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Smart Home: Household Appliance usage Recommender and Monitoring System (HARMS)

A project submitted
in partial fulfillment of the requirements for the degree of
Bachelor of Science in Computer Science

by

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UNDERTAKING

This is to declare that the project entitled "Smart Home: Household Appliance usage Recommender and Monitoring System" is an original work done by undersigned, in partial fulfillment of the requirements for the degree "Bachelor" at the Computer Sciences Department, College of Computer Sciences and Information Technology, King Faisal University.

All the analysis, design, and system development have been accomplished by the undersigned. Moreover, this project has not been submitted to any other college or university.

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ABSTRACT

The demand on energy sources such as electricity is increasing as the population is increasing, which results in high billing costs and more energy consumption. There are more factors resulting from these issues. For example, the decreased awareness from residents about how to save energy, especially kids and elderly people who forget about turning off home appliances and lights when they are not needed to be on. HARMS provide a smart solution through the concept of machine learning (ML) and recommendations, it will monitor power consumption, show recommendations (through a recommender system) and control home appliances based on the resident's behaviors, when they are willing to turn on the room light or any other home appliance and when to turn them off in order to enhance energy saving. HARMS will also track inhabitant usual and unusual behavior to take an action. We must note that due to this exceptional situation (Covid-19 Pandemic), HARMS may be done either using actual hardware, simulation, or both. The hardware parts will consist of microcomputer, motion, light, and current transformer sensors. The software parts will consist of a control system which collects data from sensors and monitors the power consumption, database to store the collected data, appropriate algorithms for the recommender system and android application to interact with the residents. Regarding the simulation will consist of a web-based application to represent the home environment and the appliances, including the control and the recommender systems. This project will be experimented at the College of Computer Sciences and Information Technology (CCSIT) at King Faisal University (KFU).

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1 Introduction

Electricity energy consumption is a form of energy consumption that is consumed by electronic and electric appliances. In 2016, a huge demand for energy resources around the world led to a great increase in energy consumption due to the growth of the world population. According to BBC, it is predicted, between 2005 and 2030, that energy demand will expand by 50% and the population will rise by 1 billion during the next 10 years. Growing expectations in increasing population yields to expand living standards which contribute to putting more demand on energy resources. Globally, electricity consumption is an issue due to a large focus on industry, and high appliance usage from houses. Accordingly, overusing energy increases the carbon footprint. More electricity is used, more emissions are produced which affect the environment. In Saudi Arabia, electricity consumption represents more than one-third of the country's total daily oil production and high electricity consumption is one of the challenges it has faced till 2020.

This report is organized as follows. Section 1.1 gives a background of electricity consumption in Saudi Arabia and proposes a solution to utilize energy efficiently. Section 1.2 discusses the motivation to build such a system. Section 1.3 describes the issues related to high energy consumption. Section 1.4 presents HARMS modules and delimitations. In section 2.1, it defines the use cases of HARMS. In section 2.2 and 2.3, they present the software and hardware requirements which used to design and develop the system. Section 2.4 provides the expected outcomes of HARMS. Section3 shows the work plan we are following throughout this semester.

1.1 Background

KSA has seen an increase in energy consumption from 2000 to 2020. Saudi households consume around 50% of national power consumption. As a result of the summer climate in Saudi Arabia, most of the power is used for cooling systems and air conditioning which increased the payment up to 100% [3]. In 2014, the kingdom ranked between 10 countries that consume high energy per capita [4]. In 2018, there has been a substantial increase in electricity price, as shown in figure 1 and figure 2, which concerns the Saudi government about its economy in the future and the impact on the total energy consumption [5]. Therefore, it introduced the Saudi Energy Efficiency Center (SEEC) that seeks to rationalize the usage of electricity to conserve the natural resources in KSA as well as promote the economy and social welfare of the kingdom's population.

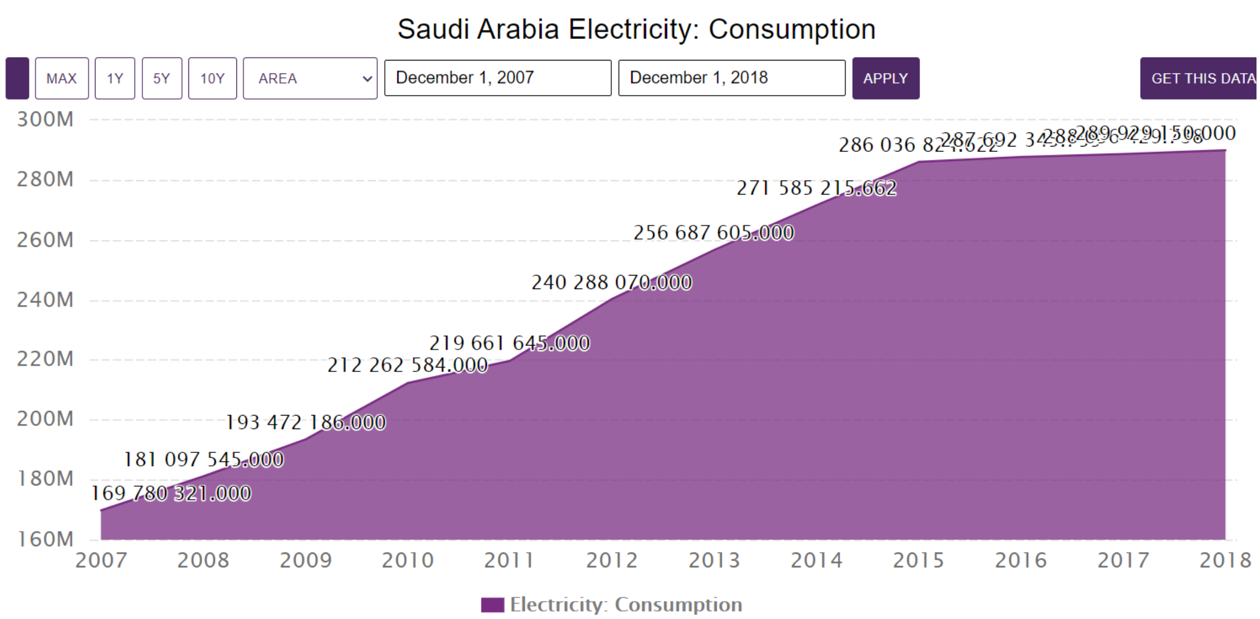


Figure 1 Electricity consumption in Saudi Arabia (2007-2018) [6].

Geographical analysis of the company's revenues:

The following table shows a geographical analysis of the company's sales according to the regions (sectors) in which it operates:

Operating Areas						
Year	Description	Central	Eastern	Western	Southern	Total
2018	Revenue/Sales	18,752,377	16,508,094	18,358,051	6,004,932	59,623,454
2017	Revenue/Sales	14,856,954	13,334,402	13,329,644	3,925,163	45,446,163

	For the year ended	
	31 December 2018	31 December 2017
Electricity sales	59,623,454	45,446,163

Figure 2 Annual report of Saudi Electricity Company showing the difference of revenues in 2017 and 2018 [6].

Another primary element that contributes to the increase in electricity consumption is the inhabitant behavior with domestic appliances which causes him to spend more on electricity. 62.6% of households spend about 20% of their salary on electricity. Nearly, 4% of the inhabitants spent more than 30% of their income along with the consequence that they must either compromise their savings or decrease spending on other necessary expenses to handle the high electricity bills [4].

The rise of electricity bills over recent decades in Saudi Arabia, combined with the growing fears over the impact of the high household consumption needs a convenient solution to solve those issues and optimize energy efficiency. To accomplish those objectives, a recommender system is one of the powerful suggested methods that predict user profile and electricity usage of domestic appliances. It automates the cheaper suggestions to cut down the high energy consumption.

In a 2019 study, the authors conducted a survey in Jeddah to examine user behavior in residential building's energy performance. They concluded that it needed an urgent intervention to enhance energy consumption [5]. Another research has been executed to gain knowledge about how people identify the home of the future and what assumptions they have of occupation in such a home. Many interested people reported that their major concerns are comfort tasks and home control, such as controlling heating, lights, and windows. To achieve these goals, it is crucial to build a recommender system that examines user energy profiles and appliances that have been utilized via established sensors. The recommender system assists inhabitants by monitoring user energy profiles to make cheaper suggestions and adjust energy-saving options [7].

Based on studies discussed, we propose a Household Appliance usage Recommender and Monitoring System (HARMS) that is used to reduce energy consumption by monitoring and controlling household appliances and provide efficient and real-time recommendations of what appliance we can use base on sensor data and learning algorithms that will run over the system and provide efficient and effective recommendation for the user base on the sensor reading.

1.2 Motivation

HARMS project's aim is to reduce the energy consumption. Generally, the use of electricity is increasing in the kingdom of Saudi Arabia, which increases the electricity expenses. Figure 3 shows the bulletin of household energy survey 2019, The General Authority for Statistics. It reported that 52% of households believe the energy rationalization measures would cut expenses, and 46% are willing to buy power saver or energy rationalizer. As the amount of electricity consumption in the Kingdom of Saudi Arabia reached its peak, especially in the summer and the winter season due to the frequent use of air conditioners and to the frequent use of heaters that cause a large amount of energy to be spent, especially when turned on and off randomly or turn it on permanently. The intended system can be effective in overcoming the problems of consumption. Therefore, HARMS could help the citizens lowering the electrical consumption.

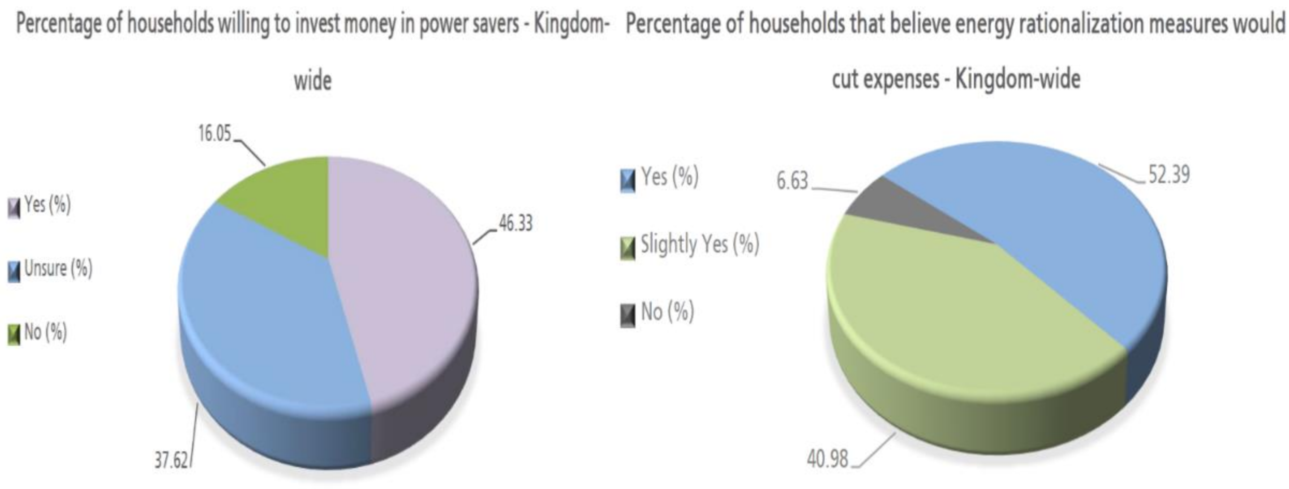


Figure 3 Bulletin of household energy survey 2019, The General Authority for Statistics.[3]

1.3 Problem Statement

The Age of technologies today achieves a lot of the promises to bring comfort for the human in many aspects. Recently, Saudi inhabitants complained about high electricity bills. As a result, they tend to put a lot of pressure on themself to reduce the usage of electricity even though that will sacrifice their comfort [7]. Below are the known problems when it comes to high energy consumption in Saudi Arabia:

- **High Energy Cost.** Due to the rise in cost per kilowatt-hour, the cost of electricity becomes high. Thus, the usage of different electric appliances in the home contributes to high the number of Kilowatts consumed as well as increasing cost.
- **Unattended Appliances**. This is where the user has forgotten to turn off a certain appliance. Because a human by nature may forget to turn off an appliance because of the distraction that surrounds him. This action will lead to inefficient consumption of energy therefore cost will increase.

- **Unawareness of Energy Consumption.** This is a problem when the users are unaware of the amount of current energy consumption. Subsequently, they are tending to use too many appliances in an inefficient way which later becomes a problem when the user is shocked due to the high consumed energy in their home.

1.4 Scope of The Project

The proposed project HARMS is a monitoring and recommender system for household appliances that can be used as a tool to decrease energy consumption in KSA. The HARMS will be divided into different modules such as: (1) Mobile application that will serve as an intermediary software in between system operations and the user to provide real time notifications that can display the recommendation, energy usage and monitoring appliances consumption so users can easily interact with the system. (2) Central Control Module that will be installed in computer, it will process data from censors to provide recommendation to the user. Also, monitoring, and computation appliance usage which can be accessed using the system dashboard. (3) Sensor module, which are interconnected modules that plug with appliances to get data from each appliance and send it to the (2) module. In simulation, the module we will design a web page, which will be divided into two parts, first part will represent the home environment, and second part which control panel that will represent the home appliances and sensors. They can also be used by multiple users since every user will have different profile and uses different appliance. system will run in local area network for security. The system can be accessed via the local area network (LAN).

Due to the limitation of hardware and equipment that can acquired we propose to implement the system by simulation of the process, and a few of hardware parts. For testing purposes when are limiting the HARMS project will only provide one appliance that will be monitored such as light regarding the simulation, we consider three appliances microwaveOven, refrigerator, and toaster and one user.

Regarding the HARMS project delimitations, even though the system will provide energy consumption in detail the system will not compute the electric bill of the user. Also, for the purpose of testing HARMS project will work as local area network.

1.5 Comprehensive Analysis of Related Work

Smart home systems were widely researched in various technical fields, mainly targeting user instructions. HARMS will recommend and monitor users' habits in using home appliances. Recent studies in automated smart home systems related to HARMS were divided into recommender system, applications of the recommender system, how predict next action by implementing machine learning algorithms, and how recommender is used in home automation. In this section we will discuss some systems and research papers representing some of the features that we are planning to implement in HARMS project in addition to the different parts and methodologies used within these systems.

1.5.1 Applications of Recommender System

A recommender system basically is a system that seeks to suggest items for the user. Baptiste et al. [8] (2019) have presented an introduction to recommender systems. Finding that the recommender systems are considered as algorithms, aiming to predict relevant items to the users. They categorized the types of recommender systems into three types: Collaborative filtering method, Content-based method, Hybrid method.

The recommender systems have been apparent and developed in many different up-to-date applications. James, Benjamin, et. al. [9] have discussed the video recommender system implemented at YouTube. The recommender system goal is to produce efficient and diverse video recommendations based on recent user personal interests. After gathering user's activity (watched, liked, favorited videos) and video data, such as description and title, an association rule mining technique is used for mapping between the videos. James, Benjamin, et. al. found out that recommendation has been a very successful feature that accounts for 60% of all home page video clicks. Similarly, Netflix's recommender system is a collection of several algorithms serving various use cases that come together to make up the complete Netflix system. The system helps effectively manage the process of choosing a movie [10]. Furthermore, Enrique et al. [11] have presented a " which App?" application. It is used for recommending new applications to the users based on applications previously downloaded. It uses five different filtering techniques whose results complement each other to obtain both accurate and diverse suggestions. Whereas in Elsevier et al. [12] (2010) have used collaborative filtering methods and matrix factorization for predicting student performance which aims to decrease the time taken to learn algebra and minimize the role of standardized tests.

1.5.2 Recommender System in Smart Home

Dmitry et al. [13] (2013) presented a system that makes recommendations based on the user habits as an additional method which is called "user behavior-based approach". Forecasting of the user's needs can be responded by expecting peaks of energy consumption or resolving the conflicts usage between the home residence. They claimed that simple algorithms, which rely on the correct and perfect information collection, might be applied for extrapolating to the user for the future. They came up with an algorithm of Mining Cluster-Based Statistical Usage Pattern for an appliance, that depends on the starting time and the period of domestic appliances usage. In 2014, Sungjoon et al. [14] proposed two algorithms: DBN-ANN and DBN-R based on the deep learning or Deep Belief Network (DBN) to prognosticate diverse actions in the house. They used the n-gram algorithm to process the natural language and predict the user habit. Also, they applied the Q-learning algorithm, which is built up to predict the period time of turn on-off appliances, such as light to schedule the actions of the appliances. They tried to understand the relationships between past actions and the future action by deep learning approaches. They used the deep learning prediction in two different ways, which are: Efficient Online Learning Using Bootstrapping which is proposed bootstrapping to calculate the base distribution more efficiently in the Gibbs sampling step, and Deep Architectures for Prediction: They proposed DBN-SVM, and then presented two prediction models, DBN-ANN and DBN-R by the deep architecture. DBN-SVM is a hybrid model which mixes between a DBN and support vector machine (SVM). Likewise, SVM has been applied in [15] to predict house inhabitants depending on user daily routine and activities. Authors trained the SVM algorithm to build the Behavior Classification Model (BCM) which contains the behavior of each user. BCM plays an important role to split one user from another to be able to predict the house inhabitant. The model was tested by using 10-fold cross validation which achieved 90%.

However, in [16] authors have created a MavHome project that seeks to maximize inhabitant comfortability and reduce operation cost. The system was built to monitor the pattern of inhabitant mobility and device usage. The system starts collecting data through established sensors and then applies 3 different algorithms. First algorithm is Lezi-Update which divides the history into chunks to study user location. Second algorithm is Smart home Inhabitant Prediction (SHIP) that was proposed by the authors to predict the next user action more likely to occur. Last algorithm applied is Episode Discovery (ED) that discovers the significant patterns occurring daily and weekly in order to automate them. They agreed that Lezi-Update is the most optimal method to the location management problem. Regarding SHIP, its accuracy was 80 percent which is considered efficient to predict next activity. Finally, ED results showed that it can be an excellent choice for device automation.

Michael et al. [17] presented a case study of a recommender system for smart homes that aims to save energy without lower residence comfort. It is Starting with analyzing the user data by using pattern mining algorithms and then applying Machine Learning (ML) techniques to recommend action that reduces energy consumption. They note that the patterns with high confidence and high length tend to receive better feedback than the other patterns. The system is improved to generate the least number of the helpful recommendations. In comparison with what Michael et al. discussed, Maria et. al. [18] have proposed a Smart Home Energy (SHE) project using Jubatus client/server structure which implements several classifiers that ended up with 74% accuracy in training and testing collected consumption data. In addition, the recommendation engine was built using Mahout tools to generate cheaper energy-saving options. The accuracy of this module was measured, and it has achieved 90%.

In [19] research, the authors apply a ML algorithm called ClusTree, which is a self-adaptive stream clustering algorithm to detect unusual behavior from home energy data. This knowledge is used to develop systems that can raise just-in-time warnings to save energy. They claimed that the ClusTree algorithm is efficient, effective, and outperformed the Classical Change Detection Page-Hinkley Test (PHT) by at least 20 %. Katharina (2014) proposed a method that is equivalent to the Naïve Bayes classifier method without the temporal properties and without any non-specificity to build a smart home recommender system. The system learns the user's habits first. Then, generates constantly personalized recommendations that predict the next action based on the user's current situation. She found out that her method produces correct recommendations with 61% and 73% accuracy for the two used datasets, outperforms a Naïve Bayes classifier, and is stable when it comes to the choice of parameters since we avoid extreme values. Also, the system addresses the issues of complicated user interfaces and inflexible home configurations. [7]. Table 1 shows the difference between HARMS and other systems discussed earlier.

Based on those studies, we perceive that they adapt the same procedure in building a recommender system in smart home systems. Therefore, we suggest applying ML or Data Mining algorithms to extract and learn the user pattern from the collected history. After studying user interaction with appliances, we will feed the data to a matching algorithm, so the system is able to predict and recommend the most likely next user action. we have found that there are numerous algorithms that are being used to mine the data, such as ClusTree, and pattern mining algorithms. On the other hand, we have identified different algorithms for the recommender system. For instance, Deep Belief Network (DBN),N-gram, Q-Learning, Episode Discovery (ED), and SVM.

According to the researches we analyzed; pattern mining algorithms is a more suitable unsupervised approach that can be applied in the smart home domain to learn behavior patterns other than the supervised techniques which need manual annotation and limits system scalability. Similarly, Clustree is one of the efficient algorithms that has high performance in mining user patterns and can detect any changes in time or appliances replacement. Furthermore, Q-Learning was recommended to use in recommendation due to its robustness in predicting items to users. Likewise, SVM have been used in several smart home projects and always provide accurate results. In [20], it has measured and achieved 90%. Finally, ED has evaluated, and the results demonstrated that it can be used to assist in the automation of appliances interactions and produces a very efficient approach for recognizing important episodes in a stream of data.

Features \ Systems	HARMS	Unsupervised Detection of Unusual Behaviors from Smart Home Energy Data	An Unsupervised Recommender System for Smart Homes	MavHome	SHE	Smart home User's Behavior Prediction	Human Behavior Prediction for Smart Homes Using Deep Learning
Recommend Appliance to Use	Yes	No	Yes	No	No	Yes	yes
Energy Consumption Monitoring	Yes	Yes	No	No	Yes	No	No
Energy Saving	Yes	Yes	No	No	Yes	Yes	Yes
Monitoring Unusual Usage	Yes	Yes	No	No	No	No	yes
Calculate Energy Consumption for Individual Devices	Yes	No	No	No	Yes	No	No
Send Notification to User Mobile	Yes	No	Yes	No	No	No	No
Activity Automation	Yes	No	Yes	Yes	No	Yes	Yes

Table 1 Comparison between HARMS and other systems

2 Detailed project requirements

This section will present the detailed requirement of the system that will include different use cases, software, and hardware specifications. Also, there will be discussions about the used dataset, algorithms that we plan to use in the system.

2.1 Functional Requirements

The Functional Requirements Specification documents the operations and activities that a system must be able to perform. Functional Requirements describe the data entered into the system, the operation performed by each module, the workflows that the system follows, and show some reports or other output such as generate recommendations in our system. The functionality of our system is done inside two main parts: the dashboard system and mobile app. These parts will have different use cases, and we will describe what each part is able to provide the user with.

2.1.1 Use case Flow of Events for Dashboard

The dashboard is the first component that processes ML algorithms and delivers the result to the user via the router to the mobile application. Also, it is the place where the user can set the configure of the system by adding his profile or adding a new appliance to the system. Figure 4 shows the use case diagram for the system dashboard.

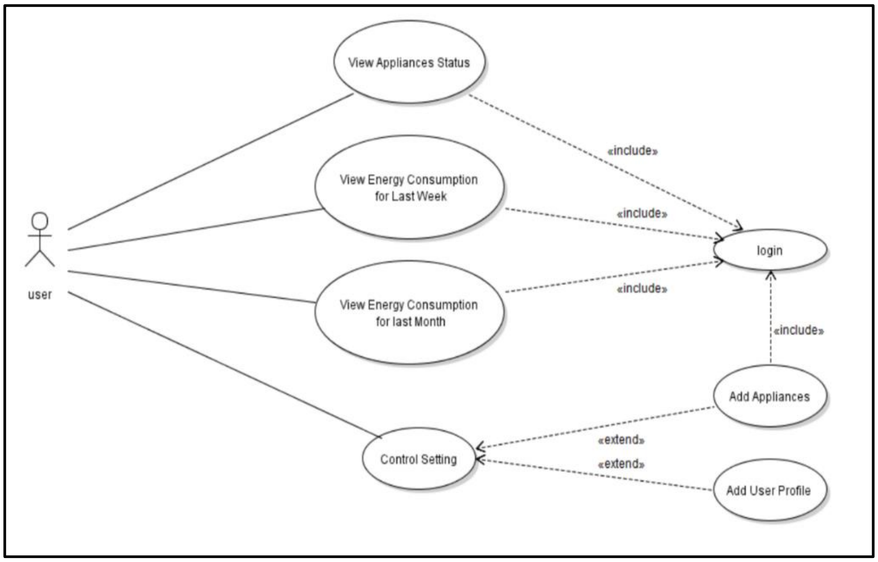


Figure 4 Use case of dashboard system.

