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Enhanced Secured Model for Smart Homes Using Human Activity Recognition and User Behaviour Analysis

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Enhanced Secured Model for Smart Homes Using Human Activity Recognition and User Behaviour Analysis

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ABSTRACT

This paper proffers a secured and cost effective solution for capturing data, translating this data into pre-labeled activities and then further categorizing these activities into behaviors which are either normal or abnormal based on a generated training dataset. In this research, a wooden smart home prototype was constructed with sensors and actuators in order to capture activities in the home. The sensors and actuators are interfaced with the Human Activity Recognition model which was developed using Gaussian Naïve Bayes algorithm. Output from the HAR model is passed as input into a second model which we refer to as the User Behaviour Analyser (UBA). The UBA was developed using the Support Vector Machine algorithm. This second model makes the final prediction of whether the home is safe or not based on its training. The solution is built around the raspberry Pi 4 computer board running the linux-based raspbian O.S. Experiments were performed on the developed system which gave an Accuracy of 95%, Precision 100%, Recall 92% and F1_Score of 96%.

Keywords; Activity Recognition, User Behaviour Analysis, Smart Home, Internet of Things, Security.

1. INTRODUCTION

Home Control Systems, what are also known as Smart Home Automation Systems, are designed to make almost all the daily tasks within a household electronic and easy to do. Gone are the days when we have to control the temperature, the climate of the house, the lighting, the water heater, the volume of the music, and so on by physically adjusting them with our hands. Today, we can accomplish all of those feats by a few simple touches on your mobile phone. Smart homes have long held the promise of making our everyday environments secure and productive. Individuals spend the majority of their time in their homes or workplaces and feel that these places are their sanctuaries. In order to preserve that feeling, smart homes can make use of technologies such as embedded sensors and machine learning techniques to detect, identify, and respond to potential threats. While stand-alone security systems have been used in homes for many years, they cannot make adequate use of the rich information that is available from sensors integrated throughout the home and algorithms that can reason about normal and abnormal behavior in the home. Dahmen *et al.,* (2017), introduced a smart-home based approach to home security.

This approach is built on the foundation of the smart home infrastructure developed at the Center for Advanced Studies in Adaptive Systems (CASAS), in which sensors are embedded in the environment. The sensors collect information about the state of the home and resident. The locations of each sensor are predefined in terms of functional areas of the home, which supports the creation of generalized activity models. Activity learning techniques use this information to identify and reason about routine or normal behavior in terms of recognized and forecasted activities. This identified behavior forms the basis for threat detection based on sensing abnormal behavior. Once the abnormal behavior is identified as a threat, the home selects an action to take as a response. Human activity recognition aims to recognize the actions and goals of one or more agents from a series of observations on the agents' actions and environmental conditions. (Musa *et. al.,* 2021). The activity recognition algorithm label activities based on the data that are collected from sensors in the environment. Once this information is provided, situations that are relevant to home security such as sleeping, entering/leaving the home, cooking, and performing activities that use valuable items can be easily recognized. The goal of an activity recognition algorithm is to map a sequence of sensor readings, or sensor events onto a value from a set of pre-defined activity labels. Activity recognition can be viewed as a type of supervised machine learning problem.

2. LITERATURE REVIEW

Samaneh and Cook (2019), mentioned that Activity learning encompasses valuable capabilities such as activity recognition, activity detection, activity segmentation and activity forecasting. Their research focused on activity segmentation or the problem of segmenting behavior based sensor data into sequences, each corresponding to a single activity. They propose a novel transition-aware activity segmentation approach which identifies the transition between activities by detecting change points in the corresponding time series-based data. This change point detection technique is effective for behavior-driven sensor data analysis and they showed that using such technique can identify where the sensor data of one activity ends and another begins. They hypothesized that activity segmentation can improve the performance of activity recognition on non-scripted activities by distinguishing activity boarders and integrating features related to the entire activity segment.

