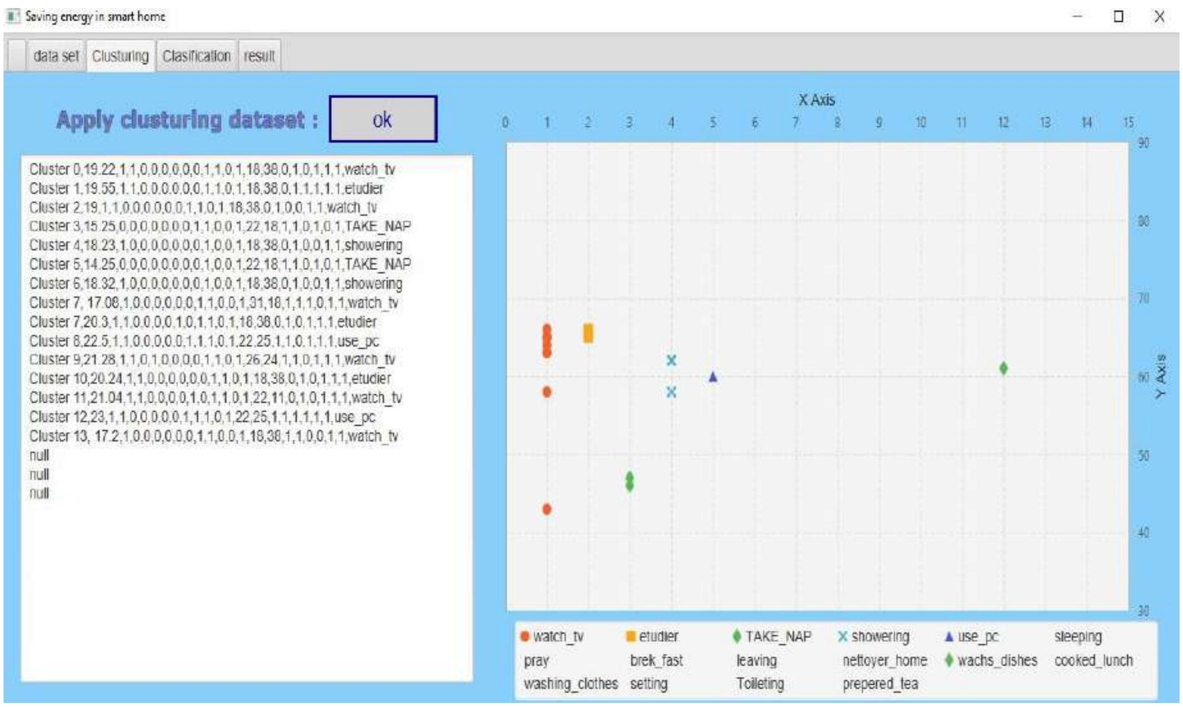


Figure 3.15: Clustering in application

3.4.3 Display of classification(chart):

The last chart represent the classification the new data so each new data was classified to nearest point.