To fully understand the use cases for the dashboard system below are the detailed discussions of each use case flow of the event.

1. Flow of Events for the View Reports Use Case

1.1 Preconditions

The user must log in to the system.

1.2 Main Flow

This use case starts when the dashboard system gets the result after processing different algorithms to view different graphical reports like the following: View Energy Consumption for Last Week, View Appliances Status, and View Energy Consumption for last Month. The graphical reports show the result in a readable form, which helps to improve the associated habits.

- For viewing " View Energy Consumption for Last Week" report, the S-1 sub-flow is performed.
- For viewing " View Appliances Status ", the S-2 sub-flow is performed.
- For viewing " View Energy Consumption for last Month " report, the S-3 sub-flow is performed.

1.3 Sub-flows

S-1: View Energy Consumption for Last Week:

The dashboard requests the database to give information about the amount of consumed energy for each device. By the end of the week, the system will calculate the average of the total energy consumed by all the appliances in the home. Consequently, the system performs the following :(1) takes the result and views it for the user to know his/her consumption pattern. (2) saves the calculated result in the database as well.

S-2: View Appliances Status:

The dashboard checks the Raspberry pi module (relay module) to know about the currently active devices. As a result, the dashboard can view for the user a visualized list of all the current active home appliances.

S-3: View Energy Consumption for last Month:

The dashboard requests the database to provide the calculated information for the last four week and take this information and showing it to the user as a visual chart to enable the user to notice the differences in energy consumption between last four weeks.

2. Flow of Events for the Control Setting Use Case

2.1 Preconditions

The user must log in to the system.

2.2 Main Flow

This use case begins when the user chooses to open system setting option. The dashboard system enables the user to select the desired activity: Add User Profile or Add Appliances.

- If the activity selected is" Add User Profile ", the S-1 sub-flow is performed.
- If the activity selected is "Add Appliances", the S-2 sub-flow is performed.

2.3 Sub-flows

S-1: Add User Profile:

The system enables the user to add his profile information to configure the system, so its stores and manipulates his information to generate recommendations for him.

S-2: Add Appliances

The dashboard system displays a screen containing fields, where the user can enter related information about the new appliance. Once the user confirms the adding, the device information will be stored in the database, and the appliance will be added to the devices list in the system.

2.1.2 Use case Flow of Events for Mobile Application

The mobile application is the second component of our system that provides specific functions to enable the user to have some control over the system. Figure 5 shows the use case diagram for the mobile application.

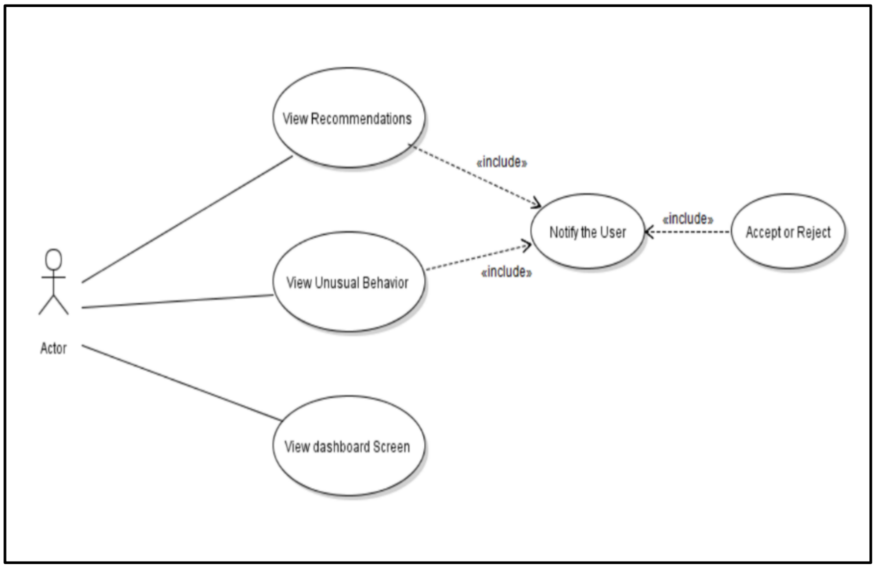


Figure 5 Use case of Mobile Application.

Below, we provide a detailed description about each use case flow of event:

1. Flow of Events for the View Recommendations Use Case

1.1 Preconditions

The user must log in to the system, and ML algorithms must execute in the background before this use case.

1.2 Main Flow

This use case executed when the dashboard system generates the recommendation after processing the user behavior in using the home appliances. The mobile application receives notifications from the dashboard system. These notifications are about the next action the user will perform. As a result, the mobile view these recommendations to the user in the following form "would you like to turn the light in room 1?" (E-1) and the action will be automated after 60 seconds of viewing the recommendation.

1.3 Alternative Flows

E-1: The dashboard system waits for 60 sec to receive the canceling order from the mobile application that controlled by the user to omit to send the signal to the Raspberry pi module.

2. Flow of Events for the <u>View Unusual Behavior</u> Use Case

2.1 Preconditions

The user must log in to the system, and ML algorithms must execute in the background before this use case.

2.2 Main Flow

Unusual behavior happens when the device is working outside the regular usage time. Executing the use case happens when the dashboard system processes the monitoring algorithm and detects the unusual behavior of appliances usage. The mobile application receives notifications from the dashboard system. These notifications make sure the user knows about these changes. So, the mobile application views the notifications as the following form "The light is not turn off in the regular time, do you want to keep it on?" Consequently, gives the user the ability to react (E-1).

2.3 Alternative Flows

E-1: The dashboard system receives the canceling order from the mobile application and send the signal to the Raspberry pi module to turn off the specific appliance.

3. Flow of Events for the <u>View dashboard Screen</u> Use Case

3.1 Preconditions

The user must log in to the system, and ML algorithms must execute in the background before this use case.

3.2 Main Flow

This use case starting when the user opens the mobile application of HARMS and clicks the "View Dashboard" option. The screen of the dashboard will appear on the user mobile screen. The user will be able to see different reports for his consumption to let the user making decisions based on results that appear to him. Also, the user can see the list of activated devices throughout the home. The dashboard will be updated continuously to reflect the changing status of the home appliances immediately.

2.2 Non-Functional Requirements

- **Usability:**

  The usability related to how easy the user will use and interact with the mobile application. Where the HARMS system interfaces are clear, simple, and compatible with other application the user already used. For example, the interface will include some graphical icons and symbols that reflect the device name or action can take.

- **Reliability:**

  The reliability of the system depends on delivering the correct result to the home user. In which the system shows different and correct reports on a specific time. For example, by the end of the week, the system shows the user with average energy consumption by applying the appropriate calculations. Also, the system lets the user know about the currently activated appliances.

- **Scalability:**

  Scalability can be achieved by adding new appliances to the system. Where the attached sensors to these appliances start to collect and save their information in the system database. So, the dashboard takes the appliances' information and start to manipulate them in the system.

- **Security:**

  Since HARMS is a local network. The system will only be accessible by mobile that its IP address is registered. Consequently, if another mobile connects to the network it cannot access the system because its IP address is not registered.

- **Portability:**

  HARMS application is a portable. It shall run in any mobile phone.

2.3 Data Requirement

To test HARMS operations and its provided functionality we will feed the system with two different datasets. In the following, we will describe both datasets and discuss their usage in our system.

UCI ADL Binary Dataset[1] consists of information about Activities of Daily Living (ADLs) done by two users in their home. There are two instances of data in this database. Each one belongs to a different user and summing up to 35 days of fully labeled data. The user in the dataset is described by three files like the following:

[1]The dataset is available at https://archive.ics.uci.edu/ml/datasets/Activities+of+Daily+Living+(ADLs)+Recognition+Using+Binary+Sensors

1. Description: it describes the content of the other two files including the number of house's room, number of labeled days, names of the activity performed by the user, sensors type, and devices name.

2. Sensors events: it includes information related to the sensors that are embedded in the home devices:

- Start time: represents when the sensor starts recording.
- End time: represents when the sensor stops recording.
- Location: determines the device to which the sensor attached it.
- Type: identifies the sensors type.
- Place: determines at which room the sensor is place.

3. Labels of activities of the daily living: it includes information about user activities:

- Start time: represents when the user starts performing the activity.
- End time: represents when the user finishes performing the activity.
- Activity: determines what activity the user does during a specific time.

We select **sensors events** data which is the second file in the dataset because it contains the suitable information that we need to feed the system with. The system will process these data by applying ML algorithms to extract the user habit in using the home appliances and use this information to generate recommendations to the user.

The tracebase dataset [19] is another dataset that we will use in our system. The dataset is a set of power consumption traces that collected from individual electrical appliances. This dataset stores the collect readings in comma-separated value files, in which each file contains wall outlet readings for a specific electrical device. Each record in the file contains the following attribute:

(1) the date and time of its collection that follow the "day/month/year hour: minute: second" format, and the time use 24-hour notation (2) The average power consumption readings over time durations of one and eight seconds. Figure 6 show an example of a trace.

```
14/01/2012 10:48:47; 151; 156
14/01/2012 10:48:48; 147; 151
14/01/2012 10:48:49; 147; 151
14/01/2012 10:48:50; 145; 149
14/01/2012 10:48:51; 145; 147
14/01/2012 10:48:52; 145; 147
14/01/2012 10:48:53; 143; 147
14/01/2012 10:48:54; 143; 145
14/01/2012 10:48:55; 143; 143
```

Figure 6 an example of a trace [19]

The usage of the tracebase dataset in our system is to calculate the energy consumption for individual devices used in the system. As we mentioned above in the scope section, for testing purposes we will take the energy consumption data of just three devices.

2.4 Software Requirements

This section will contain software details that will be used in the design and development of the system. The table 2 below shows the software requirement.

Software name	specification	Description
Raspberry pi OS	Version 1.1	Operation the microcomputer (Raspbian)
IDE	Depends on the programming language	Create the system models
SQL Database	-	Store the results information
Python	Python 3	Used to create models for ML training
Android Studio	Version 4.0.1	Build mobile application

XAMPP	Version 3.2.4	Essentials of web services for simulation

Table 2 Software Specification

2.5 Hardware Requirements

Hardware requirements are the sensed objects which are essential parts of the system to achieve the desired work. To achieve HARMS goals, we must select the appropriate hardware parts to serve our needs Table 3 below shows the hardware requirements for the HARMS project.

Hardware name	specification	Description
Raspberry pi microcomputer	Raspberry pi 3 model b	Connect all system parts and perform processing.
Breadboard	-	used as an extender for wiring
SD Card	8 GB or more	Primary storage to store (Raspbian OS) and files
Capacitor	-	Essential component for running sensors
Motion sensor	PIR (Passive Infrared)	sense any human motions
Light sensor	GL5537 /5537 LDR	For sensing the light in the implementation area.
Current transformer sensor	-	Monitoring the electrical current
Router	-	Essentially part for LAN
Transistors / Relay module	Depends on voltage	To switch on/off

Table 3 Hardware Specification

2.6 Alternative Solution

In this section, we identified the HARMS solution processes that will be designed in the implementation phase and justified the selected solution with a comparison between other alternative solutions, in order to show the possible options and their alternatives.

2.6.1 Implementation

HARMS is based on recommending and monitoring home appliances. There are many ways to implement HARMS such as recommender and monitoring by hardware, software, and mix between software and hardware. To classify the suitable type, we will explain them one by one.

- **Hardware Implementations**

Building a physical device or electronic circuit instead of making it by a computer software. As we can see figure 7, HARMS will use the raspberry pi, sensors, wires, breadboard, SD card, Keyboard, mouse and monitor to setup the connection between raspberry pi and sensors.

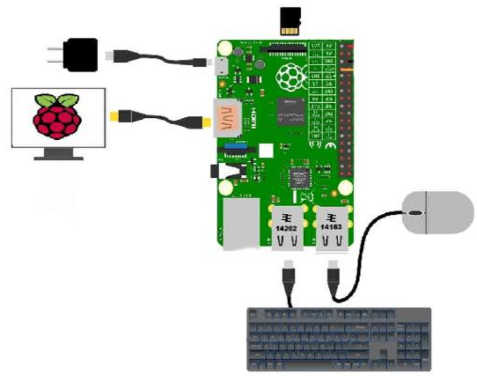


Figure 7 The connection of the Raspberry Pi and other external parts.

Also, in figure 8, will show the flow of hardware process by using a server which contain dashboard as a control system since it will apply all the ML algorithms and SQL database. After that will connect it to the router which consider as a link between each parts of the HARMS project to be display into mobile application which will allow user to interact with the system.

Pros

- Usually faster in operation.
- Meet real-time requirements.

Cons

- Takes a longer time to build.

- More expensive.
- Once it built, cannot easily interfere with, or re-programmed.
- Might be very limited.

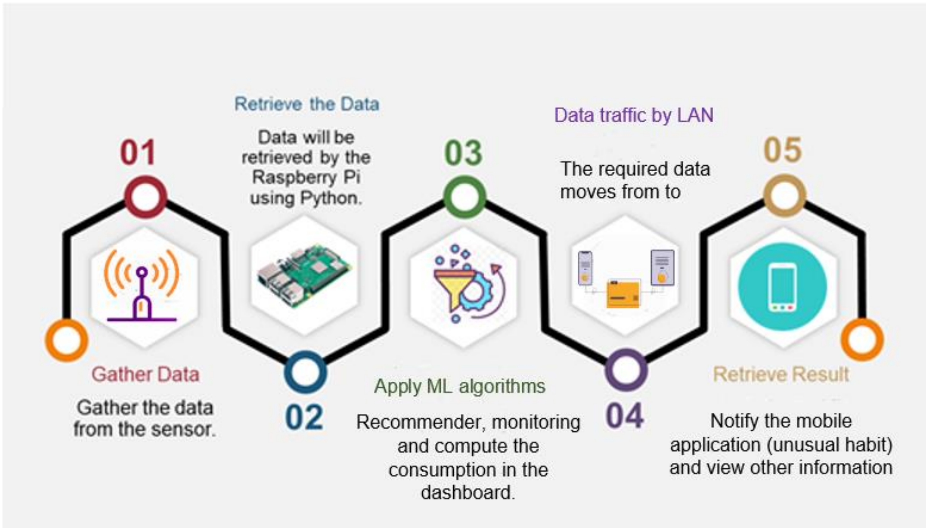


Figure 8 The flow of hardware implementations.

- **Software Implementations**

Building a simulation which represent the real-life project. The server will contain SQL, dashboard, and a web page which will divide into two parts (1) room environment (2) control panel that will provide the home appliance state. It will connect to the dashboard to retrieve the result of the algorithms apply via LAN and display them in the mobile application in figure 9 we can observe the flow of the simulation implementation.

Pros

- No limitations
- Can easily change it and reprogrammed.
- Easily to test and evaluate.

- Less efforts.
- Cost effective.

Cons

- Needs fully understand about the problem at first stage.

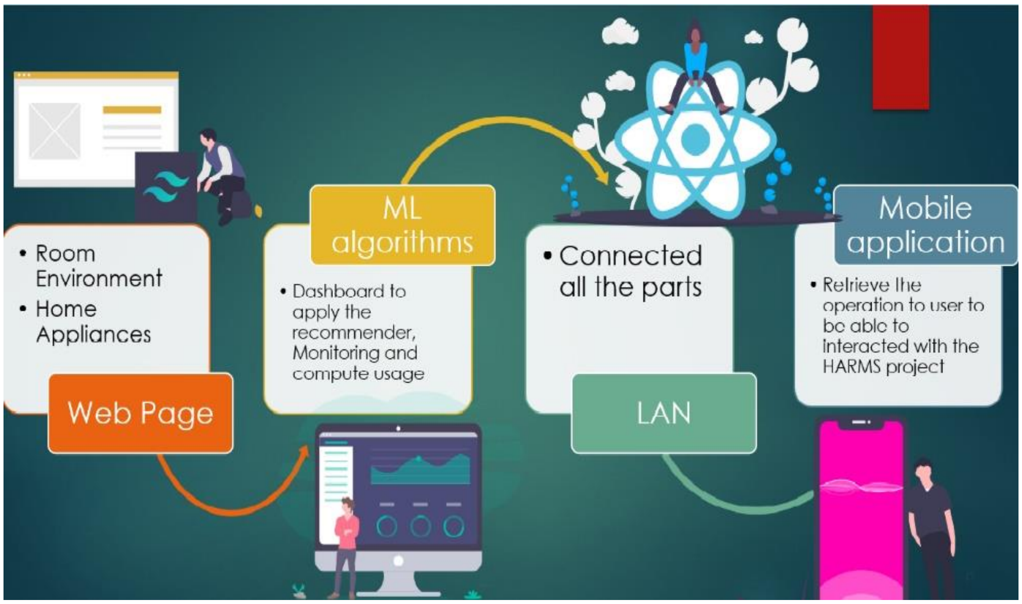


Figure 9 The flow of software implementations.

- **Mixed Approach Implementations**

As we can observed above the hardware and software implementations are complementing each other. HARMS will integrate software and hardware implementations to come up with a best solution. As we can see in figure 10 the flow of integrated system between hardware and software.

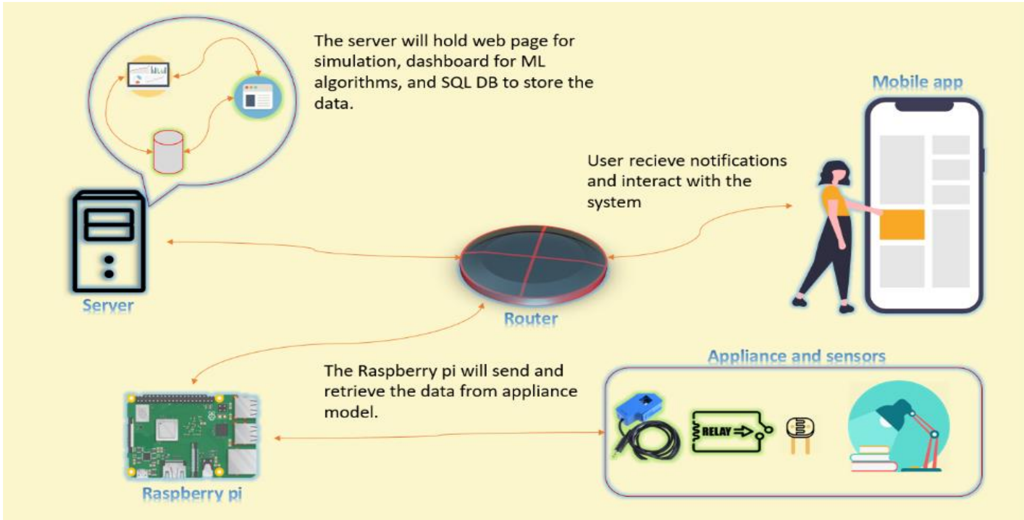


Figure 10 The flow of mixed implementations.

2.6.2 Algorithms for Recommender and User Usage Pattern for ML Applications.

Based on the researches we have analyzed; we represent all the algorithms that are applicable in the implementation of the system recommender function. Below are the details of common algorithms applied for user patterns and recommender systems along with the pros and cons of each introduced algorithm.

- **User Pattern Algorithms**

  Extracting useful patterns based on user history and building up a predictor for determining the next likely user action is essential to generate recommendations that are relevant to user routine. We introduce the following two mining algorithms which are pattern mining and Clustree algorithms.

  - **Pattern Mining Algorithms**

Pattern mining algorithms are used to derive the desired knowledge from a large stream of data**.** This technique extracts and mines the frequent and periodic user pattern with at least two activities, that is expanded until no more patterns.

Pros

Pattern mining algorithms promote and boost more efficient mining tasks.

Cons

It must meet the following conditions to have the required type of behavior patterns that are necessary for the recommender system. First, the activities must take place regularly in the data. Second, the pattern should be related to what the system is predicting and consists of one action minimum to lower energy usage.

Findings

We believe that applying such algorithms is suitable in a smart home environment. Implementing supervised techniques could result in limiting the scalability of the system. Since in HARMS we have the choice to expand the list of appliances under control, we need a flexible algorithm that coop and deal with this case.

- **ClusTree Algorithm**

It is one of the unsupervised clustering algorithms that discover and identify the groups in data automatically. It is used to identify the abnormalities in user patterns via clustering the events based on their time to distinguish the usual activities from unusual ones. It highly depends on its index structure to keep and store a compact view of the clusters. Once a new action occurs, it will be assigned to a cluster according to its similarity.

Pros

Self-adaptation is one of the ClusTree distinctions from other unsupervised approaches. Since sensors work regularly in a smart home environment, such an algorithm is needed to self-adapt and deal with changes. Furthermore, the algorithm is able to process data flow in a single pass with restricted memory.

Cons

In general, clustering algorithms faces several challenges. It is not feasible to deal with an endless stream of data and keep each object once it arrives. They should be improved to handle fast flows and deliver a result at any point in time.

Findings

ClusTree is a powerful algorithm which could track user's normal and abnormal behavior, so it is able to coop with any changes occur. Also, it is efficient because it first compresses the data to require less amount of memory. However, it is important to enhance it provide accurate just-in-time recommendations.

- **Recommender Algorithms**

Recommender systems are powerful techniques that are capable to process a huge amount of information and create a user profile to direct users toward their preferences. In this section, we discuss some of the recommendation algorithms that have been applied by many projects, such as Q-learning, Episode Discovery, and SVM.

- ### Q-Learning Algorithm

Quality learning or Q-Learning is a reinforcement machine learning algorithm. Deep Q-Learning is a new version that combines deep learning and reinforcement learning to reinforce the learning process and enhance its performance. In a recommender system, reinforcement learning techniques work differently than the traditional ML algorithms. Instead of only recommend the items that are related to user preferences, it will also recommend a new and random item that could attract the user.

Pros

One of the powerful advantages is that the reinforcement algorithms keep learning continuously whenever the user interest changes. This feature leads to a robust model.

Cons

Q-Learning has disadvantages that cannot be ignored. It uses a matrix to store user patterns. If there are many users, the data size will be too huge to handle, and it will demand a large space. Therefore, it does not work for complex groups of recommendation content.

Findings

We found that Q-Learning is interested in discovering new patterns rather than just stick to frequent actions. For example, it does not only notify the inhabitant with the relevant recommendation, but it sends random items that could interest them.

- ### Episode Discovery (ED) Algorithm

It is a modern and popular data mining algorithm that is applied to a sequence of events to be mined and predict the occurrence of an event. ED discovers inhabitant patterns within a large stream of data events. First, it gets the history of user interaction with appliances. Then discover the sequence of action in the pattern. Lastly, it needs to balance the length and frequency of an episode, and its regularity.