Dahmen *et al.,* (2017), introduced a smart home approach to home security. Their approach is built on the foundation of the smart home infrastructure at the Center for Advanced Studies in Adaptive Systems (CASAS) in which sensors are embedded in the environment. The smart home senses, identify, assess and act functions in a continuous cycle. Dahmen et al also used CASAS activity learning algorithms. By monitoring for activity-based anomalies, they were able to detect possible threats and take appropriate actions. Their proposed method was evaluated and it was able to demonstrate the partnership between activity-aware smart homes and biometric devices in the context of the CASAS on-campus smart apartment testbed. Wang et. al., (2009), designed a smart home monitoring and control system. The home can be controlled from remote locations through an embedded controller. The authors have developed different GUIs for mobile devices and PCs. Each device has a unique address and a new command format to control the devices was introduced. Although the existing protocols can be adequately used in this scenario, the researchers proposed a new protocol with a new command name. Serge and Younghwan (2015) discussed the possibility of recognizing and predicting user activities in the IoT (Internet of Things) based smart environment. They tried to find the best combination of a pattern clustering method and an activity decision algorithm amongst various works.

They used K-pattern clustering algorithm to classify varied activities and in the second phase of their system, they utilized artificial neural network based on Allen's temporal relations. Their experimental results showed that their combined method provides higher recognition accuracy for various activities as compared with other data mining classification algorithms. Abubaker *et al.,* (2019) used statistical aggregation techniques to handle the measurement of changes in different domains. The first phase of their framework is data collection and preprocessing, the second phase is data analysis using trend analysis techniques and in the third phase of the development, data created from the trend analysis is standardized to a uniform unit of measurement and then aggregated. They were able to quantify progressive changes for individual and aggregated activities. Their experimental results showed that their proposed approach can identify and distinguish normal and abnormal behaviours.

Darpan et. al., (2019) mentioned in their research 'A semantics-based approach to sensor data segmentation in real-time Activity Recognition' that although several studies have proposed methods of separating and organizing sensor observations and recognize generic Activities of Daily Living (ADLs) performed in a simple or composite manner, little has been explored in semantically distinguishing individual sensor events directly and passing it to the relevant ongoing activity. They proposed a semiotic theory inspired ontological model capable of capturing generic knowledge and inhabitant-specific preferences for conducting ADLs to support the segmentation process. They also developed a multithreaded decision algorithm system prototype. Their system was tested and the results showed that all sensor events were adequately segmented with 100% accuracy for single ADL scenarios and 97.8% for composite ADL scenarios.

3. MATERIALS AND METHODS

3.1 Architecture of Our System

The architecture of the smart home prototype system is as shown in figure 1 below.