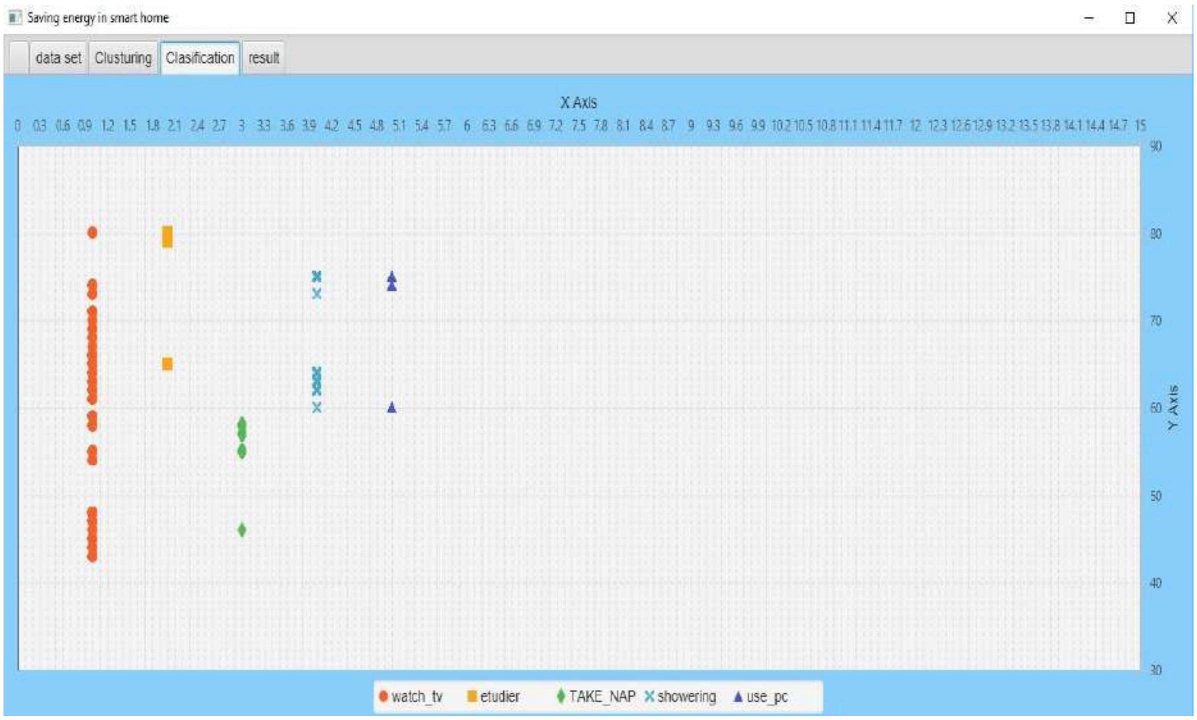


Figure 3.16: Classification in application

3.4.6 Display of result :

the last one is text area for display our result which are devices which need to be off or on, also the person is in this place or no with activity happened in time Mentioned.

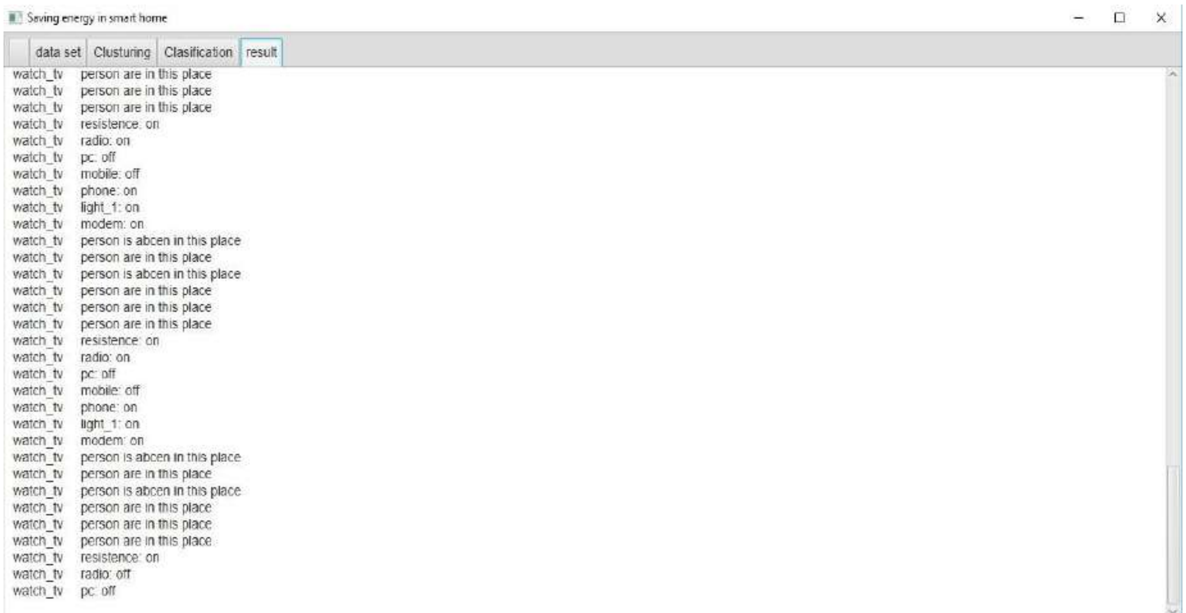


Figure 3.17: Result in application

Conclusion:

Science has been able to achieve things that werejust imagination through research and studies, Science has been able to achieve things that werejust imagination through research and studies, reaching an unexpected level, where the man can achieve his desires automatically by making all the devices of the house smart. Not only the comfort and the luxury are the feature of such smart systems but also the reduce energy consumption costs because they are the biggest obstacles that a consumer may face. Based on the previous research, we have proposed a technique that identifies the human activity in the home and employs it in several steps mentioned in our study. this allows the turned off of the operating devices is done automatically without the need to turn them manually. in this case the economy of energy will be considerable. As perspectives, we hope add new data to identify human activity and use artificial intelligence algorithms which are more successful, accurate and fast.