Pros

ED is fast and generates correct and accurate predictions if it is trained on a dataset that is noise-free. It is considered one of the efficient algorithms at home automation domain.

Cons

ED discovers the patterns occur daily or weekly but not the patterns occur different times per one week. Therefore, it is recommended to enhance the algorithm to be able discover the periodicity of the patterns.

Findings

It is a common model that is been used a lot to mine data. It is recommended to apply it in smart home environment due to its speed and efficiency. In order to achieve satisfied results, ED needs some enhancement to discover the pattern correctly and produce accurate recommendations.

- **SVM Algorithm**

It is one of the typical tools for data mining and machine learning. It delivers high performance when it comes to a real-world problem, such as text categorization, image classification, and bio-sequences analysis. In recommender systems, SVM processes the input vectors in which each vector refers to a pattern. Each vector consists of features that indicated binary sensor states (1 and 0) for the smart home. It can identify the included sensor whenever the user performs an action.

Pros

SVM is a powerful supervised classification technique. It provides high accuracy when recognizing the user. In addition, it is suitable and effective with high dimensional spaces as it operates implicit mapping through it.

Cons

It is not recommended to use SVM alone to predict user action due to the sparsity included in the user-item matrix. It will be accepted if it is combined with other algorithm or heuristic function.

Findings

SVM is a suitable model to apply since it is able to process large data and perform implicit mapping through them. Also, it always results in high accuracy. In order to work professionally in recommender systems, it is suggested to combine it with a heuristic function.

Based on findings presented in each algorithm; we conclude that we will use Pattern Mining algorithms to analyze user history and derive a pattern that occurs regularly. Then, SVM will be applied to process user patterns and build a profile which leads to generating recommendations depending on what the model has learned. We are considering using these algorithms on our project. In Implementation the mix approach is the one that will be used for the HARMS, where the simulation part will prove the concept of recommendation and monitoring. Also, to overcome the hardware and implementation environment limitations. The hardware part will give a real implementation for the project. Further, a complete test on these algorithms and implementation will be done in the appropriate analysis as part of milestone 3.

2.7 Expected Outcomes

In this report, we demonstrate our ongoing work on HARMS in which studies the daily inhabitants energy consumption behavior. The system composes into hardware and software that can be handled and utilized to consume the energy more efficiently. It will be developed to fit and maximize inhabitants comfort level through monitoring inhabitant's energy usage. Moreover, the inhabitant will be fully aware of all of the appliances that turn on via receiving frequent notifications on the Android application. In addition, the system will notify the user for any appliance he forgot to turn it off. Thus, it will utilize electricity efficiently and to not be consumed at unnecessary expenses. User awareness of the devices used, and the average power consumed weekly would drive to cutting down the high electricity cost and optimize the energy efficiency. It is expected from the system to reduce the energy consumption by real-time monitoring and controlling different devices automatically. That will lead to reduce the monthly electricity bill for the customer.

2.8 Discussion of tools and techniques used during project proposal.

To clarify our system, and to provide an almost clear idea about it, we have used the appropriate tools and techniques to achieve that.

Techniques:

- **Brainstorming:** It is a requirement elicitation technique that was used to discover the application domain, the services that the system should provide and the system's operational constraints to achieve the project's goal. We used our imagination and figured out how the system architecture will be look like, what connectivity method we will use and how the requirements will be connected.
- **Scenario identifications:** It is a requirement discovery under the requirement elicitations and analysis. It is used for strategic planning by determining future scenarios, which give a description of the starting situation, normal and abnormal flow of the actions, what can go wrong, and other states. We used it to draw the appropriate analysis part and understanding the flow of the project.
- **Focus group:** It is a requirement analysis technique that is used to gather information about the required system also, the existing systems and identifying the stakeholder requirement, by exploring the group members opinions. We had meetings to identify all the functionalities, functions and nonfunctions, hardware and software requirements.
- **Journals review:** It is a requirement analysis technique that is used to accuse the public research database such as IEEE, the deanship of scientific research at King Faisal University and other websites for checking similar projects. We

used this approach to understand the methods and algorithms of our project. Also, to identify the related work and get a clear idea about alternative solution that we have.

- **Informal review:** It is a requirement verification technique that is used on any design and project plan requirements. During informal review, the work product is given to a domain expert which is our supervisor Mr.Conrado who gives us the feedback and comments that are reviewed and corrected by us.

Tools:

- **Word Processor**: It is a desktop publishing tool that is used for reading, writing, editing, and formatting the text. We used Microsoft Word to be able to write, edit and read our milestones.
- **Gantt Chart**: It is a diagram to show the flow of our work. It is used to build our tentative work plan including different procedures and phrases that need to be done at a given point of time.
- **Presentation viewer**: Microsoft PowerPoint, it is a presentation program published by Microsoft that helps text to be written and formatted, inserting multiple graphic images, and a slide-show system to display the content. We used it to present our project and designed some figures.
- **Grammarly**: It is a website which helps in recognizing any error occurring while writing the report and any missing punctuations.
- **Citation Formatting**: It is a website called citation machine that generates APA citations for books, journals, and websites. It is used as a main source for formatting citation of the papers to APA.

- **UML**: Using three different software which are Diagram Draw.io cloud-based software,Violet UML Editor, and Lucidchart Online Editor. They have been used to provide details about the system by designing the “Use case”, “Sequence diagram”, “Class diagram”, and “System flow” with their components.
- **Wireframe:** Wireframe and Prototyping tools called MockFlow. Help to build a clean looking interface for the user in the design stage. It used to draw the wireframe figures.
- **Data Modelling**: It is an abstract view to show the structure data and its relationships between its tables. We have used an online editor which is called Creately to design the ER-model of HARMS.

2.9 Appropriate analysis

In the appropriate analysis section, we need to analyze the system by breaking it down into smaller parts and clarify the relationships between the entities in the system. This section discusses system analysis including different system diagrams and presents different views of the system.

2.9.1 System design

This section will present different diagrams designed for the system including Architecture Diagram, System flow, and Entity Relationship Diagram (ERD).

2.9.1.1 System flow chart Diagram

A system flowchart represents the processes, decisions, inputs, and outputs in visual form in which together form a system, also it shows how the data flows in a system. In the following, we will show flowchart for each system functionality. Figure 11 shows the flow to set up the user profile in the HARMS system.

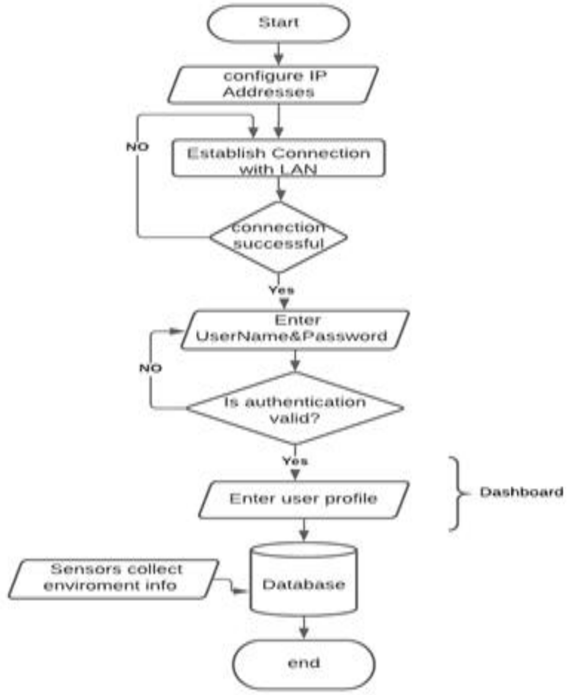


Figure 11 Shows the flow to set up user profile in HARMS.

First, the flow starts when the user logs in to the system by providing a username and password. The system will authenticate the entered username and password, and the user can access the dashboard which he can provide the user profile. After that, this profile will be saved in the database which contains all data of user profile and energy consumption for each device that was collected by the current transformer sensor, the appropriate data will be retrieved by the dashboard to perform the following functionality (1) view reports. (2) view the status of the appliances (3) generate recommendations. (3) monitoring and will discuss the flow of them in detail.

View the reports: The dashboard can view two different records for the user one for average energy consumed by all appliances per week and the other is the energy consumption for the last month. Figure 12 shows the flow about how the view reports in the system.

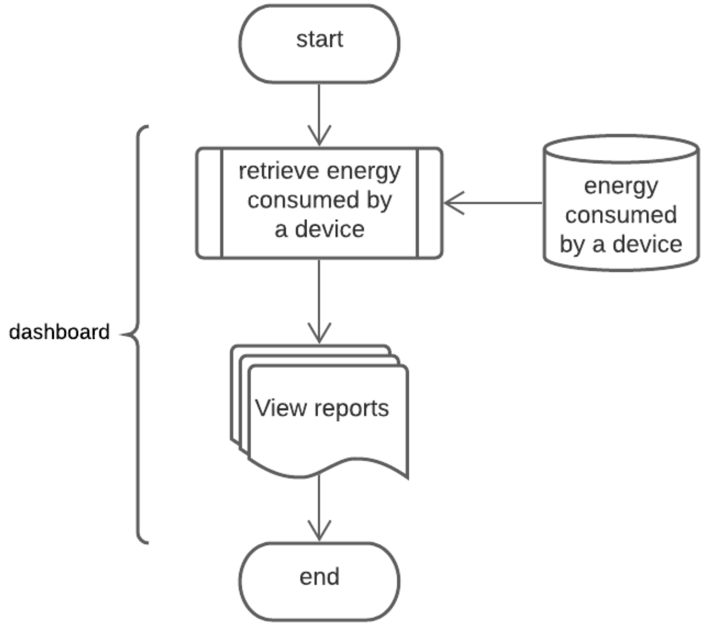


Figure 12 Shows the flow of viewing reports in the system.

To calculate the consumed energy the dashboard asks the database to retrieve the consumed energy of each device that has been used. Then, the dashboard calculates the average of the total energy consumed during the last week. The result of this calculation will display it to the user in graphical form and the result will save to the database as well. After one month, the dashboard will again query the database to provide the calculated average consumption for the last four weeks, so the dashboard can show a visual chart on the screen to clarify the variation in energy consumption among the last four weeks.

View the status of the appliances: Where the user will be able to check the status of the appliances whether is on or off throughout the home. Figure 13 shows the flow that leads to viewing the status of the appliances.

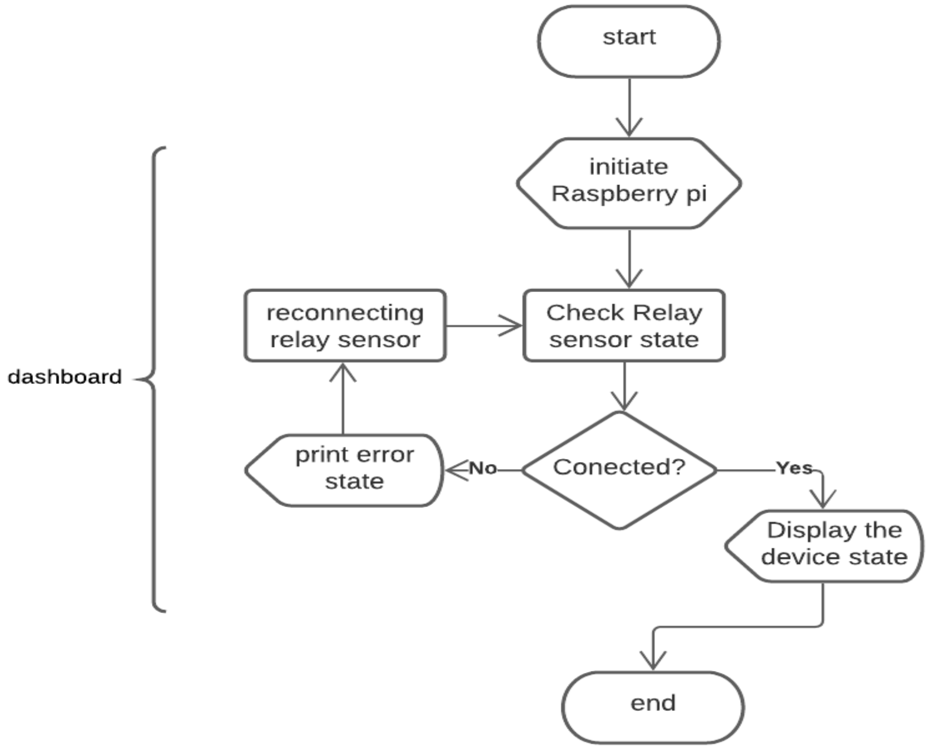


Figure 13 flow of viewing the status of the appliances.

The dashboard checks the relay module state that is controlled by Raspberry pi. if it is connecting, then the dashboard will display the device state which the on state will be represented by a green color circle next to the device name, or this circle will be red if the device is off. So, the dashboard will know which device is active or not and displays a visualized list that shows the state of all devices throughout the home. On the other hand, if the sensor is not connected error message will be displayed that indicates the connection failed, and the system will reconnect the relay sensor again.

Generate recommendation: this is how the system will generate suitable recommendations based on the user's profile. As we mention above the database stores all information related to the user habit of consuming energy. These data were collected as inputs from the environment by devices' attached sensors such as current transformer sensors. These data will be sent to the Raspberry pi for pre-processing, then it will be sent to the main system (dashboard) to store these data in the database. Figure 14 shows the flow of generating the recommendation to the user.

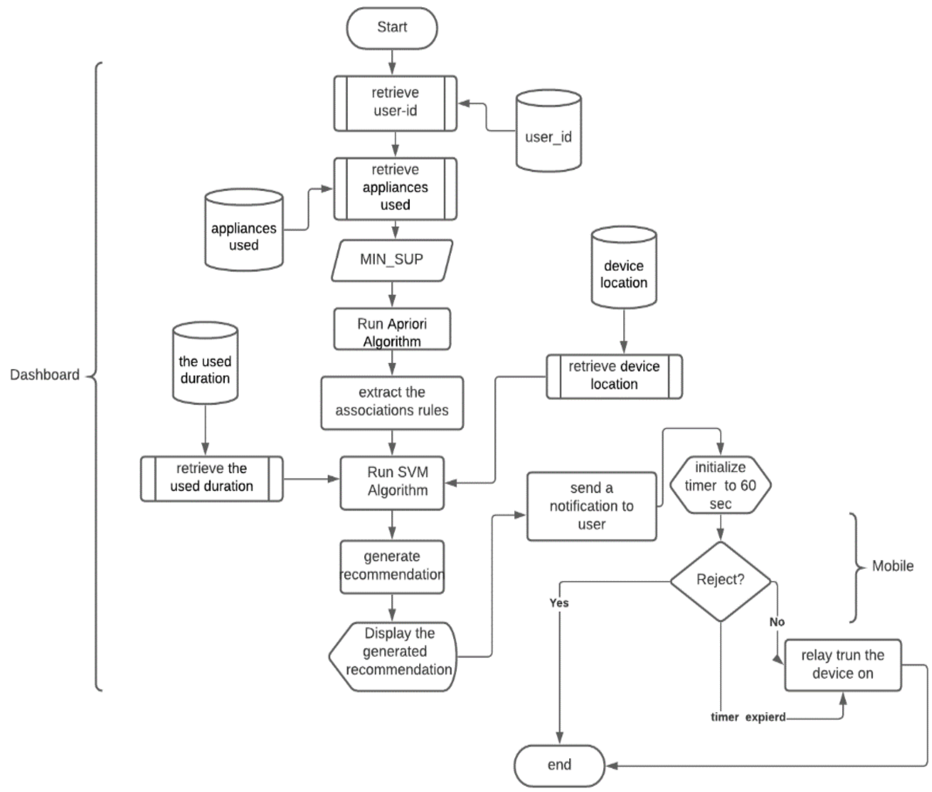


Figure 14 the flow of generating the recommendation to the user.

The dashboard retrieves from the database the user id and appliances used also the specified minimum support will be taken as a static value. First, it will feed these data to the Apriori Algorithm to extract the user behavior (association rules). Then, the output of the previous algorithm will act as input for the SVM algorithm along with the device location and the used duration from the database to generate the recommendation to the user. The generated recommendation will send to the user's mobile (which is the second main component in the HARMS system) to notify the user about the next event and let the user responds. Also, the system sets the timer to 60 sec. If the user does not respond during this time, the system will activate the device. However, if the user cancels the recommendation the cancel response will send back to the dashboard to prevent sending the order to the Raspberry pi that controls the relay module.

Monitoring: This is where the system can detect the user abnormal behaviors such as leaving the living room in which the light was on before the usual time. Figure 15 shows the flow of detecting the user unusual behaviors.

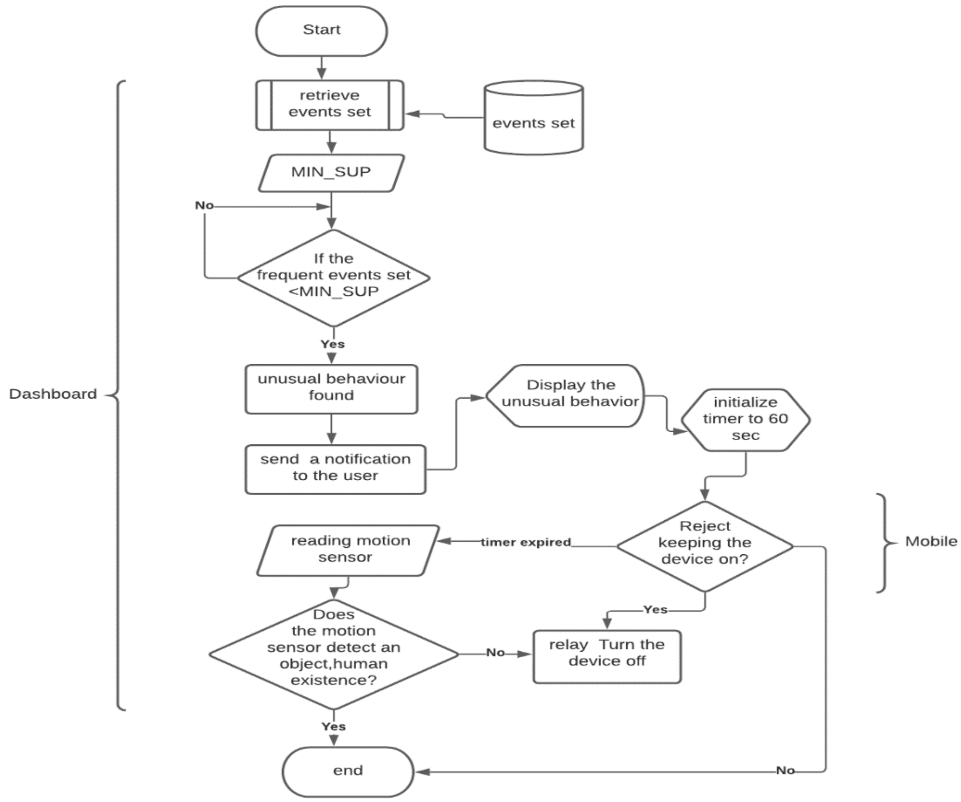


Figure 15 shows the flow of detecting the user unusual behaviors

The dashboard takes the events set, which is the output from executing the Apriori Algorithm also the value of the MIN_SUP will be taken as well. The dashboard check if the frequent events set are less than the MIN_SUP. If the result is false, that means the user does not change his/her behavior. On the other side, if the result is true, means unusual behavior found. The dashboard sends a notification to the user's mobile such as "The light is not turned off in the regular time, do you want to keep it on?". The purpose of the notification is to inform the user about the unusual behavior and let them react upon, and the system sets the timer to 60 sec, waiting for the user's response. If the system does not receive any response during 60 sec and the timer expires, the system will behave. The system checks the motion sensor if there is no human detected in the room, the system will ask the relay module to turn the device off. However, if the sensor detects human existence, the system keeps the device on. But if the user responds the system will perform the user request.

2.9.1.2 Entity Relationship Diagram

Entity Relationship Diagram (ERD) is a representation of the relationships of objects or the entities and their attributes in a database and explains the structure of databases. Figure 16 show Entity Relationship Diagram

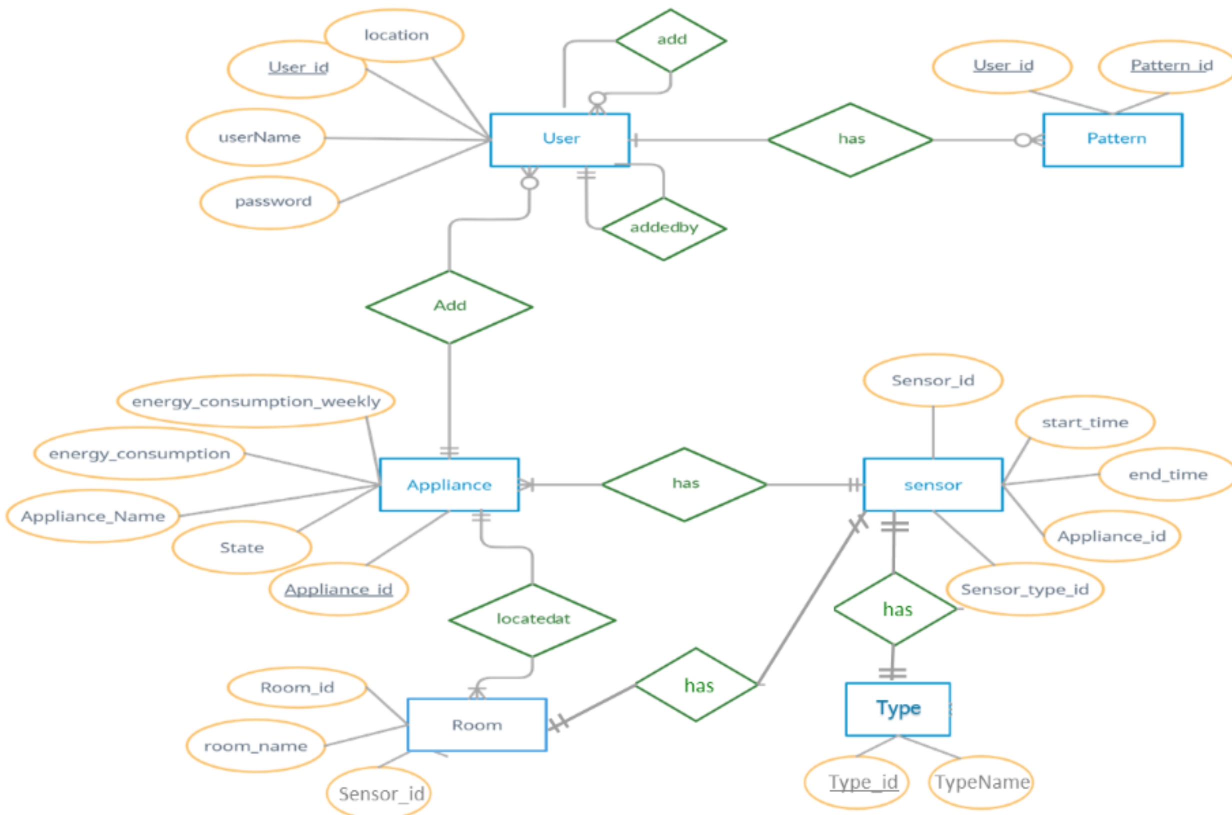


Figure 16 show Entity Relationship Diagram

Our database is composed of six tables to store the required information to let the HARMS system to operate well. The first table is for store the user profile to feed it to the system, so the system can function upon. The user table has four attributes are the user id, username, password, and the location of him (which room in the house). The user can add another resident or the user himself can be added by another user. Where each user has a specific pattern stored in the pattern table that contains user id and pattern id. In addition, the database maintains the appliances' information which is: appliance id, its name, its state whether it is on or off, the amount of energy consumes, and the weekly amount of average energy consumed by that device. Each device has two integrated sensors with it, the relay module to on and off the device, and the current transformer sensor to measure the device voltage. The sensor table attributes are sensor id, the usage starts and ends time, sensor type id and appliance id indicate the device that particular sensor is attached to it. For the purpose to avoid redundancy, we maintain a separate table for sensor types. Finally, the room entity has a room id, room name, and one sensor which is a motion sensor.