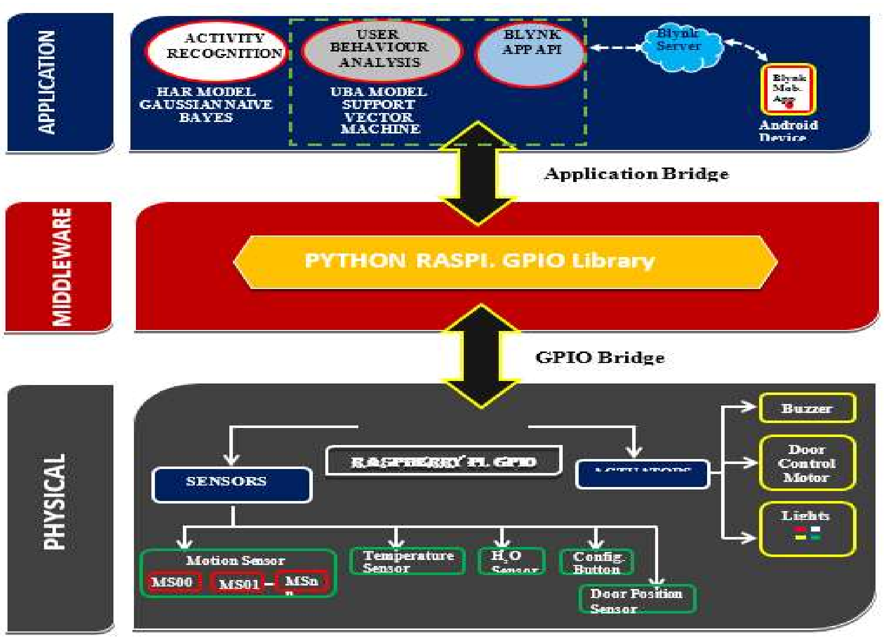

Figure 1: Architecture of the smart home prototype

The Physical Layer

The physical layer is made up of the Raspberry Pi board, the sensors and the actuators. Sensors include the motion sensors, temperature sensor, water sensor, the door position sensor and the configuration button. The actuators include the buzzer, the door control motor and the light bulbs. Sensors and actuators are connected to the Raspberry Pi board which is the micro controller.
The sensors and other effectors are wired with the GPIO (General Purpose Input and Output) pins of the raspberry pi 4 board. In this layer, data collected from the sensors serve as the inputs to the smart home system. The Raspberry Pi board is responsible for data processing. It is a single board which has the following features;

- CPU comprising of 1.5-GHz Broadcom BCM2711B0 (Cortex-A72) processor.
- 1 GB DDR4M RAM.
- 2 Nos. USB 2.0 and 3 Nos. USB 3.0 Ports.
- 500 MHz VideoCore VI GPU
- Dual Micro HDMI Ports.
- 1 Nos. Gigabit 330mbps Ethernet port.
- 802.11 ac (2.4/5GHz) WiFi and Bluetooth 5.0.

The Middleware Layer

This is the service and application support, network and communication layer. It is made up of the Raspbian Operating System running on the Raspberry Pi board, the General Purpose Input and Output (GPIO) library, the Blynk Library and Wifi.

The Raspbian OS is a Linux variant. Linux computers use text-based command-line interfaces called shell to manage and administer their servers. Since the Raspberry Pi's OS (Raspbian) is a Linux variant, the most natural way to access and issue commands or check the status of running programs, services, and different servers on the Raspberry Pi is by issuing commands on this text-based shell. There are different shell implementations but the one that is used on Raspbian by default is bash. The most well-known way of accessing shell remotely on a Linux server is through the Secure Shell protocol known, in general, as SSH. Secure Shell (SSH) is an encrypted network protocol used to send shell commands to a remote machine in a secure way.

It does two things;

1. It enables the sending of commands to a remote machine through different available tools such as the one that would be present in this project.
2. It does the sending through a secure channel established over an insecure network.

For SSH to work, there should be an SSH server already running that can accept and respond to SSH client requests. On the Raspberry Pi, this feature was enabled. The client side in this communication link is the Smart Home Android application which is running the latest version of SSH on Android. The Raspberry Pi board of the smart home system is connected to an internet enabled WiFi service via its embedded WiFi module and configured using an external IP address. This is achieved by adding the standard FTP port 21 and 20 to the port forwarding settings of the WiFi. The wifi serves as the gateway network. The GPIO libraries are also imported as part of the middleware layer. The Pi interfaces directly with sensors and actuators alike through its GPIO (General Purpose Input and Output) pins. RPi. GPIO libraries are responsible for this.

The Blynk Library is also imported as part of the middleware layer. Blynk is an IoT platform for businesses and developers. It is a hardware-agnostic platform with white-label mobile apps, private clouds, device management, data analytics and machine learning. Rather than build IoT Applications from the scratch, developers configure Blynk's Application to their own App and then write a script that will be communicating with the Blynk server which will in turn be communicating with one's Mobile App. Blynk Mobile App was configured to serve in this project as the mobile App. Settings were configured in the App for buttons that will be controlling real life physical 'things' in the home such as the bulb, alarm, light etc. It also sends notifications as well. The Blynk python library contains functions and methods used in interfacing with the blynk server in the cloud, hence the need to import the Blynk library.

The Application Layer

This layer is made up of the various algorithms and models that make the home smart. This includes the Human Activity Recognition (HAR) model which was implemented using the Gaussian Naïve Bayes algorithm and the User Behavior Analyzer (UBA) Model which was implemented using Support Vector Machine (SVM). Details of these models are discussed in the next section.