General Conclusion :

In conclusion, we have been working on how to maintain energy consumption in the smart home, which is the talk of the hour. This is through the identification of human activity and knowledge of all the devices needed in that activity. We have studied and acquainted with the previous work of people who have done work in this area to get The idea, even if small in this area, in particular, we came to the method of deducting the consumption of electricity by shutting down the equipment that is not needed by the person in that activity and to do it and we have chosen the algorithms kmeans and knn and tried to work and connect them, the result obtained as mentioned above. Tanna in the future to increase the accuracy of our program, as well as to increase the size of the database.

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Summary :
Smart Home is a set of devices that meet the human obstacles in an automatic way and the webs. We have developed a smart program that integrates with the functions of this latter, which reduces the consumption of electricity by recognizing the human activity at home based on the database we prepared after To monitor our house and classify them in the form of groups by the algorithm of aggregation and then we find a technique to make the latter work in an integrated or integrated with the classification algorithm to obtain accurate results as we entered new data and classification according to the results of the assembly to find the nearest Each group agrees with the input and comparison stage comes between the results of Algorithms to output devices that must be turned off for lack of function while in the process of one of the studied activities.
Kay words: energy- smart home –devises-activity-classification-technique Electricity- recognizing -database
Résumé :
Smart House est un ensemble de dispositifs qui rencontrent les obstacles humains de manière automatique et les toiles. Nous avons développé un programme intelligent qui s'intègre aux fonctions de ce dernier, ce qui réduit la consommation d'électricité en reconnaissant l'activité humaine à la maison basée sur la base de données que nous avons préparée. Pour surveiller notre maison et les classer en groupes par l'algorithme d'agrégation puis nous trouvons une technique pour faire fonctionner ces derniers dans un algorithme intégré ou intégré à l'algorithme de classification pour obtenir des résultats précis car nous avons entré de nouvelles données et classifications selon les résultats de l'assemblage pour trouver le plus proche et l'étape de comparaison entre les résultats des algorithmes pour produire des dispositifs qui doivent être désactivés par manque de fonction pendant le processus de l'une des activités étudiées.
Mots-clés: énergie-maison intelligente -devises-activité-classification-technique-Base de données reconnaissant l'électricité
التلخيص:
البيت الذكي هو عبارة عن مجموعة من الأجهزة تقوم بتلبية حاجبات الإنسان بطريقة آلية وبفعل الشبكات العنكبوتية . وقد قمنا بإعداد برنامج ذكي يتكامل مع وظائف هدا الأخير والذي يقوم بالتقليل من استهلاك الطاقة الكهربائية عن طريق التعرف على نشاط الإنسان في البيت اعتمادا على قاعدة بيانات قمنا بإعدادها بعد القيام بمراقبة منزلنا وتصنيفها على شكل مجموعات بفعل خوارزمية التجميع ثم قمنا بإيجاد تقنية لجعل هذه الأخيرة تعمل بشكل متكامل أو مدمج مع خوارزمية التصنيف وذلك للحصول على نتائج دقيقة حيث قمنا بإدخال معطيات جديدة وتصنيفها طبقا لنتائج التجميع بإيجاد اقرب مجموعة تتفق مع كل مدخلة ثم تأتي مرحلة المقارنة بين نتائج الخوارزميتين لإخراج الأجهزة التي يجب إيقاف تشغيلها لعدم وجود وظيفة لها في حين سيرورة احد الأنشطة المدروسة.
الكلمات المفتاحية: العملات المنزلية الذكية للطاقة - تصنيف النشاط-النشاط-الكهرباء - التعرف على قاعدة البيانات