2.9.1.3 Architecture Diagram

The architecture diagram will represent a set of concepts which are parts and components of the system as shown in the figure 17

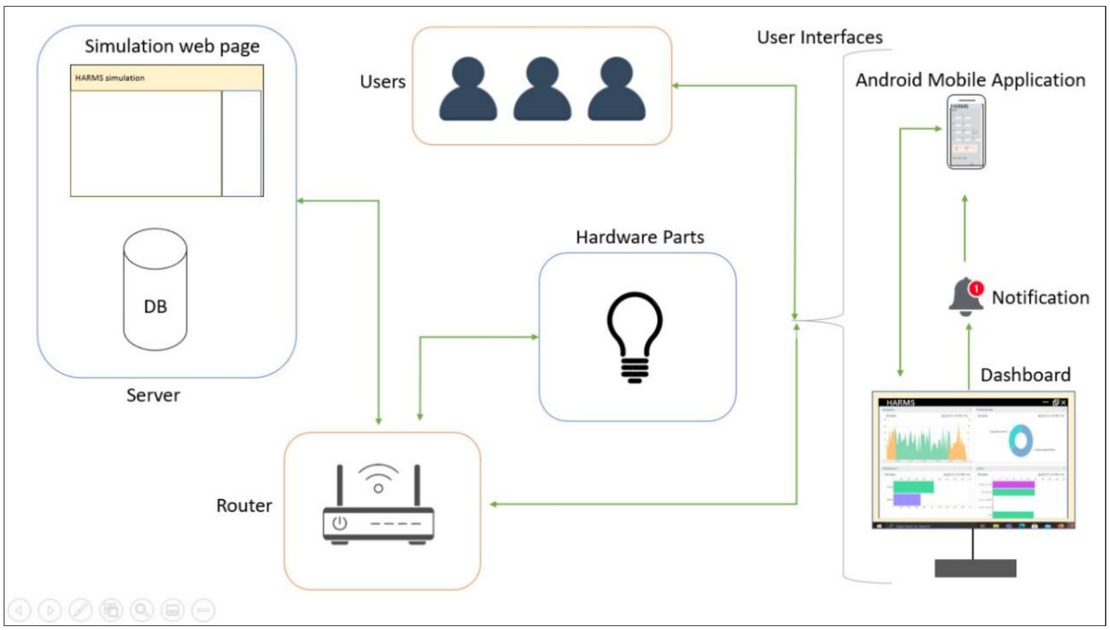


Figure 17 Architecture Diagram

Users will have two ways to access the system either using the mobile application or dashboard. The dashboard will be considered as the heart of the system since it will apply all the ML algorithms and send the results via the router to communicate with other parts. The router is the essential part for communication between all other parts using a local area network which holds the IP address of other components. The mobile application can communicate with users and send notifications about the action, to take the response from the user which will send it back to the dashboard that will process the action and send the instruction to the relay module that holds in the light by router, if there is no response from user, the system will automatically handle the situation and send the suitable instruction to other parts.

2.9.1.4 Context Diagram

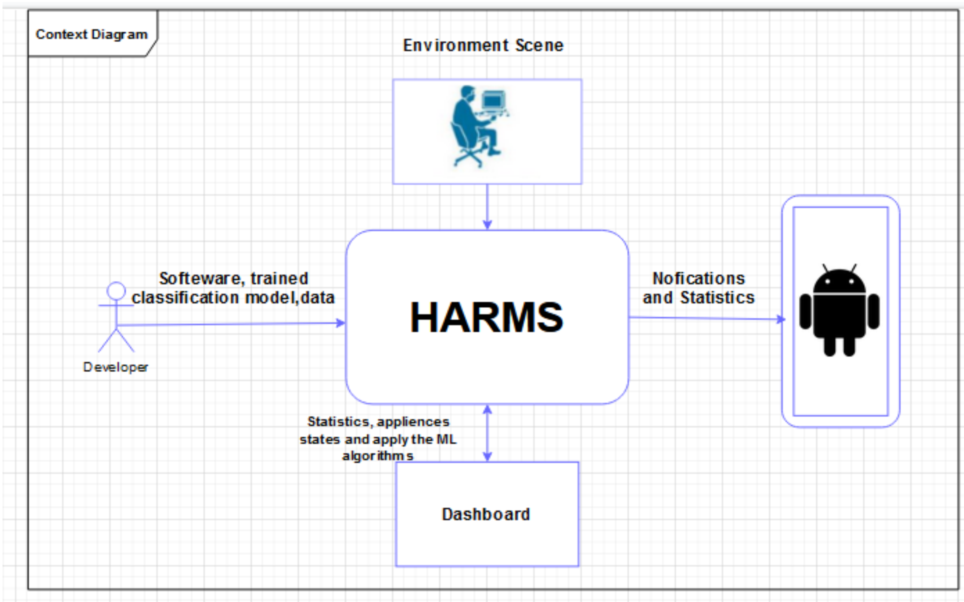


Figure 18 Context Diagram

Figure 18 shows the context diagram of the HARMS system and the interaction of external actors (scene, user, developer) with the system. The developer will have to load all software, classification models and data into the microcomputer board. Once HARMS is in operation mode, it will learn from user behavior, analyses the actions, and then inform the residents of home about the incoming actions and home appliances consumption.

2.9.2 Scenario

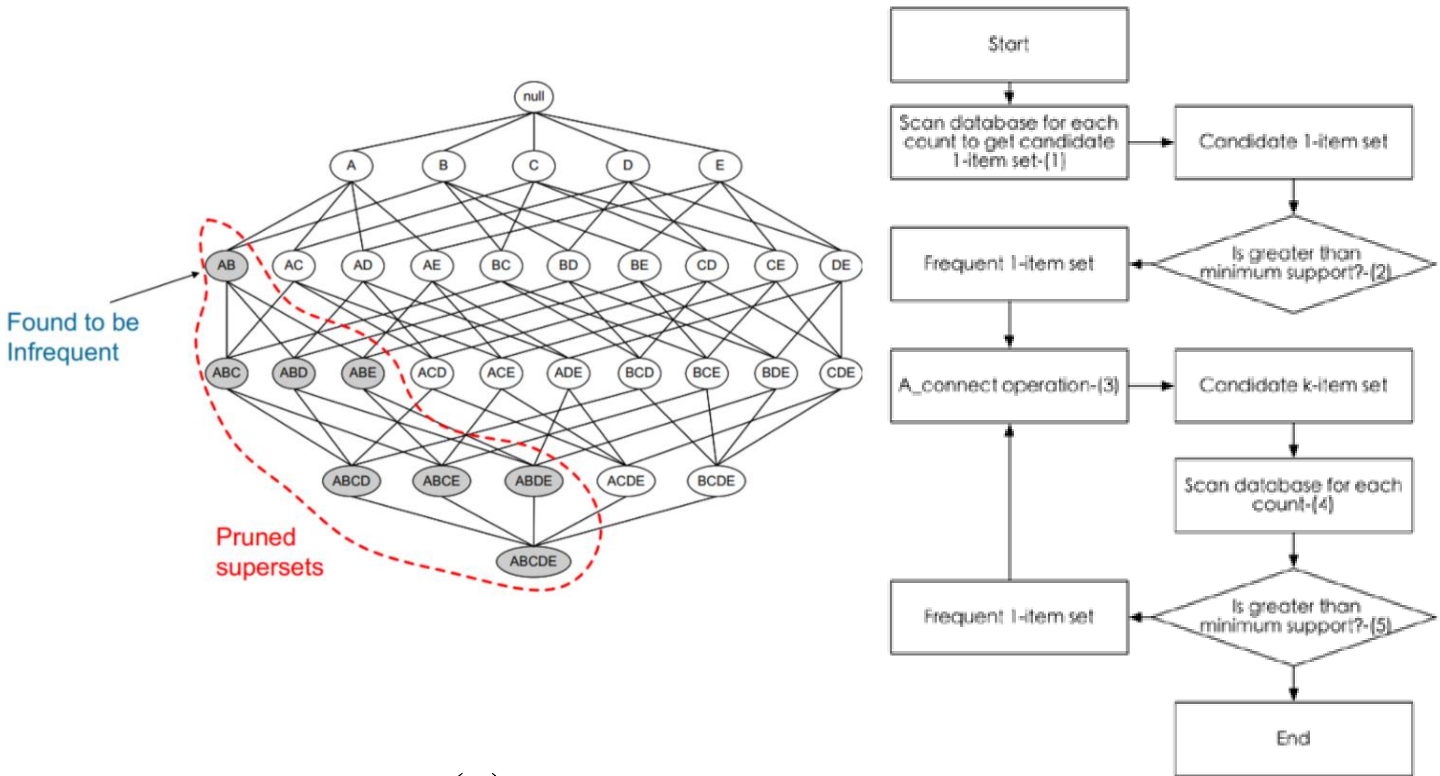
Ali used to sit in the living room from 2:00 pm to 4:00 pm. The recommender system will turn on the light at 2:00 pm and notify Ali. He will be able to cancel the action, or the system will perform the action by default. At 4:00 pm the system will communicate with the motion sensor to check if there is any motion in the room; if there is no motion, the light will be turned off which means Ali did not change his usual routine. However, if the system detects any motion will keep the light on. On the other hand, if Ali went out before 4:00 pm, the system would send an alert to Ali through a mobile application informing him with unusual behavior and waiting his response for 60 seconds either to keep or cancel the action. If the system did not get any response from Ali after 60 seconds about the unusual behavior, the system will turn off the light by default.

2.9.3 Algorithms

2.9.3.1 Apriori Algorithm

Pattern Mining Algorithms are important in data mining. Some of the Pattern Mining Algorithms implements a set of association rules which analyze subsequences to find a pattern that occurs repeatedly. Association rule mining has been applied in several fields, such as basket data analysis, web log analysis, DNA sequence analysis, and sale campaign analysis. In smart home context, mining user behavior is essential to produce recommendations for its users.[21]

One of the classical pattern mining algorithms is the Apriori algorithm. It is an iterative-based method depending on searching frequent item set. The Apriori mining process is a bit complex due to the iteration fashion. Generally, the algorithm stores the data as linear linked list and circular queue. The data is referred to the output from sensors that attached to the devices, including device id and its status. In the following figure19, it shows the pruning step and the flowchart that describes the Apriori algorithm procedure. [22]



(a) (b)

Figure 19 Apriori algorithm (a) itemset (b) flowchart [21,23]

Given a set of itemset $\boldsymbol{I = \{i1, i2, \ldots, im\}}$, and a set of affairs set $\boldsymbol{D = \{T_1, T_2, \ldots, T_n\}}$, it is called database. Every affair, $\boldsymbol{T_i}$ in $\boldsymbol{D}$ has a unique affair ID and consists of a subset of items in I, where $\boldsymbol{T_i \subseteq I}$ ***(i=1, 2,…, n).*** A rule can be described as an implication $\boldsymbol{X \longrightarrow Y}$, where ***X*** and ***Y*** are a subset of ***I, (X, Y ⊆ I). X*** and ***Y*** are the antecedent and the consequent of the association rule.

Apriori algorithm processes that itemset as the following steps: [17,21, 24]

1) Collect the number in each item set by scanning the affairs set, then form the candidate 1-itemset **C1.**

2) Compare each item set to two important factors, which is called *Support* and *Confidence*, and result in the frequent 1-itemset **L1**. *Support* indicates the popularity of

an item. Whereas *Confidence* indicates the probability of event ***Y*** being performed when event ***X*** is

3) Connection step: Form frequent 2-itemset **C2** through connecting item sets in **L1**(A_connect).

4) Pruning step as clarified in figure 17a: count the number of each itemset to get the frequent itemset regarding the minimum support.

5) Remove any itemset that has less support than the given support to form **L2.**

6) Repeat steps 3,4, and 5 until the frequent k+1 itemset does not meet the specified condition. Then, get the final frequent k-itemset.

For the recommendation system to generate suggestions, inhabitants' daily events should be mined to discover the frequent patterns. First, the database contains the user ID, the appliances that a user interacts with, the interval of usage, and the location of the appliances. The Apriori algorithm will fetch the database to get the user id and the set of all appliances that have been used by the inhabitant as a binary context to form a small events database. Now, the events database should contain the events represented on several days of user routine. In addition to the user id and the used appliances, the algorithm should be provided with a threshold value or minimum support that is ranging between 0 and 100%. Each day is a set of events represented by 0's and 1's where 0 represents the absence of using an appliance and 1 represents the presence of using an appliance. For example, the database contains 5 days (d1, d2,d5) and 5 events (1,2,3,4,5). D1 involves events 1,2 and 5. The algorithm scans the events database to generate candidate itemsets until no more frequent events can be generated. After generating the candidate's item sets, each item is compared to the specified threshold. It is a frequent itemset if its support is higher or equal to the threshold value and remove the ones that do not meet the condition. The result is the frequent events sets along with the support value of each set. We will apply association rules on the generated frequent events sets to determine the relations in between. An example of a rule would be {1,2}→{3}, that means if the inhabitant does 1 and 2, he/she also does 3.

2.9.3.2 SVM

SVMs are one of the powerful supervised ML algorithms that are implemented in many real-world applications for both classification and regression. For instance, medical imaging, image interpolation, pattern recognition, bio sequence analysis, etc. The SVM essentially segregates two classes by drawing a decision boundary which is called a hyperplane, as shown in figure 20.

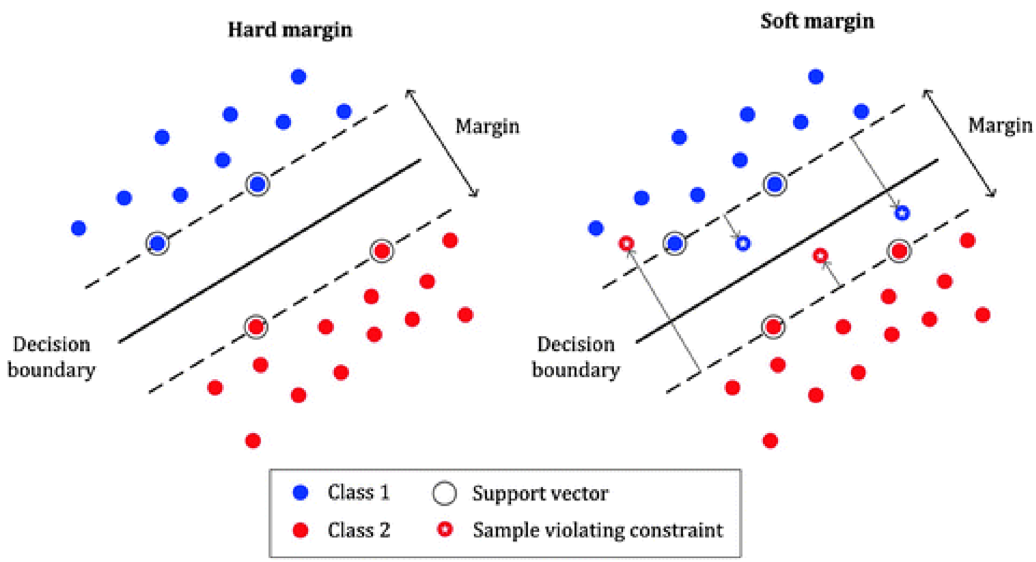


Figure 20 SVM Hyperplane [25].

SVM in its linear simplest form, trains the data by considering it as points that are distributed in the space. These points are separated by the hyperplane to maximally make a gap as wide as possible. The hyperplane needs to be optimal to classify the points correctly and predict the new data to its valid class. The distance from the hyperplane to the closest points or observation defines the *margin* of the SVMs as shown in figure 20. Mainly, the way of building the decision function of SVM classifiers is determined by a small group of data which specifies the location of the hyperplane. It is referred to the small subset of data as the *Support Vectors.* Sometimes, it is possible to have outliers in the data so SVM allows misclassification. When we allow misclassification, the distance between the observations and the hyperplane is called *Soft Margin*. Widen the margin is good because that is an excellent indication for a safety margin which makes optimal and certain classification. Also, it creates a powerful model that has low errors in measurements and low document variance to not misclassify the data. Another motivation for SVMs is that once you need to place a hyperplane between classes, you have lesser choices of where it can be positioned. Thus, the model requires lesser memory space [26,27].

As recent e-commerce applications cannot dispense of involving a recommendation feature to provide users with satisfactory experience, SVM is one of the proposed algorithms that is work efficiently and deliver state-of-the-art performance in recommendation system. We use SVM in HARMS to predict an inhabitant from inhabitant group based of their patterns. After running Apriori algorithm and generating the association rules, we will feed SVM with three inputs. The first input is the association rules which are represented as a 2D array. The second input is the duration of using the appliances. The last input is the location of the appliances. The last two inputs are involved to enhance the recommendation system. All the three inputs will receive together to SVM as a matrix. The matrix is a set of vectors. Each vector represents a pattern that refers to an individual inhabitant and composed of n components, known as *features.* The features in this case are the three inputs. And the users are the *classes* that SVM is based on to classify the patterns.

The algorithm uses the following function to draw an optimal hyperplane. The best choice will be the hyperplane that leaves the maximum margin from all classes [15]:

$$f(y) = \sum_{i=1}^{N} \alpha_i K(x_i, y) + b$$

Y represents the unclassified tested vector, xi is the support vectors, and αi their weights. The more we minimize αi, the maximum margin we get to split the classes. And b is a constant bias. K (x, y) is a kernel function to solve the nonlinearity and transform it into the required format by performing implicit mapping into a high dimensional feature space [15]. After calculating the hyperplane function, we will have a value that we can compare the input to in order to perform classification.

For unusual behavior, the Apriori algorithm will prune the events that are less than the minimum support and they will not be considered in the frequent events sets as they did not meet the condition. Once the SVM recognizes a pattern that does not belong to a user, it will send a notification through the user's mobile to inform him/her about the unusual event. Finally, SVM ends up recognizing the pattern for each inhabitant to generate a correct recommendation depending on their behavior at home.

3 Details of proposed design conforming to the problem statement

This section discusses and explains the detailed functionality of our system to solve the problem statement, the class diagram, sequence diagram, Wire frame, and wiring diagram of our system design.

3.1 Class Diagram

A Class diagram is a way to represent the system structure by showing its classes along with their attributes and methods. Also, it shows the relation between the system classes. Figure 21 Class diagram that shows the relation between the system's classes.

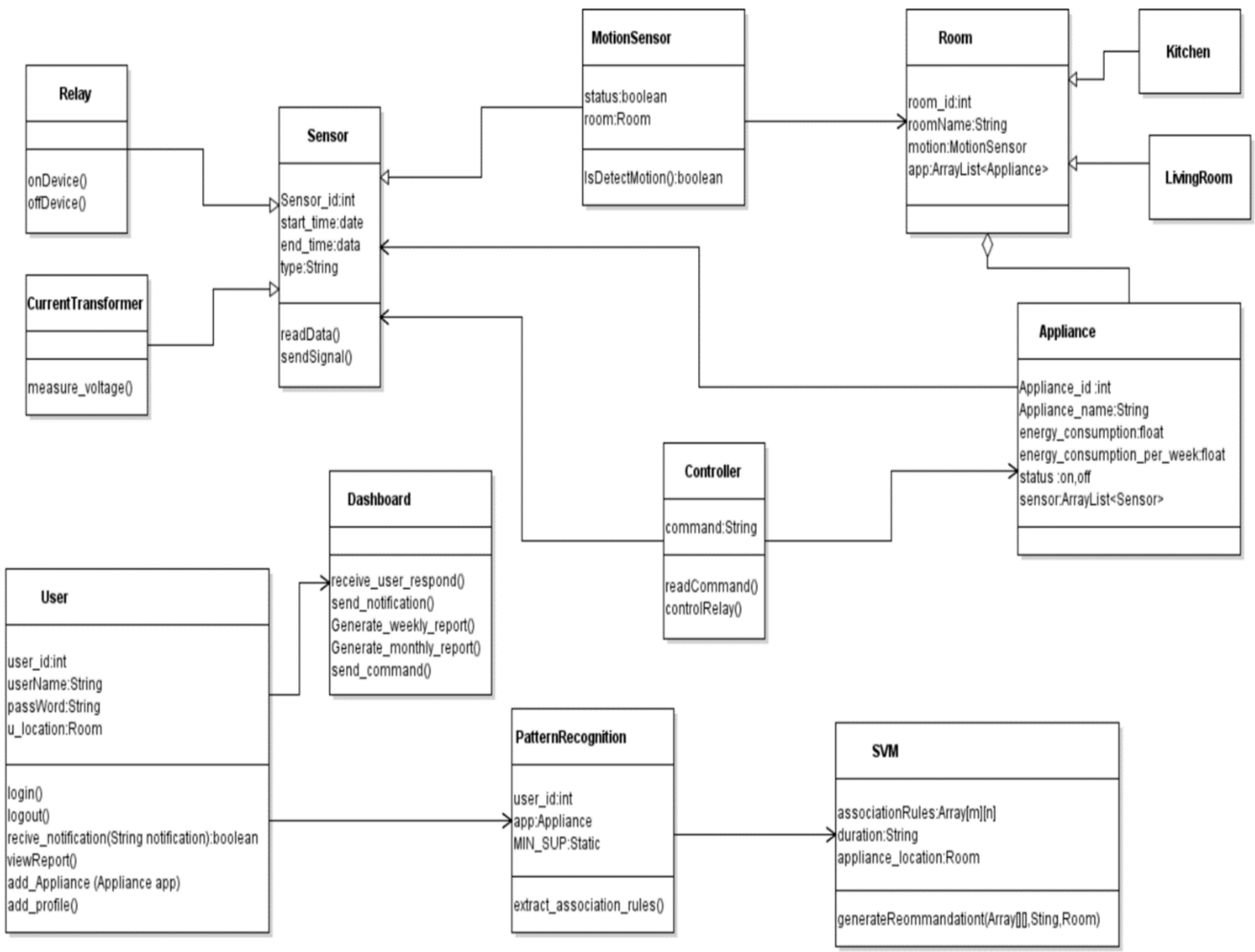


Figure 21 Class diagram that shows the relation between the system's classes

In the class diagram, there are two parent classes which are the Sensor and the Room class each one of them has its subclasses. The purpose of that is to combine the common attributes and methods needed across their subclasses. The Sensor class has two methods readData() which used to collect the data form external environment and sendSignal() that used to communicate with the Controller class that control and manage all system sensor. Sensor class has three child classes as the following :(1)MotionSensor class that has IsDetectMotion () which returns a boolean value to identify whether there is a human or not. (2) Relay class which contains onDevice() and offDevice() methods to on and off the devices. CurrentTransformer class uses the measure_voltage() method to measure the device voltage while it operates. Room class has an object from class MotionSensor used to sense if there is a human inside a particular room. Also, the Room class has subclasses and we just mention in the digram two examples kitchen and living room. Each room has one or more appliances for that reason we create ArrayList of type Appliance inside Room class. Similarly, each appliance has two sensors (relay and current transformer) so, there is a need to create ArrayList of type Sensor inside the Appliance class. In addition, you can see the User class which contains the user profile to be used to generate the recommendations to the user. To generate the recommendation, there is a need for two more classes which are PatternRecognition and SVM classes. The PatternRecognition class uses the user id, the used appliances, and the static value which is MIN_SUP as parameters of the extract_association_rules() method, in order to extract the user pattern in using the home appliances. The output of this class will act as input at SVM class, and the SVM class used the created association rules along with usage duration and appliance location (which room?) as parameters of generateRecommendation() methods .The last two data (usage duration and appliance location) are contribute to enhance the recommendations process as we mention in the

Algorithms section. The last class is the Dashboard class, which used to view the different reports and to send notifications to the user.