3.2 The Human Activity Recognition Model

The Smart Home System processes sensor information for Human Activity Recognition (HAR). In this research, Gaussian Naïve Bayes algorithm was used to develop a model to process data received from sensors into labeled Human Activities. The activities are labeled with unique names which will also aid the UBA processes. Table 1 shows the constructed activities for the smart home.

Table 1: Smart Home Activity Construction

S/N	ACTIVITY NAME	ASSOCIATED SENSORS	IDENTITY	HAR/ UBA LABEL
1.	Home Entry	MS00, MS01	HEN	HEN
2.	Kitchen Entry	MS06, MS07	KEN	KEN
3.	Rest Room Entry	MS04, MS05	REN	REN
4.	Home Exit	MS00, MS01	HEX	HEX
5.	Kitchen Exit	MS06, MS07	KEX	KEX
6.	Rest Room Exit	MS04, MS05	REX	REX
7.	Sleeping	MS00, MS01, MS04, MS05, MS06, MS07, MS08	SNG	SNG
8.	Eating	TS09, MS06, M507, MS02	ENG	ENG
9.	Bathing	MS04, MS05, WS10	BNG	BNG
10.	Cooking	MS06, MS07, TS09	CNG	CNG

S/N	ACTIVITY NAME	ASSOCIATED SENSORS	IDENTITY	HAR/ LABEL	UBA
11.	Studying	MS00, MS01, MS04, MS05, MS06, MS07, **MS02**	DNG	DNG	
12.	Stooling	MS04, MS05, **MS03**	LNG	LNG	
13.	Clothing Activity (Dressing up or undressing).	MS00, MS01, MS04, MS05, MS06, MS07, **MS11**	CAY	CAY	

Table 1 has 4 columns, serial number, Activity Name, sensors associated with each activity, and the HAR identity which is the name with which the activity will be referenced or identified in the HAR model. In all, there are 13 different activities that are recognized by the Smart Home as shown on the table 1. They are Home Entry, Kitchen Entry, Rest Room Entry, Home Exit, Kitchen Exit, Rest Room Exit, Sleeping, Eating, Bathing, Studying, Stooling and Clothing Activity. The associated sensors refer to the sensors installed in the area of the Home where an activity is taking place. Each activity can only take place in one area of the home, however a sensor can be associated with more than one activity. All Activities that are modelled and their associated sensors are as seen on table.

Highlighted sensors output 1 for that activity to be recognized by the HAR model. For example, in the first row of table 1, the highlighted sensor is MS01, this implies that MS01 output 1 for the activity Home Entry (HEN) to take place. All the other sensors are either found in that area of the home or are likely to be associated with that activity. For example, in serial number 7, the activity 'sleeping', all these sensors MS00, MS01, MS02, MS11 and MS08 are found in the living area where the sleeping activity takes place, however, MS08 is the particular sensor associated with sleeping activity and should output 1 for the sleeping activity to take place. WS01, WS01 is highlighted because it is a water sensor close to the shower as seen in figure 3.4 and should sense water flow from the shower during bathing.

The Stooling activity (LNG) has the associated sensors MS04, MS05 and MS03, MS03 is highlighted and expected to output 1 for the activity to occur as it is the motion sensor closest to the water closet. The Clothing activity (CAY) involves either dressing or undressing and its associated sensors are MS00, MS01, MS02 and MS11. However, MS11 is highlighted and is expected to output 1 for the activity to occur, it is the sensor located at the wardrobe area as seen in Table 1. The Human Activity Recognition problem is a classification problem. The features and labels are as identified in Table 2. The sensor labels in Table 2 represent the features while the Activity column represent the class labels. The model reads binary data as input from the sensors and fit it into the trained Gaussian naïve HAR classifier to predict an output which is the recognized activity. The HAR training dataset is as shown in Table 2.

Table 2: HAR Training Dataset

MS00	MS01	MS06	MS07	MS04	MS05	MS02	MS03	MS08	TS09	WS10	MS11	ACTIVITY
1	0	0	0	0	0	0	0	0	0	0	0	Hex
0	1	0	0	0	0	0	0	0	0	0	0	Hen
0	0	1	0	0	0	0	0	0	0	0	0	Kex
0	0	0	1	0	0	0	0	0	0	0	0	Ken
0	0	0	0	0	1	0	0	0	0	0	0	Ren
0	0	0	0	1	0	0	0	0	0	0	0	Rex
0	0	0	0	0	0	0	0	1	0	0	0	Sng
0	0	0	0	0	0	1	0	0	1	0	0	Eng
0	0	0	0	0	0	0	0	0	0	1	0	Bng
0	0	0	0	0	0	0	0	0	1	0	0	Cng
0	0	0	0	0	0	1	0	0	0	0	0	Dng
0	0	0	0	0	0	0	1	0	0	0	0	Lng
0	0	0	0	0	0	0	0	0	0	0	1	Cay

The following necessary steps were taken in building the HAR model;

- Define the dataset.
- Encode the features.
- Combine all features into a list of tuples.
- Generate and evaluate the model.

3.3 The User Behavior Analyzer (UBA) Model

The output from the HAR classifier are merged with the other features such as time and week day stamp, previous first activity and previous second activity to form the input features for the UBA classifier. In this research, the user behavior is described as different combination of possible outcomes based on a valid sequence of activities generated from the Human Activity Recognition Model. The rules for constructing the training dataset is as shown in table 3. Sample of the training dataset for the UBA model is as shown in Table 4.

Table 3: Rules for constructing the UBA training dataset.

S/N	ACTIVITY	ACTIVITY MEANING	NEXT POSSIBLE ACTIVITY
1.	HEN	Home Entry	KEN, REN, HEX, SNG, DNG, CAY
2.	KEN	Kitchen Entry	CNG, KEX
3.	KEX	Kitchen Exit	SNG, CAY, DNG, REN, HEX, ENG
4.	CNG	Cooking	HEX
5.	HEX	Home Exit	HEN
6.	REN	Rest Room Entry	LNG, BNG, REX
7.	LNG	Stooling	BNG, REX
8.	BNG	Bathing	LNG, REX
9.	REX	Rest Room Exit	SNG, CAY, DNG, HEX
10.	SNG	Sleeping	KEN, REN, CAY, DNG, HEX
11.	CAY	Clothing Activity	DNG, HEX, SNG, REN, KEN
12.	DNG	Studying	HEX, CAY, REN, HEN, SNG
13.	ENG	Eating	KEN, SNG, REN, CAY, HEX

Table 3 has four columns, serial nmber, activity, activity description, next possible activity and thirteen rows which represents features to the UBA model. The list of the activities on the Next possible activity column are activities that can possibly occur after the one on the activity column has taken place. For instance, in serial no. 1, after HEN (Home Entry), KEN, REN, HEX, SNG, DNG and CAY are the activities that can occur. Outside these activities, any other activity occurring after Home Entry (HEN) will lead to abnormality.

Table 4: Sample of the UBA training dataset.

Weekday	Day Hour	Current Activity	Previous 1 Activity	Previous 2 Activity	Normality
Sunday	0	Dng	Kex	Bng	No
Sunday	3	Sng	Lng	Ren	Yes
Sunday	7	Hex	Cay	Kex	Yes
Sunday	9	Hen	Hex	Kex	Yes
Sunday	16	Kex	Ken	Eng	Yes
Monday	1	Dng	Hen	Eng	No
Monday	5	Lng	Ren	Kex	Yes
Monday	8	Eng	Kex	Cng	Yes
Monday	11	Hex	Rex	Cay	Yes
Monday	18	Hen	Hex	Dng	Yes
Tuesday	1	Sng	Dng	Kex	Yes
Tuesday	4	Rex	Bng	Ren	Yes
Tuesday	8	Cay	Hen	Lng	No
Tuesday	16	Hex	Dng	Bng	No
Tuesday	21	Ken	Eng	Hex	No
Wednesday	0	Ren	Sng	Eng	Yes
Wednesday	4	Sng	Kex	Ken	Yes
Wednesday	9	Hex	Cay	Dng	Yes
Wednesday	18	Cay	Rex	Lng	Yes
Wednesday	22	Kex	Cng	Ken	No