3.2 Sequence Diagram

Sequence diagram represents the flow of the system in which it describes the sequence of interactions between actors with the objects of the system. All interactions are represented as arrows in a chronological manner. Figure 22 shows the normal sequence diagram.

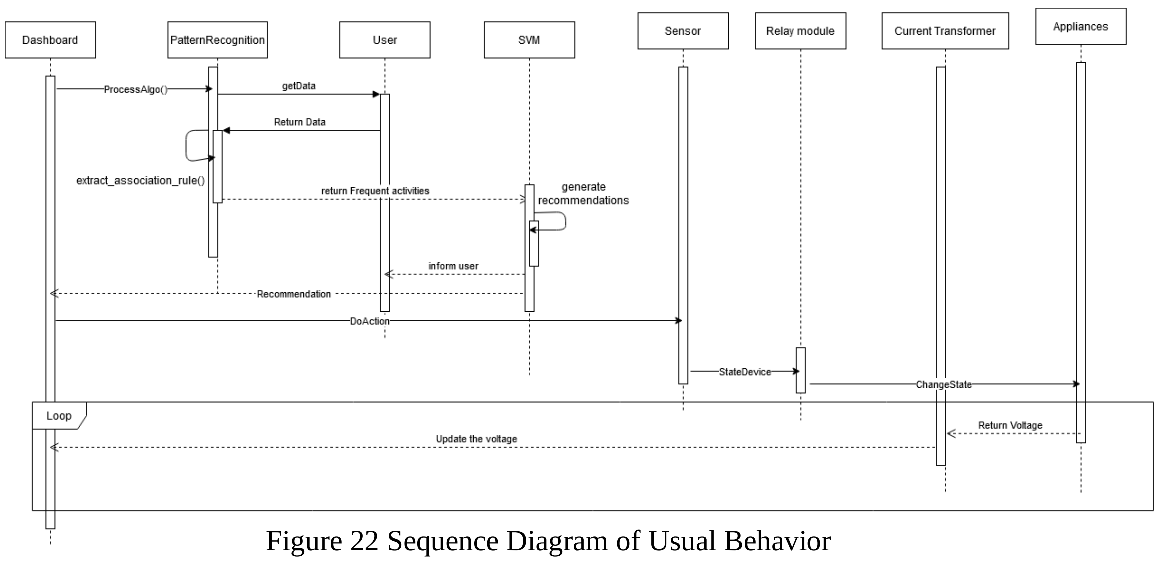


Figure 22 Sequence Diagram of Usual Behavior

The system starts with processing the algorithms, where the pattern mining algorithm will take the needed data help to observe and recognize the frequency actions. Pattern recognition will return the result of its process to SVM, that will generate the recommender events to user then send the recommendation to dashboard. Dashboard will send the instructions to the sensor part, that will send it to relay module that will change the state of appliance. As we can observed the current transform sensor will monitoring the electrical current of the applinces and send the updated result to the dashboard. However, in figure 23 we can observe the abnormal behavior.

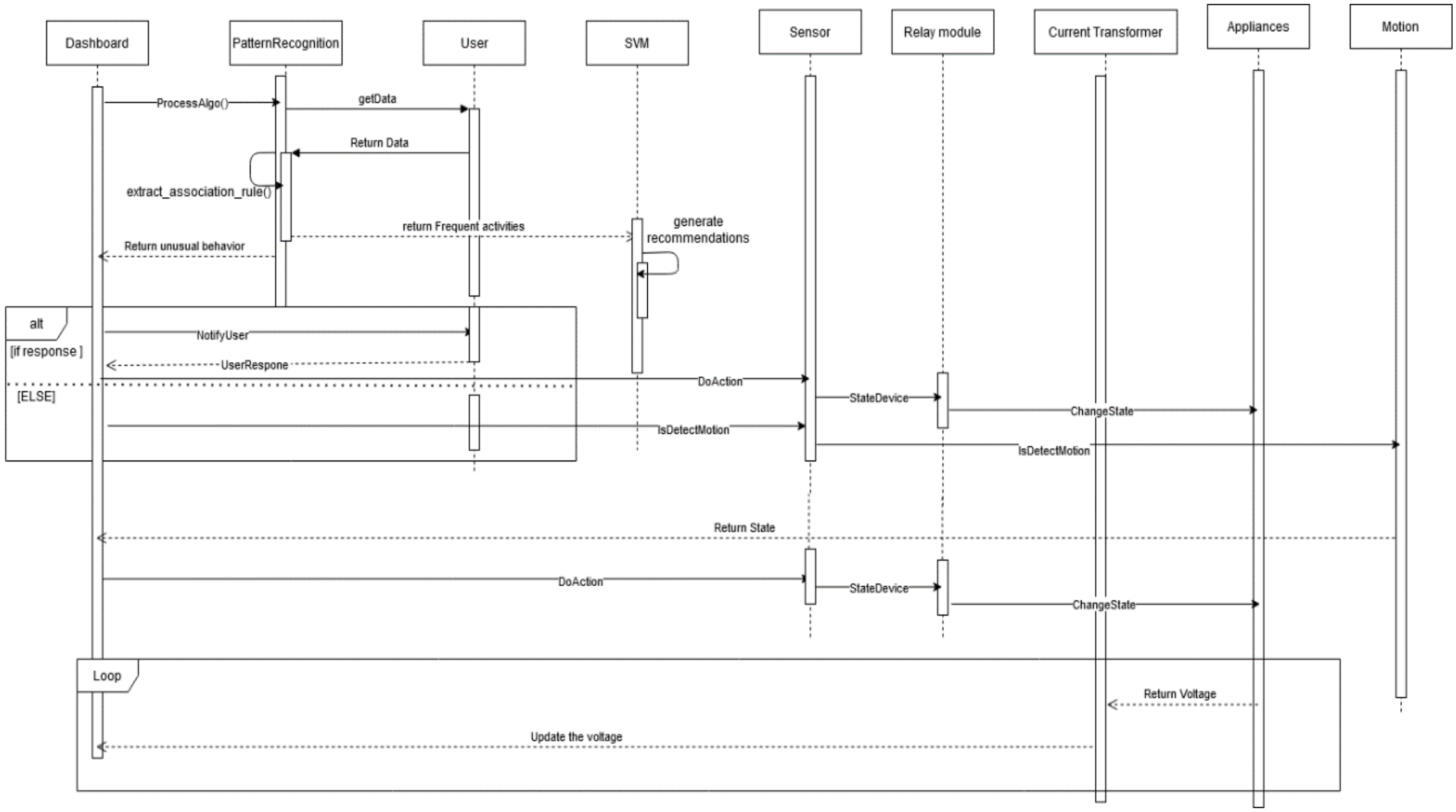


Figure 23 Sequence diagram for Abnormal Behavior

Normally the system starts with processing the pattern mining algorithm, in which it will get all needed data that useful to recognize the frequency actions. In this case if pattern mining observed any abnormal behavior it will notify the dashboard, where the dashboard will inform user and waited his/her response. As it clears it will enter if-else condition, if the user response then the system will follow the user instruction and moved normally. However, if there is no response from user the system must acted based in its knowledge, where the dashboard will send a query to sensor to identify the motion state of the room. Based on sensor result the system will be moved.

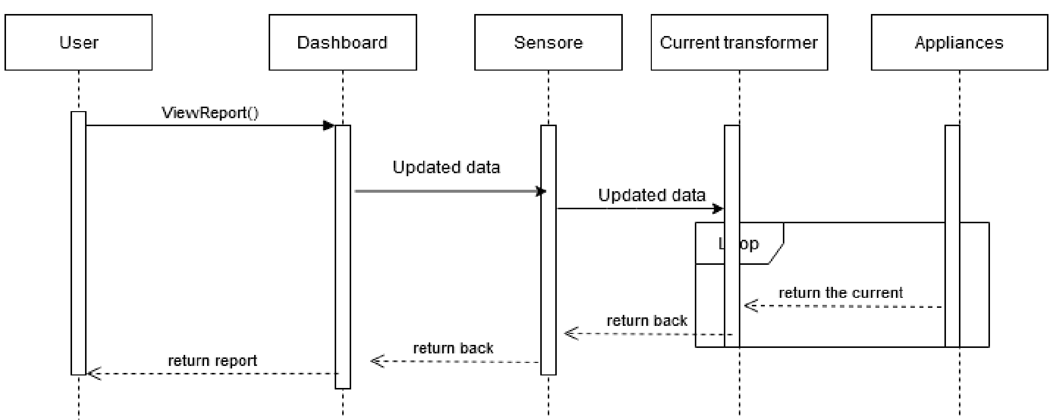


Figure 24 Sequence diagram of viewing the reports

Figure 24 shows the sequence interaction to get the report that arranged in time. In which the user will send a query to view the report. Dashboard will transform the acknowledge that received from user to sensor where the sensor will get the updated data from current transformer sensor. Data will be transforming until received the user.

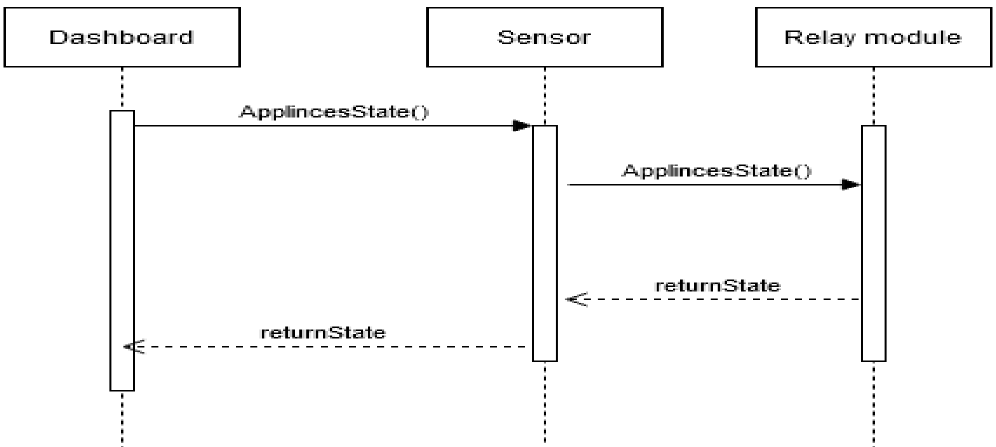


Figure 25 Sequence diagram of viewing appliance state

Figure 25 will show the interaction arranged in time between the objects to view the state of appliances. The dashboard will dispatch about appliances state to the sensor, Sensor will move the dispatch into relay module where the relay will check the appliances state and callback the sensor with the result. Sensor will return the appliances state to the dashboard.

3.3 Wiring Diagram

Wiring diagram represents the electrical circuit. It will show the components needed of the project and the power with the connection between each device as showing in figure 26.

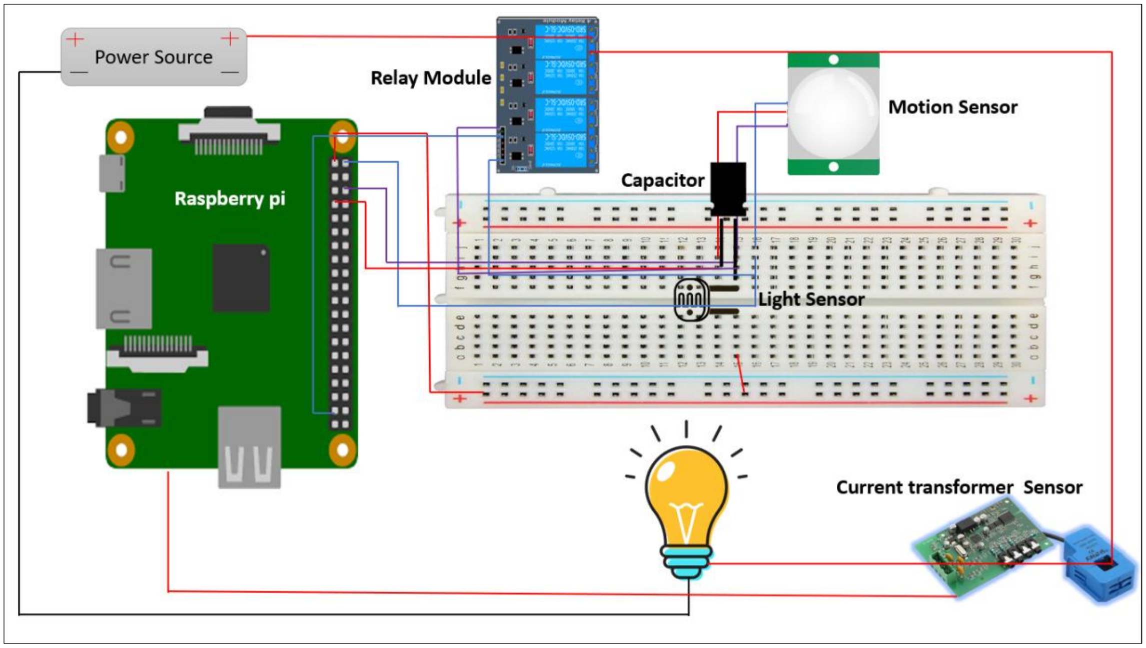


Figure 26 Wiring Diagram

The Raspberry pi will be connected to the motion sensor to sense any movement at the home, light sensor to sense the light, capacitor as an essential part for light sensing, current transformer sensor to be able to compute the power usage, relay module to switch on/off, and a power source.

3.4 Wire Frame

Wireframe is an image or set of images that represent the functional elements of a website. It is used for planning a site's structure and functionality. Figure 27 shows the simulation web page.

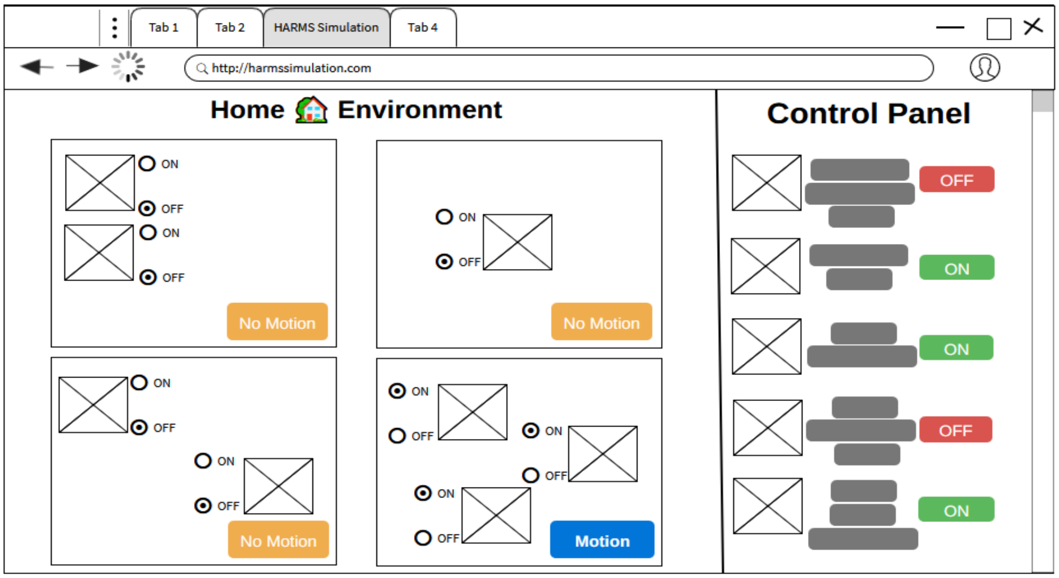


Figure 27 Wire Frame of simulation page

The simulation web page will be divided into two panels. The first panel which is called control panel will represent the appliances state and a few information about them like location etc. Second panel which will represent the home environment, each rectangle considered a room. In each room there is a motion button to tell the system where you are. Also, there are the appliances with radio buttons that represent the appliances state whether on or off where they can change by system after applying a recommender to the user or manually by the user. Figure 28 shows the wireframe of the dashboard.

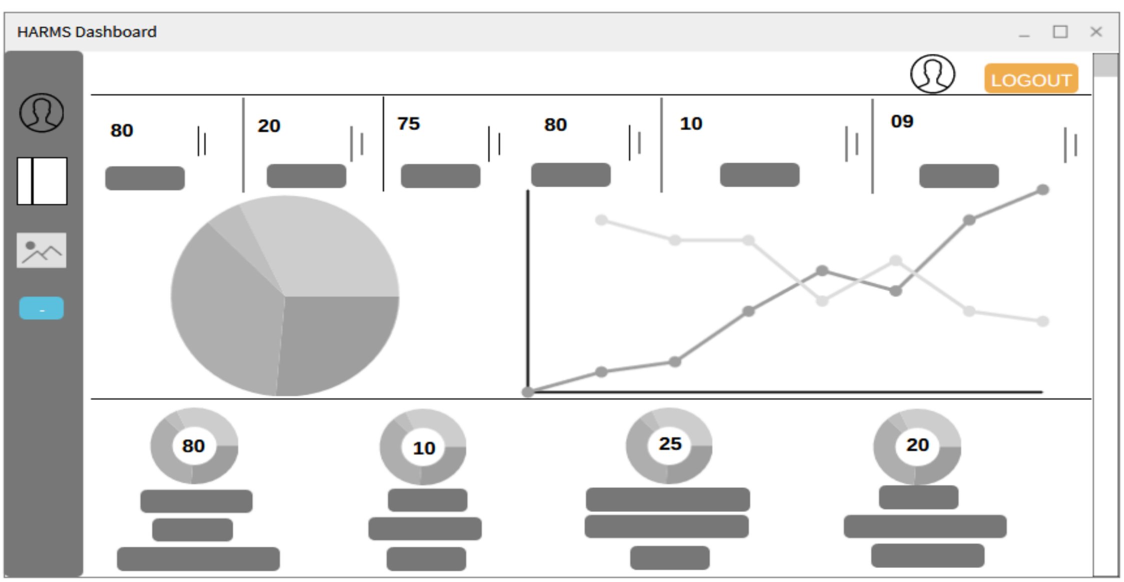


Figure 28 wireframe of the dashboard

The dashboard can view: the energy consumption for the last week, the energy consumption for the last month, and the appliances state Figure 29 and figure 30 shown the control setting where the users can add new appliances and add user profiles.

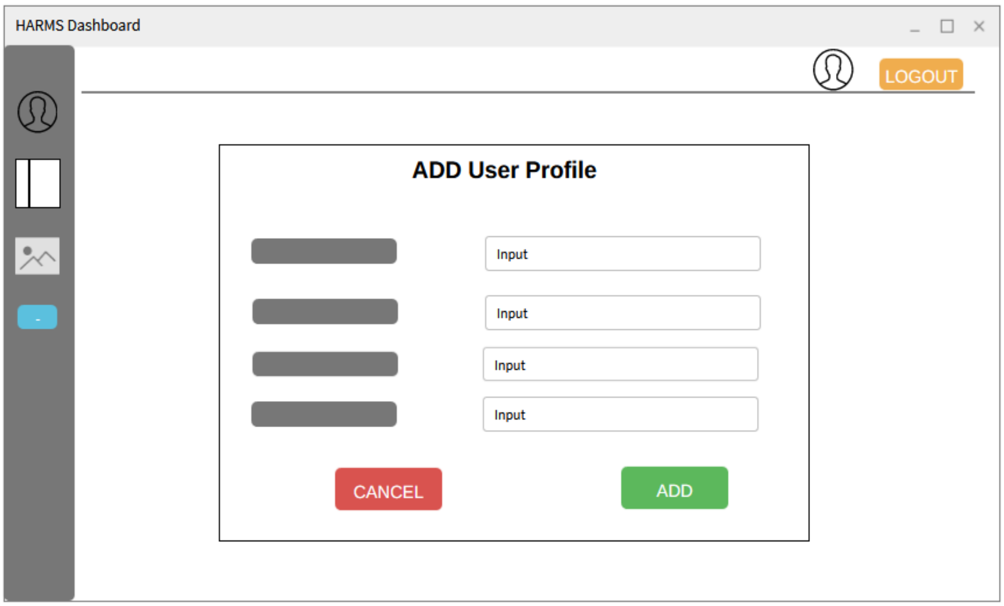


Figure 29 Add user profiles.

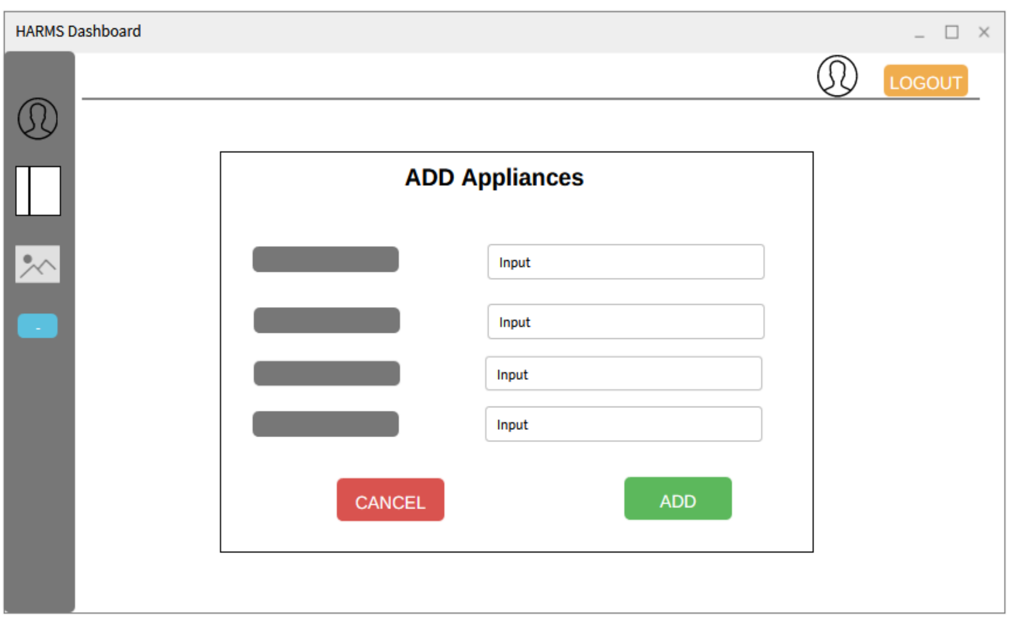


Figure 30 Add new appliances.

Also, in all of figures 31, 32, and 33 showing the wireframe for the mobile application that clearly view the functionality of the HARMS app which include on view the recommendation and unusual behavior with a button that can move us to the dashboard.

Figure 31 shows the home interface for Android application which is contain the functionality of the app. Also, it shows the user profile and logout option. At the middle will give the user a list of the recommunication and unusual actions, where the user can reject the recommendation actions or by default will occur. In the unusual actions the user has two options either to keep this action or reject it. At the bottom of home interface, it shows the dashboard button which will redirect the user to view the dashboard.

Notification part, as shown in figure 32, will help the user to be aware of the home applinces events. In which will give you an updated notification about the recommender actions and unusual actions.

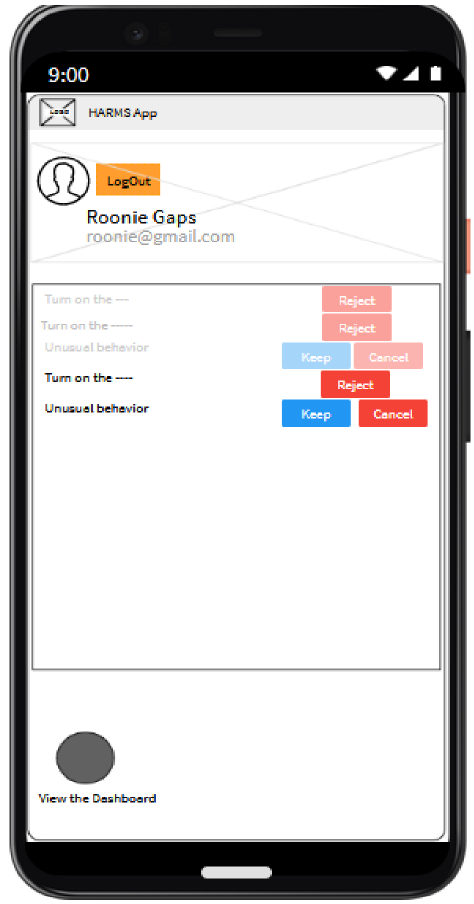


Figure 31 Wireframe of home interface app

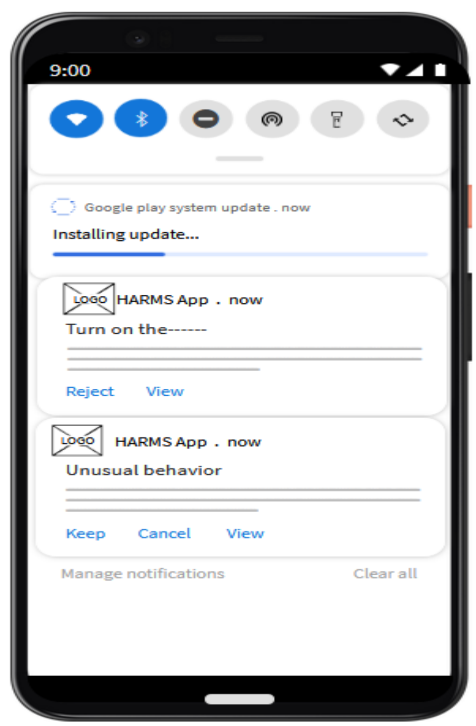


Figure 32 Wireframe Mobile APP

Figure 33 shows the dashboard interface. That come from pressing the dashboard button in the home interface. It shows the state of applinces and statistic of the energy consumption in different period.

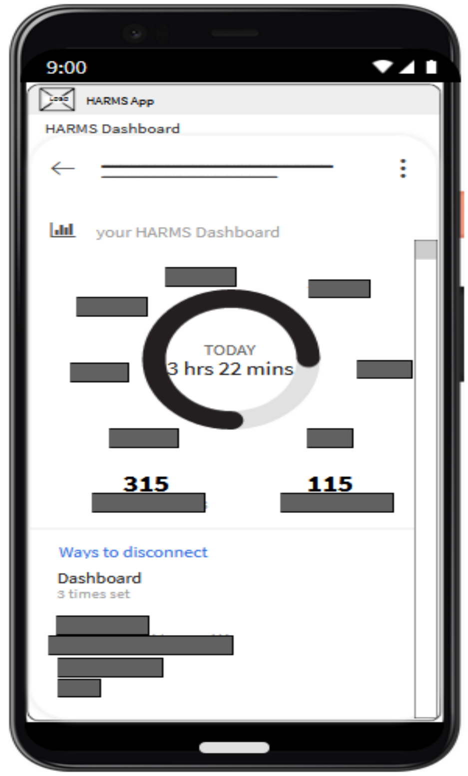


Figure 33 Wireframe Mobile APP

3.5 Description of tools and techniques used during project implementation

In this part, we will use the raspberry pi 3 model b, light sensor, motion sensor, relay module, current transformer sensor, wires, breadboard, SD card, keyboard, mouse, and monitor or TV to setup/connect the raspberry pi with the sensor. Also, all the other needed software.

<u>Tools</u>

1. **Android SDK:** is a set of development and debugging tools for Android that is included with Android Studio that we will use to develop our android application.
2. **Android studio software:** use to design, test, develop, and build the mobile application.

3. **Python:** is an interpreted, high-level, general-purpose programming language. We will use the python language to write the code for the setup of the sensors and apply ML algorithms that will be held in the dashboard.
4. **MySQL:** will be used to build our database schema, tables, and columns.

<u>Techniques:</u>

1. **Recommendation** → SVM.
2. **Monitoring** → Pattering mining algorithm.
3. **Test case generation:** It is a requirement validation technique. Will be used by developing tests for the requirements, to check testability, validity, consistency, completeness, realism, and verifiability of the system.
4. **Black Box Testing:** is a software testing technique under validation and verification requirements. By testing the functionalities of software applications with no need to have full knowledge of internal code structure, implementation details and internal paths. It will focus on input and output of the system and it is based on software requirements and specifications.
5. **selenium testing** is a validation and verification technique. will be used for testing web applications. It provides a playback tool which is used for functional testing with no need to learn a test scripting language (IDE) work in all operating systems Windows, Linux, and macOS.

4 Details of project implementation conforming to project proposal

While researching how to use the tools mentioned before, the following is the state of the art of the implementation phase considering that there are three main parts: front that have the designer of mobile application, Simulation, dashboard and back end parts that continues the hardware parts, the algorithm, and the database.

4.1 Front End Part

4.1.1 Mobile Application

For creating the interface of our application, we used Android Studio as we mentioned previously. We create all the pages we needed using the XML and we add the functionality to them using JAVA. The figures below show some of the pages from our application.

Figure 34 Login Mobile Interface

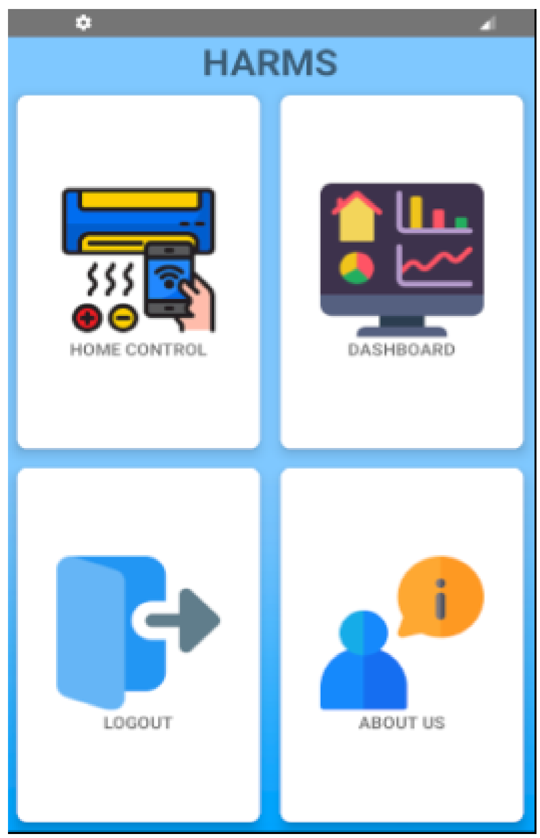


Figure 35 Main Home Interface

Figure 36 Control Home

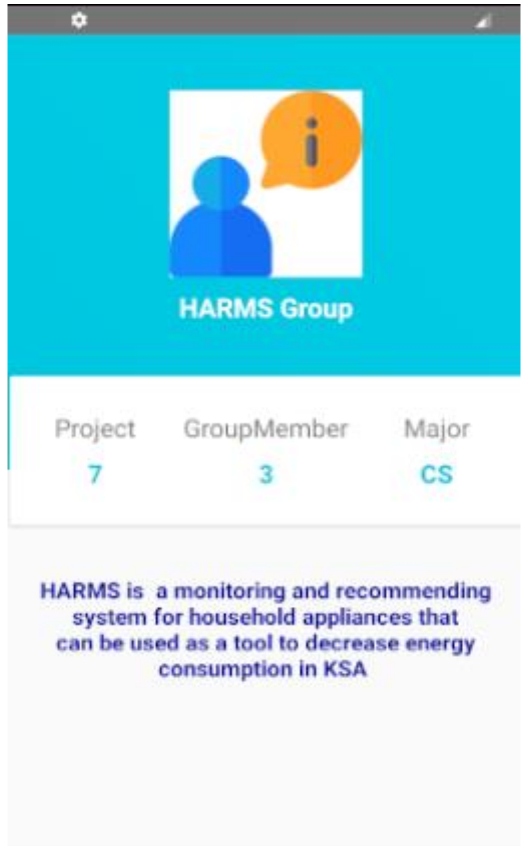


Figure 37 About Us

4.1.2 Simulation Environment

For the simulation we used a web application development language (HTML, CSS, JS and PHP) with phpMyAdmin database to control the home environment and give information of the appliances usage time and consumption to database as shown below.

Figure 38 Simulation web page

The simulation page is divided into two-part represent home and the control panel. The home part shows different rooms inside the home along with appliances and a motion button in each. Turning on/off an appliance consider as usage and will store all the related information of that usage in the database such as the room name and usage duration.

4.1.3 Dashboard

To designing the interfaces of Dashboard's functionality, we built a web application using the python programming language to create all the needed pages. The first page that will appear is the login page as shown in figure 39.

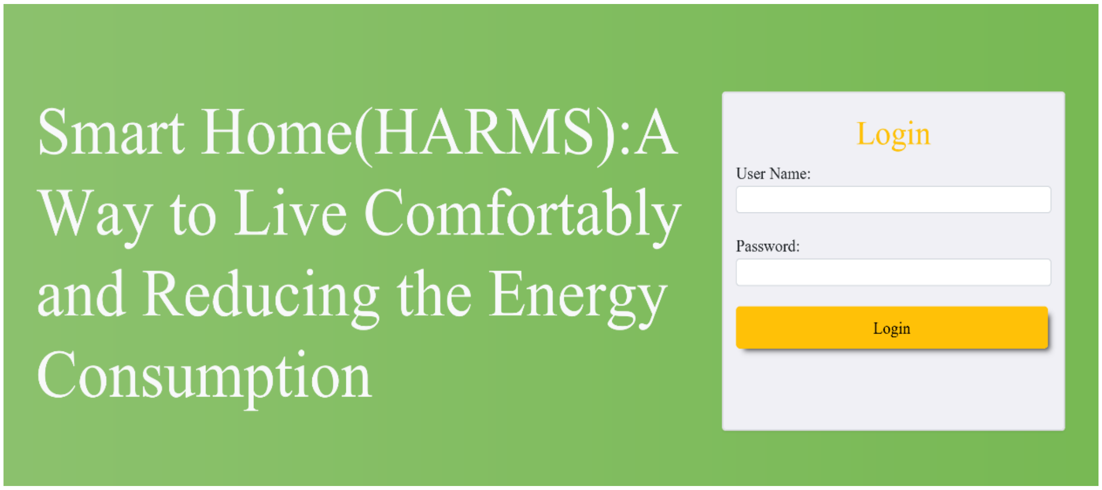


Figure 39 login page

If the dashboard is first time opened, the user will enter the fixed username "Admin" and the default password " Sam*Nab*Mar" that was provided to him. After the login, the system will ask the user to change the password and confirm the change after click save as shown in figure 40.

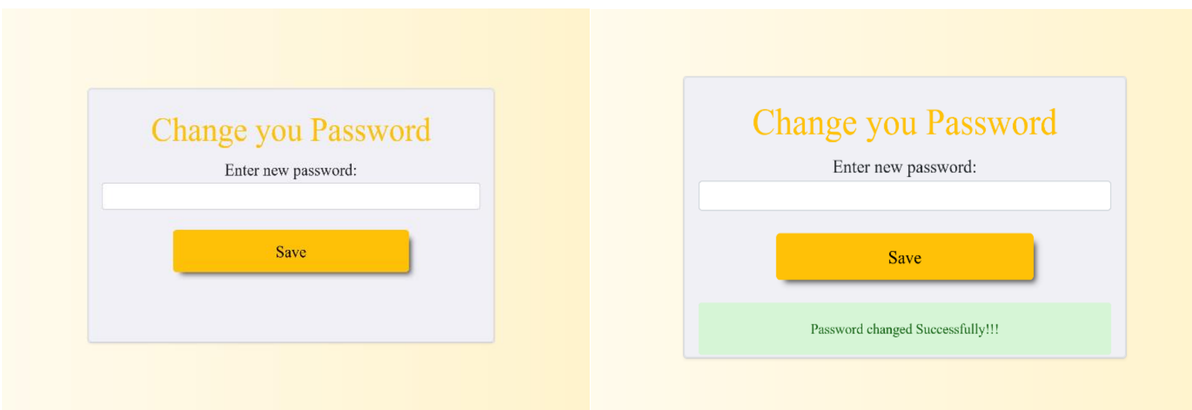


Figure 40 change password page

By login to the system, the user can see the dashboard, which shows different graphical representations that give the user a quick view of what is happening inside the home as shown in figure 41.

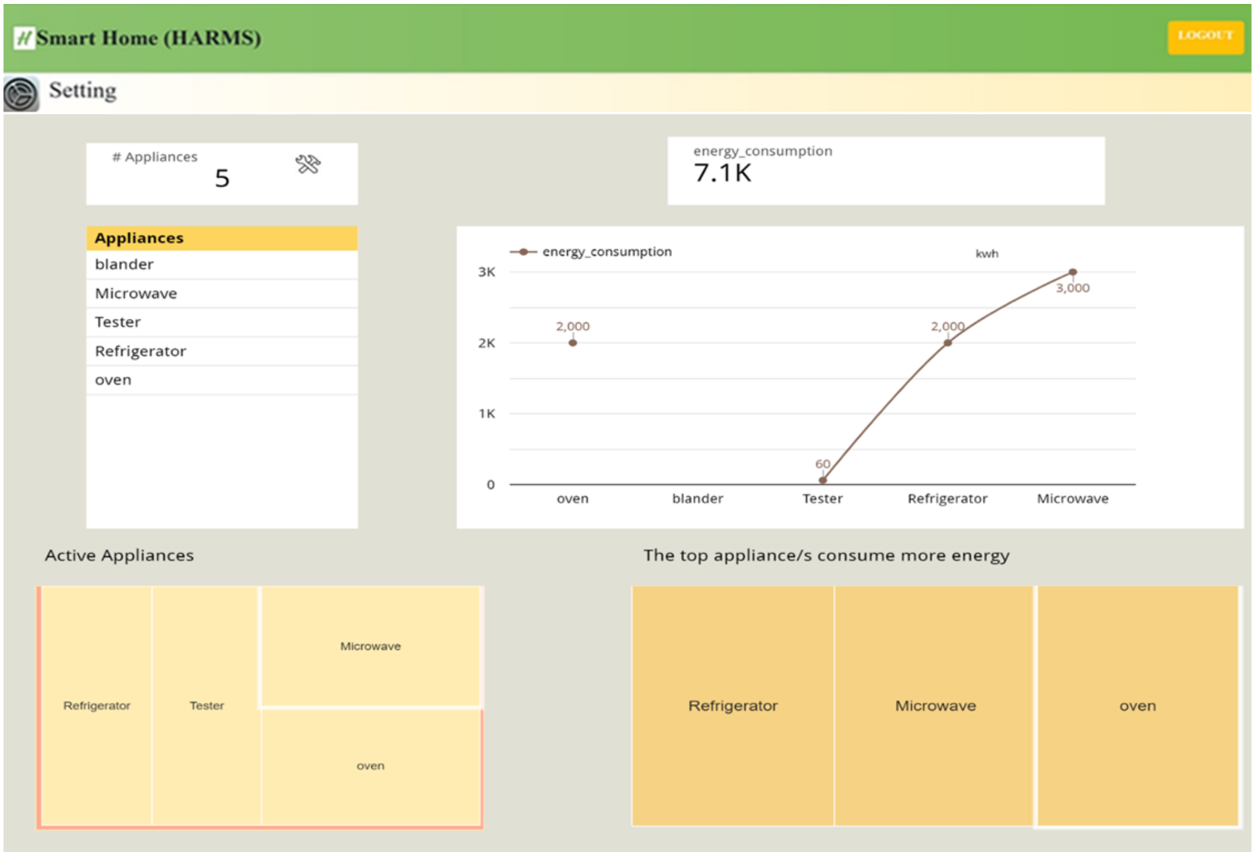


Figure 41 dashboard page

The dashboard shows at the top left how many and the names of appliances in the system. Whereas at the top right there is the amount of energy consumed by each device. Besides, it displays the current active appliances at the bottom left of the screen. On the other hand, the dashboard shows the top appliance/s that consume the most energy at the bottom right.

The dashboard page contains a setting button at the top left of the screen. By clicking the setting button, it displays various options that allow the user to control the system data. Figure 42 shows different user services through the system.

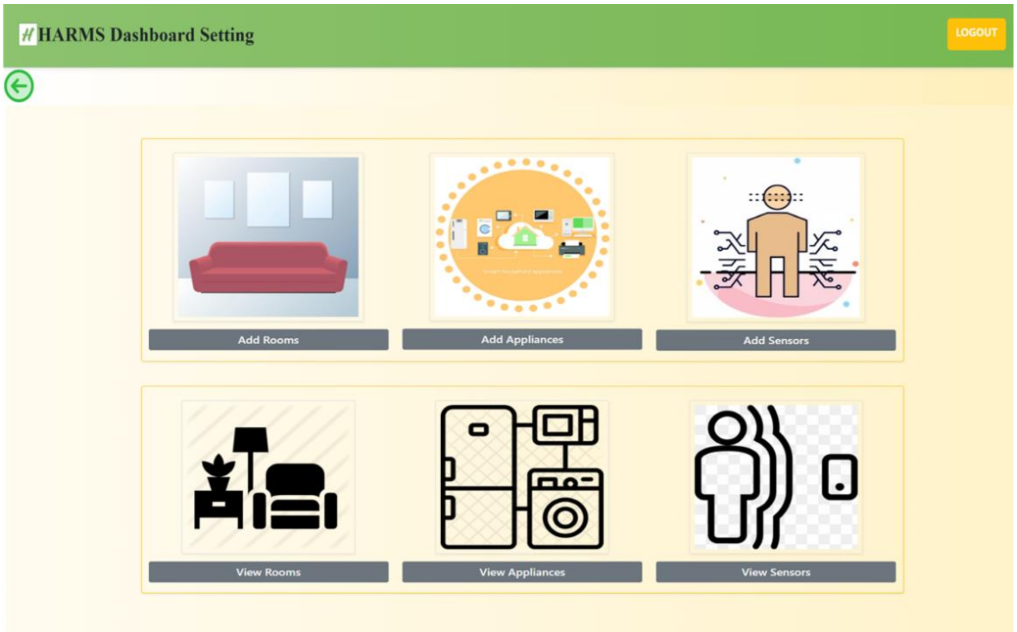


Figure 42 shows different user operations.

This page gives the user the ability to access the system settings and makes changes to them such as adding homerooms, home appliances, and sensors. Moreover, viewing related information to sensors, appliances, and rooms. The user's activities related to adding information have the same format. Similarly, all the viewing information also has the same format. We will demonstrate one example from each type. Figure 43 page of adding an appliance.

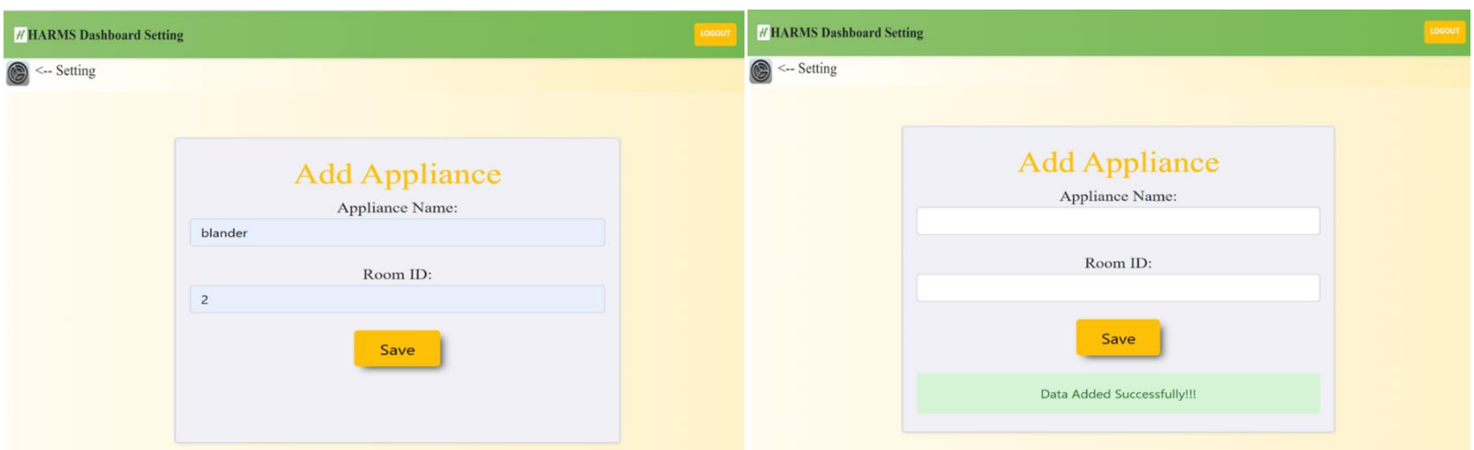
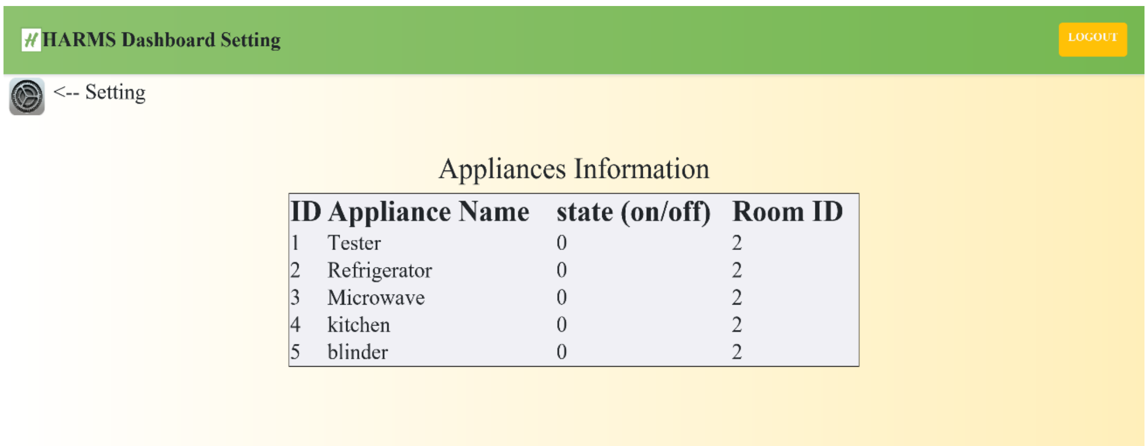


Figure 43 page of adding an appliance.