The five input features are Hour (hour of the day), Day (day of the week), Current Activity (current activity input), Previous 1 Activity (1st previous activity), and Previous 2 Activity (2nd previous activity). Normality which is either Yes or No is the classification. As seen on table 4, on Sunday by 0hr i.e by 12.00am, Current Activity is Dng(Studying), Previous 1 Activity is Kitchen Exit and Previous 2 Activity is Bng(Barthing). The combination of these five inputs results in 'No', meaning that it is abnormal to have this sequence of events. On the second row, still on Sunday between 3am and 7am, Current Activity is sleeping, Previous 1 Activity is Stooling and Previous 2 Activity is Rest Room Entry and the outcome of these sequence of activities at this time of the day as determined by the home occupant is 'Yes', meaning that this is his/her normal behavior pattern and there is no anomaly.

Once there is a change in the state of any of the sensors, it generates an interrupt which triggers the HAR to run. The HAR runs and analyses the sensor input which it interprets to an activity. This is automatically saved as the 'Current Activity'. The initial current activity is shifted to 'Previous1Activity' and the initial Previous1Activity is shifted to 'Previous2Activity' and the initial Previous2Activity is discarded as it is no longer needed. During implementation, the HAR and UBA algorithms are combined on a single script, which runs on the Raspberry Pi. This enables the output from the HAR to be passed as input to the UBA.

Once the UBA model is executed and the outcome is 'Yes', it means that the Home is normal and there are no security threats. When the outcome of a prediction is 'No', it means that there are inconsistent activities going on in the Home and the security alert is triggered. The support vector machine was used in developing the model taking the following steps:

- Import the dataset
- Classifying the predicators and target.
- Initializing Support Vector Machine and fitting the training data.
- Predicting the classes based on input from the HAR model.
- Comparing actual classes and predictions.
- Calculating the accuracy of the predictions.

3.4 Components Integration

Figure 2 shows the various components of the system and how they are integrated.

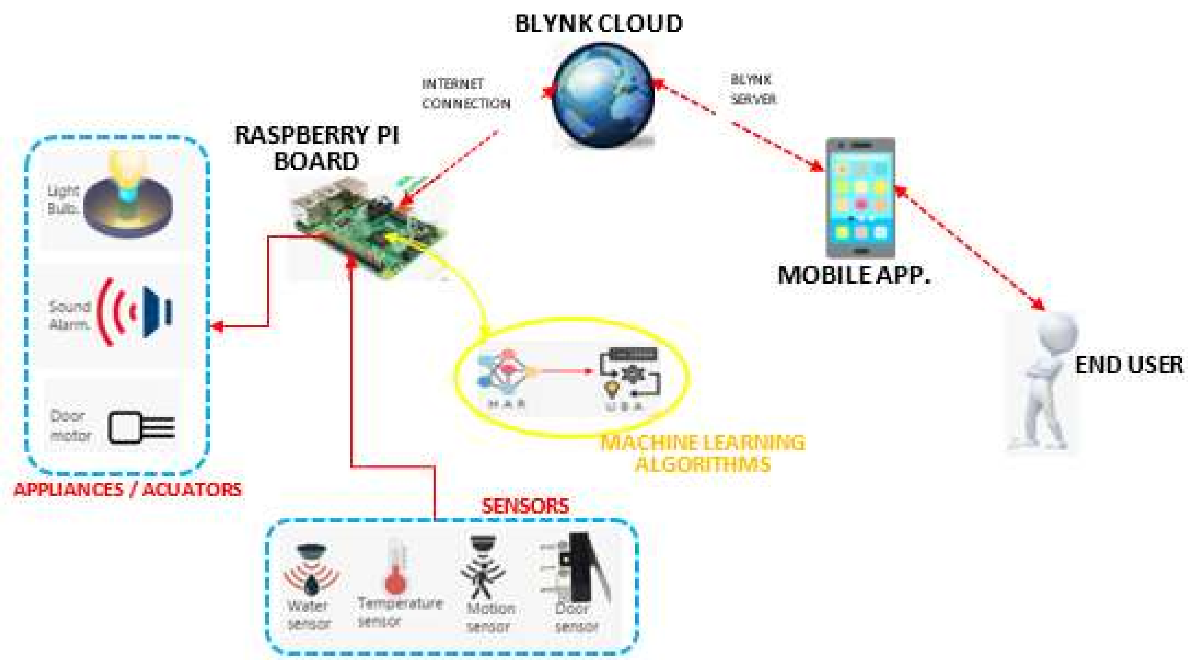

Figure 2: Device and components integration.