Here the user can enter the name of the appliance and the room id which indicates the location of the appliance. After clicking Save, the system will show a confirmation message. Viewing functions enable the user to view the system data. For example, figure 44 views the appliances in the system.



4.1.3.1 Changes on Dashboard

As we mention in the scope of the project, our system is built to handle one user and monitor how he/she uses home appliances. For that reason, we removed two functionalities which are "Add a Family Member" and "View all Family Members". Also, we removed the usernames information from the dashboard screen. Moreover, the dashboard screen shows the amount of energy consumed by each device instead of displaying energy consumed during the last week and month.

4.2 Back End Part (Server Side)

For our application, we are using the phpMyAdmin database to send and retrieve the data. Where user have ability to login to the system and we use a WebView to view the dashboard from mobile application.

4.2.1 Hardware part

In this part, we used the raspberry pi 3 model b+, sensors, wires, breadboard, SD card, keyboard, mouse, and monitor or TV to setup/connect the raspberry pi with the sensors.

1. Set up Raspberry Pi:

- We inserted the microSD card into the USB card reader.
- Connected the card reader to the computer.
- Downloaded SD Formatter (Raspberry Pi Imager v1.5).
- Downloaded the ZIP file of Raspbian.
- We use Etcher to flash the OS of raspberry pi "Raspbian" to the SD card.
- After that, we inserted the microSD card into the Raspberry Pi.
- We plugged the USB keyboard and mouse into one of the USB ports.
- We plugged the HDMI cable into the monitor or TV and another end of the cable into the Raspberry Pi HDMI port.
- Connected the power supply to the Raspberry Pi, as shown in figure 45.

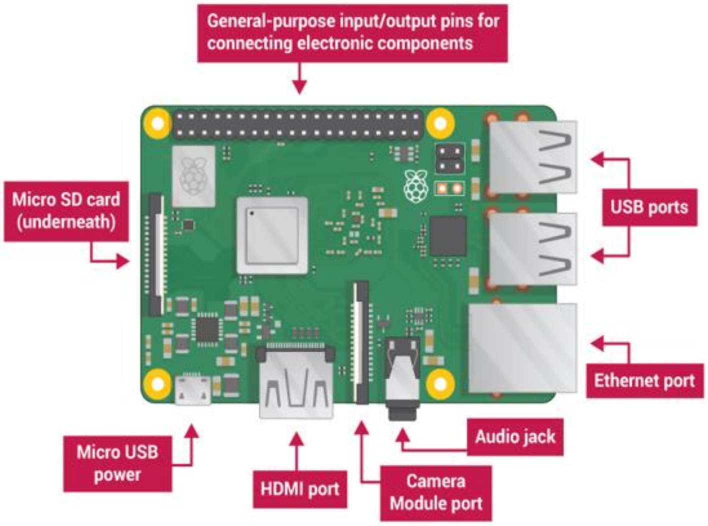


Figure 45 Configuration of Raspberry pi 3

2.Connect the raspberry pi to motion (PIR) sensor: We connected the GPIO from raspberry pi by wires and protoboard with the PIR sensor.

- pi 5V to sensor VCC
- Pi GND to sensor GND
- Pi GPIO 4 to sensor OUT, as shown in figure 46

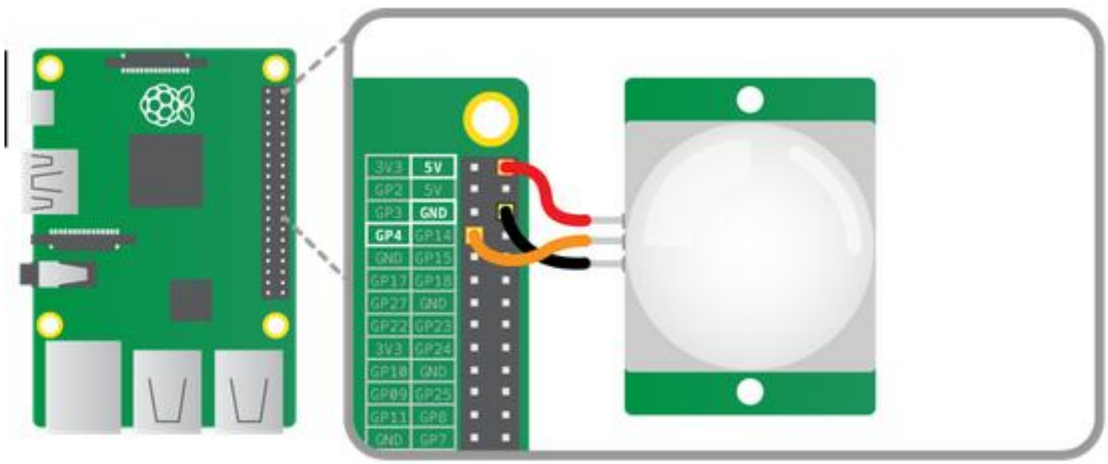


Figure 46 Motion sensor Wiring

<u>To test the motion sensor</u>

- We opened Mu, created a new file, and save it as motion.py.
- Then choose the mode in which we want to use Mu. We choose Python 3 since we are creating a new Python script. →

```
from gpiozero import MotionSensor
pir = MotionSensor(4)
```

- print motion detected if the sensor have detected any movement. →

```
while True:
    pir.wait_for_motion()
```

print (“Motion detected”)

2. Connect the raspberry pi to Relay Module sensor: We connected the GPIO from raspberry pi by wires and protoboard with the Relay Module sensor.
    - pi 5V to sensor VCC
    - Pi GND to sensor GND
    - Pi GPIO 7 to sensor SIGNAL as shown in figure 47

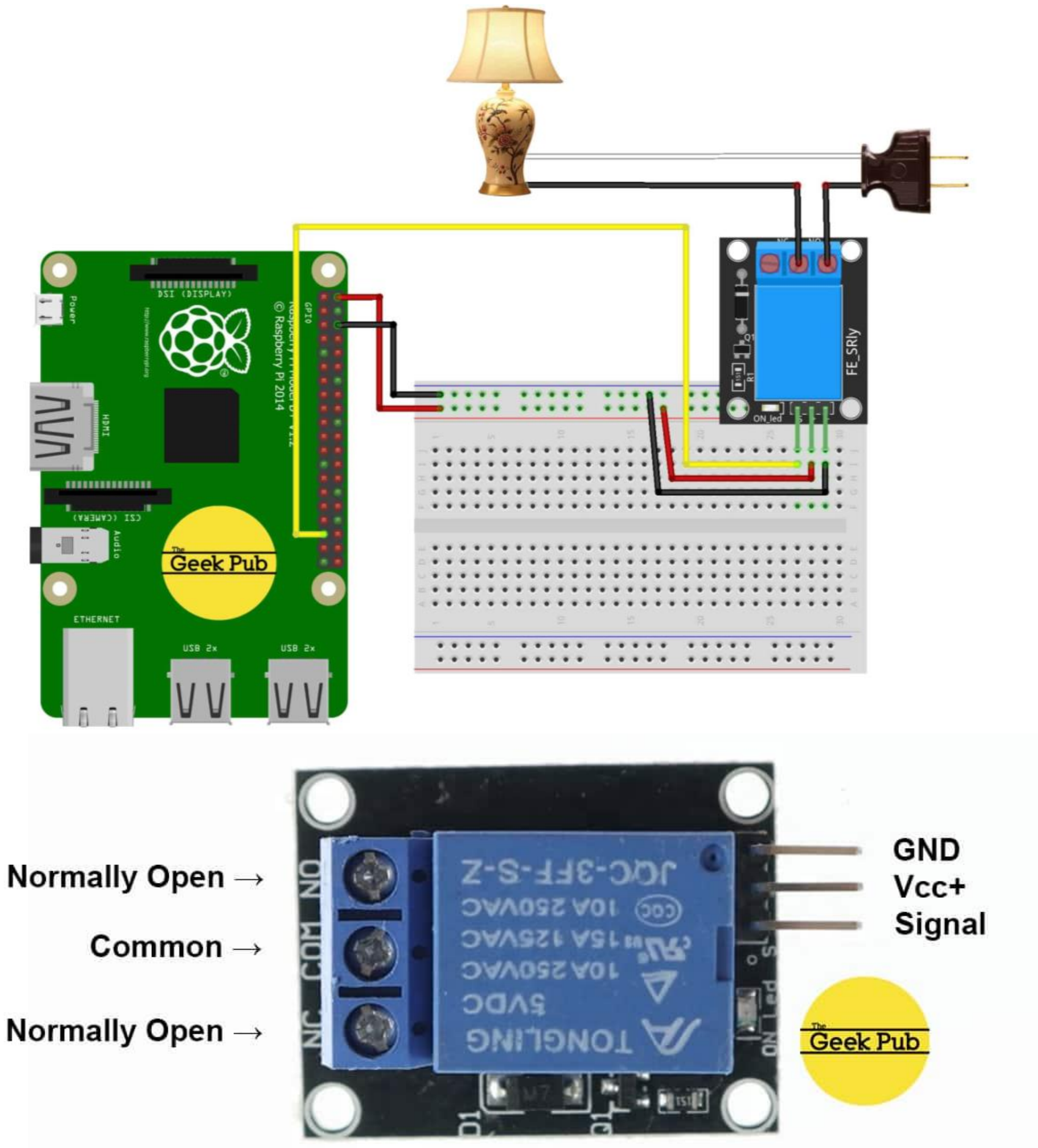


Figure 47 Relay Module configuration & wiring

To test the relay module

- We opened Mu, created a new file, and save it as relay.py.
- Then choose the mode in which we want to use Mu. We choose Python 3 since we are creating a new Python script. →

```
Led1 = 21
Import RPi.GPIO as GPIO
Import time
GPIO.setmode(GPIO.BCM)
GPIO.setup(led1, GPIO.OUT)
while True:
        GPIO.output(led1, True)
        time.sleep(2)
        GPIO.output(led1, False)
        time.sleep(2)
```

3. Local Area Network (LAN):

we connect the router to the laptop, we visit 192.168.1.1 and login using default username and password which is “admin” for both, from the listed options we selected advance → NAT → DMZ to access HARMS from extern networks and write the IP of router will be used and should start by 192.168.1…., in our case the IP was 192.168.1.30 with name HARMS_Network. for port mapping option we used TCP/UDP protocol, and the remote host take the router IP and finally the port wanted to listen to it, in our case we used port 80 and the mapping name which XAMPP. To check if the port working, we go to canyouseeme.org website and write the port number after running XAMPP as showing in figure 48.

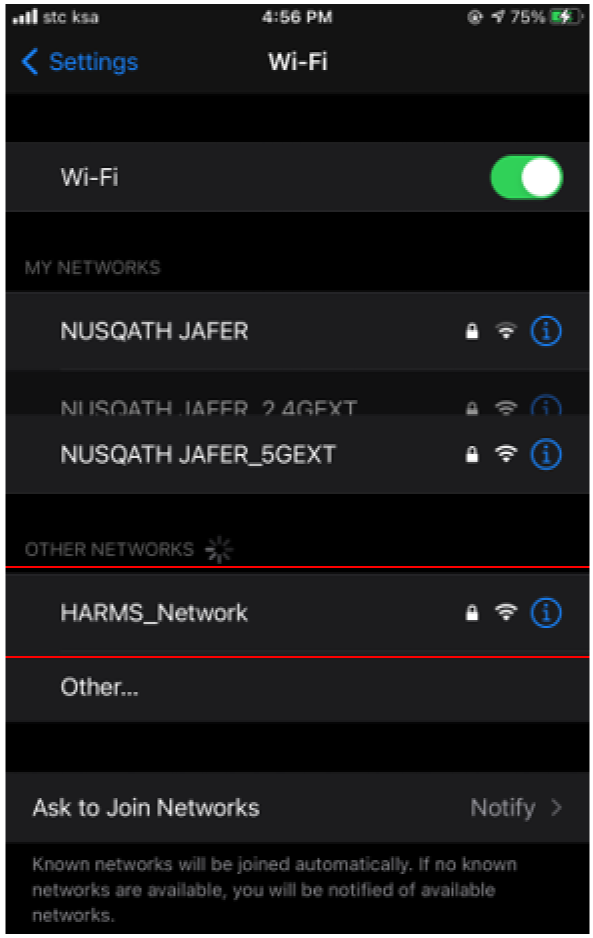


Figure 48 Lan of HARMS

4. Current transformer:

   Since the Raspberry pi have no analog input, we use Arduino as an adapter, after we cut the TRS cable of the current transformer since there was no plugged for TRS in the Arduino**,** we found three wire red, white and gray. In electrical wiring color code standards**,** we found that red indicate volte, white nature and we can ignore gray since it uses as a difference between the two wires, we use 3 resistors and one capacitor. Finally, we connect the Arduino to Raspberry pi.

4.2.2 Recommendation System

Recommender system is the core module in HARMS. It aims to recommend the next right appliance that the inhabitant can use based on the daily habits. It has been developed by combining the Apriori and SVM algorithms.

We first performed preprocessing and cleansing operation the UCI ADL Binary Dataset to reach a clean dataset, as shown in figure 49

	StartDate	StartTime	EndDate	EndTime	Location	Place
2	2011-11-28	02:27:59	2011-11-28	10:18:11	Bed	Bedroom
3	2011-11-28	10:21:24	2011-11-28	10:21:31	Cabinet	Bathroom
4	2011-11-28	10:21:44	2011-11-28	10:23:31	Basin	Bathroom
5	2011-11-28	10:23:02	2011-11-28	10:23:36	Toilet	Bathroom
6	2011-11-28	10:25:44	2011-11-28	10:32:06	Shower	Bathroom
7	2011-11-28	10:34:23	2011-11-28	10:34:41	Fridge	Kitchen
8	2011-11-28	10:34:44	2011-11-28	10:37:17	Cupboard	Kitchen
9	2011-11-28	10:38:00	2011-11-28	10:42:41	Toaster	Kitchen
10	2011-11-28	10:38:33	2011-11-28	10:38:40	Fridge	Kitchen
11	2011-11-28	10:41:29	2011-11-28	10:41:36	Cupboard	Kitchen
12	2011-11-28	10:41:43	2011-11-28	10:41:59	Cooktop	Kitchen
13	2011-11-28	10:41:59	2011-11-28	10:42:55	Microwave	Kitchen
14	2011-11-28	10:49:48	2011-11-28	10:51:13	Basin	Bathroom
15	2011-11-28	10:51:41	2011-11-28	13:05:07	Seat	Living
16	2011-11-28	13:06:04	2011-11-28	13:06:06	Basin	Bathroom
17	2011-11-28	13:06:07	2011-11-28	13:06:31	Toilet	Bathroom
18	2011-11-28	13:09:31	2011-11-28	13:09:35	Maindoor	Entrance

Figure 49 Dataset after preprocessing

The data has been restructured into a proper format to meet Apriori specifications where each record represents a pattern in a specific date as shown in the following figure 50. Now the data is ready to be mined via Apriori algorithm to generate the association rules.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	2011-11-28	Bed	Cabinet	Basin	Toilet	Shower	Fridge	Cupboard	Toaster	Cooktop	Microwave	Seat	Maindoor
2	2011-11-29	Bed	Toilet	Basin	Cabinet	Shower	Cupboard	Toaster	Fridge	Microwave	Seat	Cooktop	Maindoor
3	2011-11-30	Bed	Toilet	Shower	Cupboard	Fridge	Microwave	Toaster	Basin	Cabinet	Seat	Cooktop	Maindoor
4	2011-12-01	Bed	Toilet	Cabinet	Basin	Shower	Toaster	Cupboard	Fridge	Microwave	Seat	Cooktop	Maindoor
5	2011-12-02	Basin	Seat	Bed	Toilet	Cabinet	Shower	Cupboard	Fridge	Toaster	Microwave	Cooktop	
6	2011-12-03	Bed	Toilet	Cabinet	Basin	Shower	Toaster	Cupboard	Fridge	Microwave	Seat	Maindoor	
7	2011-12-04	Bed	Toilet	Cabinet	Basin	Shower	Fridge	Cupboard	Microwave	Toaster	Seat	Maindoor	
8	2011-12-05	Basin	Bed	Toilet	Shower	Seat	Cupboard	Fridge	Toaster	Microwave	Maindoor	Cooktop	
9	2011-12-06	Toilet	Basin	Bed	Cabinet	Shower	Toaster	Cupboard	Fridge	Microwave	Seat	Cooktop	
10	2011-12-07	Basin	Seat	Toilet	Bed	Cabinet	Shower	Toaster	Cupboard	Fridge	Microwave	Cooktop	Maindoor
11	2011-12-08	Bed	Basin	Toilet	Cabinet	Shower	Toaster	Cupboard	Fridge	Cooktop	Microwave	Seat	Maindoor
12	2011-12-09	Basin	Bed	Toilet	Cabinet	Shower	Toaster	Cupboard	Fridge	Cooktop	Microwave	Seat	Maindoor
13	2011-12-10	Basin	Seat	Bed	Toilet	Cabinet	Shower	Cupboard	Toaster	Fridge	Microwave	Cooktop	Maindoor
14	2011-12-11	Maindoor	Seat	Basin	Bed	Toilet	Shower	Toaster	Cupboard	Fridge	Microwave	Cooktop	
15	2011-12-12	Bed											
16	2012-11-11	Seat											
17	2012-11-12	Door	Seat	Basin	Toilet	Bed	Fridge	Microwave	Shower	Cupboard	Maindoor		
18	2012-11-13	Door	Basin	Bed	Fridge	Microwave	Toilet	Maindoor	Cupboard	Seat			
19	2012-11-14	Door	Basin	Toilet	Bed	Fridge	Microwave	Seat	Cupboard	Shower	Maindoor		
20	2012-11-15	Door	Basin	Toilet	Bed	Seat	Fridge	Microwave	Shower	Maindoor	Cupboard		
21	2012-11-16	Door	Basin	Toilet	Bed	Fridge	Microwave	Shower	Maindoor	Seat	Cupboard		

Figure 50 Restructuring dataset

During the execution of Apriori, The Confidence is set to 0.9 and the Support to 0.2. Thus, it generateed the frequent sets that are frequently appearing in the dataset with 0.2. Then, we applied *association_rules()* to produce the rules that only meet 0.9 confidence or more which indicates probability that both antecedent and consequent appearing in the same pattern, as displayed in figure 51.

	A	B	C	D	E	F	G
1	antecedents	consequents	antecedent supp	consequent s	support	confidence	lift
2	frozenset({' Door '})	frozenset({'Basin'})	0.361111111	0.80555556	0.361111	1	1.241379
3	frozenset({' Door '})	frozenset({'Bed'})	0.361111111	0.77777778	0.361111	1	1.285714
4	frozenset({' Door '})	frozenset({'Fridge'})	0.361111111	0.94444444	0.361111	1	1.058824
5	frozenset({' Door '})	frozenset({'Maindoor'})	0.361111111	0.63888889	0.333333	0.923076923	1.444816
6	frozenset({' Door '})	frozenset({'Seat'})	0.361111111	0.91666667	0.361111	1	1.090909
7	frozenset({' Door '})	frozenset({'Toilet'})	0.361111111	0.91666667	0.361111	1	1.090909
8	frozenset({' Maindoor '})	frozenset({'Basin'})	0.222222222	0.80555556	0.222222	1	1.241379
9	frozenset({' Maindoor '})	frozenset({'Bed'})	0.222222222	0.77777778	0.222222	1	1.285714
10	frozenset({' Maindoor '})	frozenset({'Fridge'})	0.222222222	0.94444444	0.222222	1	1.058824
11	frozenset({' Maindoor '})	frozenset({'Seat'})	0.222222222	0.91666667	0.222222	1	1.090909
12	frozenset({' Maindoor '})	frozenset({'Toilet'})	0.222222222	0.91666667	0.222222	1	1.090909
13	frozenset({'Door'})	frozenset({'Basin'})	0.222222222	0.80555556	0.222222	1	1.241379
14	frozenset({'Basin'})	frozenset({'Fridge'})	0.805555556	0.94444444	0.805556	1	1.058824
15	frozenset({'Basin'})	frozenset({'Seat'})	0.805555556	0.91666667	0.777778	0.965517241	1.053292
16	frozenset({'Basin'})	frozenset({'Toilet'})	0.805555556	0.91666667	0.777778	0.965517241	1.053292
17	frozenset({'Door'})	frozenset({'Bed'})	0.222222222	0.77777778	0.222222	1	1.285714
18	frozenset({'Bed'})	frozenset({'Fridge'})	0.777777778	0.94444444	0.777778	1	1.058824
19	frozenset({'Bed'})	frozenset({'Seat'})	0.777777778	0.91666667	0.75	0.964285714	1.051948
20	frozenset({'Bed'})	frozenset({'Toilet'})	0.777777778	0.91666667	0.75	0.964285714	1.051948
21	frozenset({'Cabinet'})	frozenset({'Cupboard'})	0.305555556	0.66666667	0.305556	1	1.5
22	frozenset({'Cabinet'})	frozenset({'Fridge'})	0.305555556	0.94444444	0.305556	1	1.058824

Figure 51 The association rules

In the following, there is a description of each column presented in figure 51:

- **Antecedents**: It is the IF component in association rules.
- **Consequents**: It is the Then component in association rules and both antecedents and consequents are disjoint. Giving an example, ‘if the inhabitant uses {CookTop}, then he/she will use {Fridge}’
- **Antecedents support:** It indicates how the rules’ items in the antecedents are frequently occur together in the database, such as {Fridge, Microwave} are occurring together with 33% in the database.

- **Consequents support:** It indicates how the rules' items in the consequents are frequently occur together in the database, such as {Basin, Toilet} are occurring together with 69% in the database.
- **Support:** It indicated how the rules' items are frequently occur together in the database.
- **Confidence:** It describes a conditional probability which the consequent will occur given the occurrence of the antecedent. For instance, 'If the inhabitant uses {CookTop}, then he/she will use {Fridge} with 91%'.
- **Lift**: It refers to the strength or quality of a rule over the random co-occurrence of the antecedent and the consequent. If the lift value < 1, it will not indicate a real cross-selling opportunity.

Subsequently, we preprocessed the association rules to form a suitable format for the SVM by representing the rules as integers rather than strings. We have encoded each appliance with an integer number and reflected the changes on the association rules to form a sequence of integers as shown in figure 52. For example, Basin:1, Toaster: 13, Fridge: 7, Microwave: 10, and so on.

	A	B	C	D	E	F
1	consequents	antecedents				
2	1	6				
3	2	6				
4	7	6				
5	9	6				
6	11	6				
7	14	6				
8	1	9				
9	2	9				
10	7	9				
11	11	9				
12	14	9				
13	1	6				
14	7	1				
15	11	1				
16	14	1				
17	2	6				
18	7	2				
19	11	2				
20	14	2				
21	5	3				

Figure 52 Numeric representation of association rules

SVM requires the data to be consistent, so we had to fill it with zeroes to form a sparse matrix. We considered the *antecedents* as the features and the *consequents* as the target. For training purposes, we split data into 70% for the training and 30% for the testing. After training SVM, it was able to recommend the next right appliance.

4.2.2.1 Changes on the Recommender System

We have mentioned in the Details Requirement that we will input to SVM three inputs, including patterns, duration, and user location. However, we trained SVM with the extracted user pattern only. For the duration and location, we made a calculation to compute the duration of using a specific appliance every day and then communicated with the motion sensor to detect the user's motion and took it into consideration when an appliance turns off.

4.2.3 HARMS Database

Database is an essential part of HARM system where the acquired data can be stored and retrieved to manipulate it in the proper manner to achieve the system objective. Figure 53 shows the schema of HARMS database.

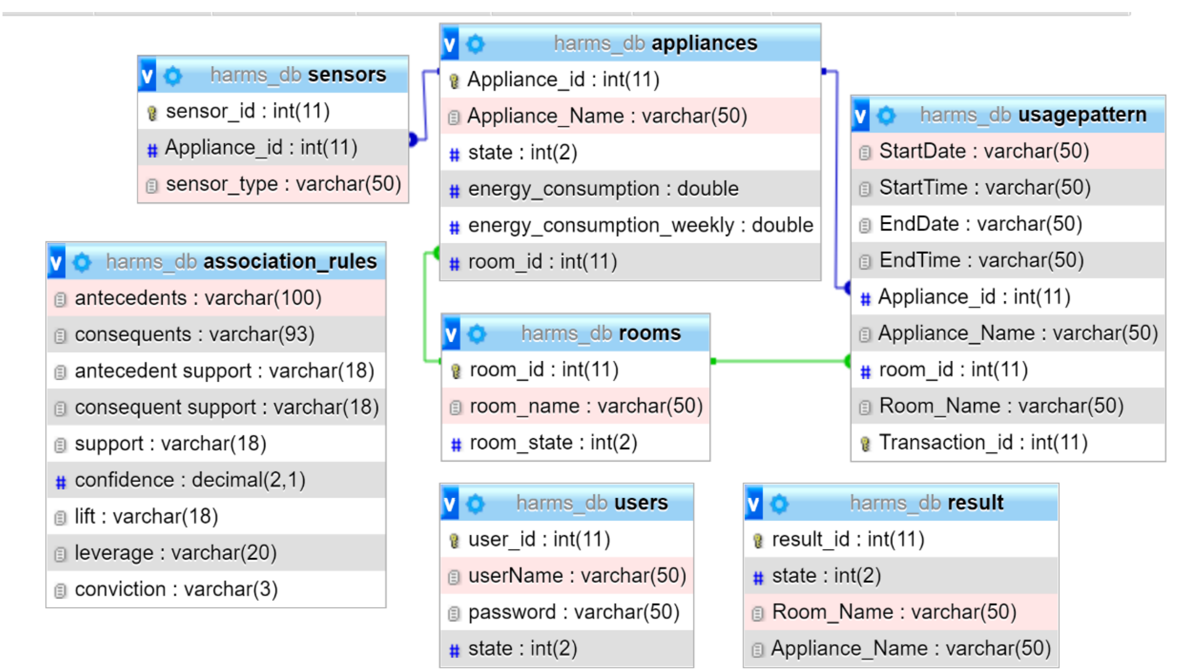


Figure 53 The schema of HARMS database.

In the actual implementation, our database consists of seven tables that store all needed information, so the system can use them to perform its functionality. Based on the tables utilization, we divide the database tables into two-part as the following:

4.2.3.1 Table for Account Management

The users table is used for account management, where the table contains the fixed username "Admin" and the default password " Sam*Nab*Mar". The state attribute is used to ask the user to change the password. Figure 54 shows the users table.

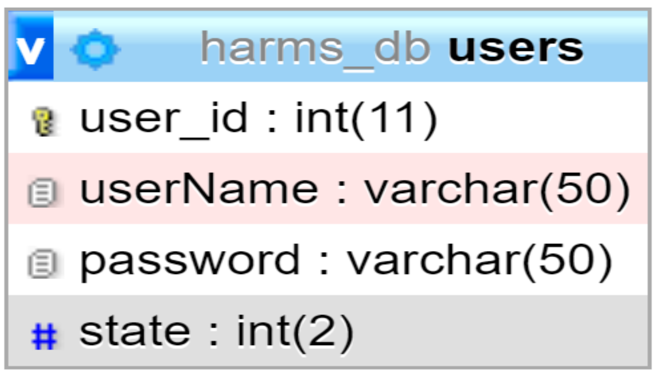


Figure 54 users table.

After changing the password, the new password will be stored in the password column.

4.2.3.2 Tables Used for Recommender and Monitoring System

The six remaining tables are used for recommendation see figure 55. Both the *appliances* table and the *rooms* table are linked to the *usagepattern* table that the system will retrieve its data to apply the algorithms. *Appliances* table store all information related to the home's appliances such as id, name, energy consumption…etc. The *sensors* table used to identify which sensor is attached to a particular device. Similarly, the *rooms* table stores information related to the home's rooms. As the name implies, the *association_rules* table is used to store the association rules, which is the output from applying the *Apriori* algorithm. Besides, the result table stores the final recommendations that will be notified to the user. Figure 56 show the sample of database tables (usagepattern table).

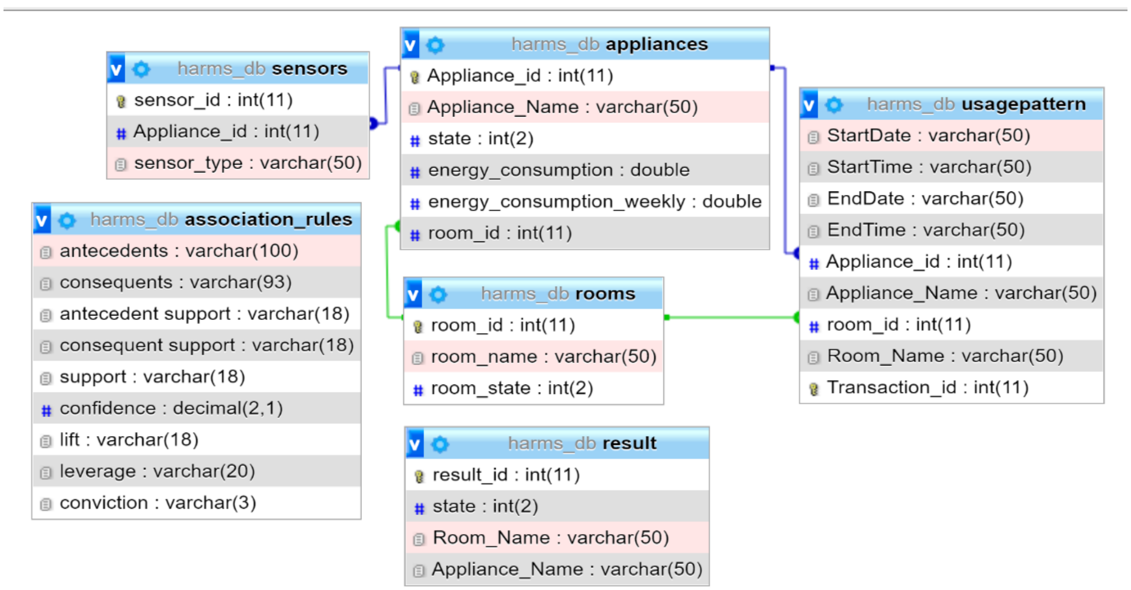


Figure 55 The related tables for recommendation system.

StartDate	StartTime	EndDate	EndTime	Appliance_id	Appliance_Name	room_id	Room_Name	Transaction_id
Mar/03/2021	12:44:58 AM	Mar/03/2021	12:45:15 AM	1	Toster	2	Kitchen	8
Mar/03/2021	12:45:10 AM	Mar/03/2021	12:45:37 AM	2	Refrigerator	2	Kitchen	9
Mar/03/2021	12:45:21 AM	Mar/03/2021	12:45:35 AM	3	Microwave	2	Kitchen	10
Mar/03/2021	12:45:22 AM	Mar/03/2021	12:45:36 AM	1	Toster	2	Kitchen	11

Figure 56 Sample of database tables (usagepattern table).

The usagepattern table has nine columns to record the usage of a particular device such as the usage period that starting from turning the appliance on until it is turned off. The data of these columns were acquired from the simulation page that simulates the user activity. These data will be used by the Apriori algorithm to generate the association rules.

4.2.3.2 Data base changes

There are many changes that we made to our previous database schema, after starting the implementation phase, and we end up having seven tables instead of six tables. That was because applying the following modifications:

- Replacing pattern table with *result* table to store the final recommendations.
- The Type table is replaced by a column in the sensors table.
- Makes a new table called *usagepattern* to record the usage of appliances at home.
- Makes a new other table called *association_rules* to store the association rules.

4.3 Overall project outcomes/results

Through the partial implementation of HARMS, we were able to implement 90% of the recommendation system in which the Apriori has been applied on the user pattern to generate association rules and then applied the SVM to recommend next action. Furthermore, we have designed the mobile and web application and connect them to phpMyAdmin, so the user is able to interact with them and perform the preferred functionalities that ranging from adding room, user, to viewing reports. We developed 100% of the HARMS simulation environment, set up the configuration of the hardware modules and connect them together by 100%. In addition, we have been able to establish 100% of the local network that enables other HARMS's parts to communicate including, mobile application, dashboard, simulation environment, hardware modules, and the database. Finally, we tested the recommendation with the simulation environment data and hardware modules.

4.4 Mastery of Tools and Techniques Used in Project Implementation

In this section, we will present the tool and techniques that we used during the implementation phase.

4.4.1 Personal Computer:

A personal computer, we use it to download the software that we need to build a mobile app, simulation web page and dashboard. Most coding of the project will be performed using the personal computer.

4.4.2 Smartphone:

We are using a smartphone that is viewing the application that designed and test the functionalities which the application has.

4.4.3 Android SDK:

Android SDK is a set of development and debugging tools for Android that is included with Android Studio that we used to develop our android application.

4.4.4 Java programming:

Android apps can be written using Kotlin, Java, and C++ languages. In our application, we used the Java programming language to write/create the functionalities of the mobile application.

4.4.5 XML:

Extensible Markup Language (XML) is a markup language that defines a set of rules for encoding documents that use for designing the interfaces of the mobile application.

4.4.6 Raspbian, Raspberry pi:

- Raspbian is a computer operating system for Raspberry Pi.
- Raspberry pi is a low cost, credit-card sized computer that performs most of the functionalities supported by any computer. In our project, we used the raspberry pi to send the data from-to senor.

4.4.7 Open-source web application:

The open web-based platform is very interactive and flexible to develop open-services and software via a set of programming languages, such as Google Colab. It supports workflows in data science and machine learning and facilitates the usage of libraries and plugins. We have used it to develop the recommendation system with Python.

4.4.8 Data visualization dashboard

Data and information can be visualized through graph, charts, and maps to understand the trends and patterns. Google Data Studio is one of the Data visualizations tools which transforms the raw data into easy-to-follow reports and dashboards without need to write a code or queries. We adopted Data Studio in HARMS to create reports to help inhabitants monitor their home activities.

4.4.9 PyCharm

Is a cross-platform IDE for Python programming language. We use it to design the system interfaces that are related to the dashboard, dealing with the phpMyAdmin database to store and retrieve data, and writing the code of the ML algorithms. So, eventually what has been written in Google Colab will be move-in PyCharm IDE.

4.4.10 phpMyAdmin

It is open-source software and a third-party tool. It can manage the tables and data inside MySQL. The reason for choosing it to build our system database is that it can handle the administration of MySQL over the web.

4.4.11 Apriori Algorithm

It is a data mining algorithm that is used to analyze the frequents subsequences. We have implemented Apriori in HARMS to extract the inhabitant's daily pattern and generate the association rules to find the relationships between the appliances used.

4.4.12 SVM Algorithm

It is s the powerful supervised ML algorithms that are implemented through many real-world applications for both classification and regression. In HARMS, SVM has been implemented to recommend the next right appliance based on the association rules that's been generated from Apriori.

5 Analysis of overall result through comparison, validation, or verification

<table>
<tr><td colspan="2">Project Name: HARMS System</td></tr>
<tr><td colspan="2">Test Case # 1</td></tr>
<tr><td>Test Case ID: LOGIN-01</td><td>Test Designed by: <Salma, Nabaa, Maryam></td></tr>
<tr><td>Test Priority (Low/Medium/High): High</td><td>Test Designed date: <3-5-2021></td></tr>
<tr><td>Module Name: Login screen</td><td>Test Executed by: <Salma, Nabaa, Maryam></td></tr>
<tr><td>Test Title: Verify login with valid username and password</td><td>Test Execution date: <3-5-2021></td></tr>
<tr><td>Description: Test the login page</td><td></td></tr>
<tr><td colspan="2">Pre-conditions: User has valid username and password</td></tr>
<tr><td colspan="2">Dependencies:</td></tr>
</table>

<table>
<tr><th>Step</th><th>Test Steps</th><th>Test Data</th><th>Expected Result</th><th>Actual Result</th><th>Status (Pass/Fail)</th><th>Notes</th></tr>
<tr><td>1</td><td>Navigate to login page</td><td>Username (First name): Admin</td><td>User should not be able to login</td><td rowspan="4">The system will not move the user to the next page. the system will reshown the login page and display the following message " ** Your Password or Username is not correct, please try again** "to let the user enter information again.</td><td>Fail</td><td rowspan="4">The user will not be able to login since he provides the wrong information</td></tr>
<tr><td>2</td><td>Provide valid username</td><td>Password (Maaa15)</td><td></td><td></td></tr>
<tr><td>3</td><td>Provide valid password</td><td></td><td></td><td></td></tr>
<tr><td>4</td><td>Click on Login button</td><td></td><td></td><td></td></tr>
<tr><td colspan="7">Post-conditions:
User is validated with database and successfully login to the system</td></tr>
</table>

Test Case # 2	
Test Case ID: Add a room-02	Test Designed by: <Salma, Nabaa, Maryam>
Test Priority (Low/Medium/High): High	Test Designed date: <3-5-2021>
Module Name: Add a room screen	Test Executed by: <Salma, Nabaa, Maryam>
Test Title: Adding new room information to the system	Test Execution date: <3-5-2021>
Description: Test Add room page	
Pre-conditions: User fills valid information of a new room	
Dependencies:	

Step	Test Steps	Test Data	Expected Result	Actual Result	Status (Pass/Fail)	Notes
1	After user log In	room Name: living room	User should be able to add a new room	The system will display a confirmation. message " Data Added Successfully!!! "	Pass	
2	Navigate to system setting					
3	Navigate to add room page					
4	Fill room name blank					
5	Click on save button					

Post-conditions:
room information is successfully inserted to the database.

Test Case # 3	
Test Case ID: Add an applaince-03	Test Designed by: <Salma, Nabaa, Maryam>
Test Priority (Low/Medium/High): High	Test Designed date: <3-5-2021>
Module Name: Add an appliance screen	Test Executed by: <Salma, Nabaa, Maryam>
Test Title: Adding new appliance information to the system	Test Execution date: <3-5-2021>
Description: Test Add appliance page	
Pre-conditions: User fills valid information of a new appliance	
Dependencies:	

Step	Test Steps	Test Data	Expected Result	Actual Result	Status (Pass/Fail)	Notes
1	After user log In	appliance Name: microwave	User should be able to add a new appliance	The system will display a confirmation. message " Data Added Successfully!!! "	Pass	
2	Navigate to system setting	Room id:2				
3	Navigate to add appliance page					
4	Fill details in their appropriate blanks					
5	Click on save Button					

Post-conditions:
Appliance information is successfully inserted to the database.

Test Case # 4	
Test Case ID: Add sensor-04	Test Designed by: <Salma, Nabaa, Maryam>
Test Priority (Low/Medium/High): High	Test Designed date: <3-5-2021>
Module Name: Add sensor screen	Test Executed by: <Salma, Nabaa, Maryam>
Test Title: Adding new sensor information to the system	Test Execution date: <3-5-2021>
Description: Test Add sensor page	
Pre-conditions: User fills valid information of a new sensor	
Dependencies:	

Step	Test Steps	Test Data	Expected Result	Actual Result	Status (Pass/Fail)	Notes
1	After user log In	sensor Name: Motion Sensor	User should be able to add a new Sensor	The system will display a confirmation. message " Data Added Successfully!!! "	Pass	
2	Navigate to system setting	appliance id:2				
3	Navigate to add sensor page					
4	Select the appropriate sensor from the dropdown list , and fill the blank by appropriate appliance id					
5	Click on save Button					

Post-conditions:
Sensor information is successfully inserted to the database.

Test Case # 5	
Test Case ID: View reports -05	Test Designed by: <Salma, Nabaa, Maryam>
Test Priority (Low/Medium/High): High	Test Designed date: <3-5-2021>
Module Name: View reports screen	Test Executed by: <Salma, Nabaa, Maryam>
Test Title: View reports	Test Execution date: <3-5-2021>
Description: Test view reports service	

Pre-conditions: User is able to view all rooms, appliances, and sensors that were added to the system.

Dependencies:

Step	Test Steps	Test Data	Expected Result	Actual Result	Status (Pass/Fail)	Notes
1	After user log In		The system will provide the user with the appropriate report.	The selected report will be generated	Pass	
2	Navigate to system setting					
3	Navigate and choose one to view rooms or appliances or sensors					

Post-conditions:
System will provide the admin with the appropriate report.

5.1 Recommender System

We have trained SVM to build a model that is able to recommend the next appliance. For better results, we trained and tested the data with and without the random_State parameter. We have recorded various accuracy measurements over different number of classes. Classes reflects the next appliance that will be recommended. The result is shown in table 4.

		Without Random_State parameter		With Random_State parameter	
		Training Data	Testing Data	Traning Data	Testing Data
No. Of classes	2	0.77	0.59	0.76	0.60
	3	0.73	0.57	0.74	0.53
	4	0.70	0.51	0.71	0.48
	5	0.61	0.40	0.63	0.39
	6	0.61	0.40	0.63	0.39
	7	0.60	0.40	0.61	0.40
	8	0.54	0.33	0.53	0.33
	9	0.54	0.33	0.53	0.33
	10	0.74	0.26	0.47	0.28
	11	0.43	0.22	0.44	0.21
	12	0.40	0.18	0.39	0.19

Table 4 Accuracy measurements during training and testing phases.

We have observed that training and testing the data with and without the random_State parameter reaches and approximate result of accuracy. We have found that as more appliances are added to the dataset, the accuracy goes down. We believe that it occurs due to the following reasons:

1) Sparsity of the matrix affects the performance of SVM.
2) High dimensionality and verity of classes.
3) Generation of huge and unique association rules causes the model to be trained improperly.

5.2 Comprehensive remarks on overall project outcome and achievements

5.2.1 Conclusions

In summary, we presented our ongoing work on HARMS. Our approach in implementing the recommendation system is to apply a data mining algorithm to find the association rules and train SVM to generate recommendation. We have shown the implementation of different parts of the system, including, interfaces, simulation environment, and hardware modules. Following that is a validation of the functionalities of the system's interfaces and attempting pass or fail situations.

5.2.2 Recommendations

Based on the result found out in our recommender system, we recommend looking for other algorithms such as Decision tree that can increase the prediction's accuracy to recommend the next appliance. Another improvement to our system is to compute the electric bill of the user. For future work, other researchers can find out how to include other users in the system to send appropriate recommendations to each home resident based on their daily activities and monitoring their usage. To achieve that, we suggest making use of advanced techniques such as Image Recognition or Biometrics (through the user's fingerprint) to identify each user's consumption while utilizing the home appliances.

5.3 Identified tasks and a realistic work plan

Table 5 shows the realistic work plan for the that we have followed throughout the project proposal and implementation, it shows milestone 1 until 5 tasks with their work timeline by weeks.

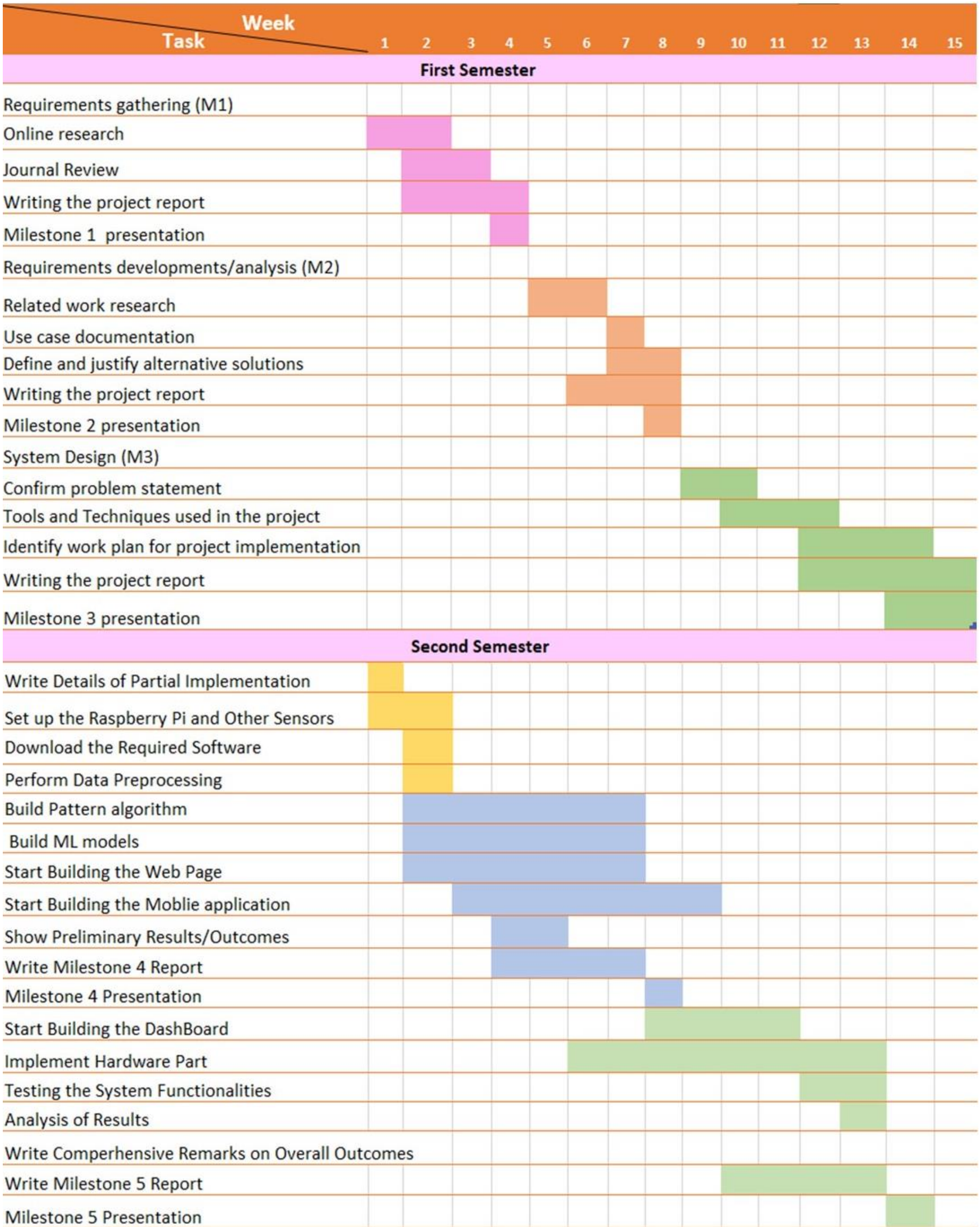


Table 5 The realistic work plan project for HARMS.

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