The ninth step in the IoT design methodology is the integration of the devices and components. The various devices including all hardware of our system would be integrated and synced with the mobile application for best functionality. The system is built around the Raspberry Pi 4 board running Linux-based Raspbian OS. Motion sensors and other effectors were interfaced with the general purpose input/output (GPIO) pins of the Pi for collating information about the home and residents. The information is passed on to the machine learning HAR algorithm, then the machine learning UBA algorithm for anomaly evaluation. Whenever an anomaly situation is decided, the home system responds through notification to home system's mobile application of original residents or an audible alarm. Figure 2 shows the component integration of the system.

The sensors (water, temperature and motion) are interfaced with the processor i.e. the Raspberry Pi board. The appliances and actuators (light bulb, sound alarm or buzzer and door motor) are also interfaced with the processor via the GPIO pins on the Raspberry Pi board. The machine learning algorithms (HAR and UBA) are also integrated into the Pi board. The Home owner or end user uses the configured Blynk Mobile App to communicate with the Pi board through internet connectivity. The Pi board sends messages to the end user through the blynk server. Connection to the blynk server is via the internet. Figure 3 shows the complete system installed on the desktop wooden home.

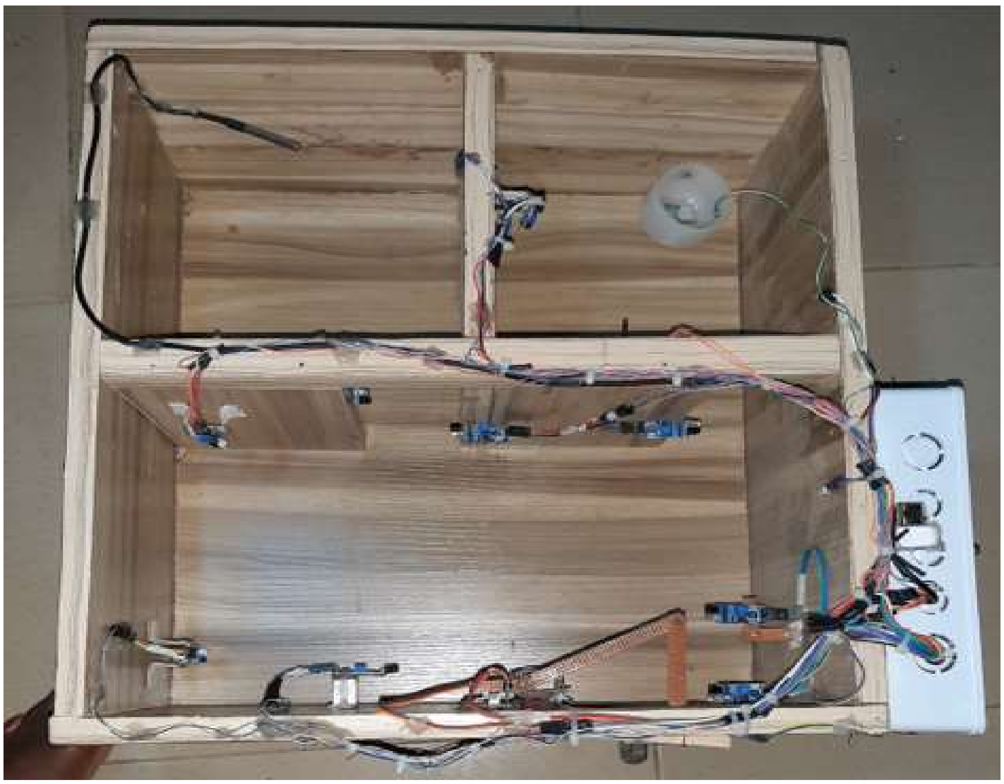

Figure 3: The modelled desktop wooden home.

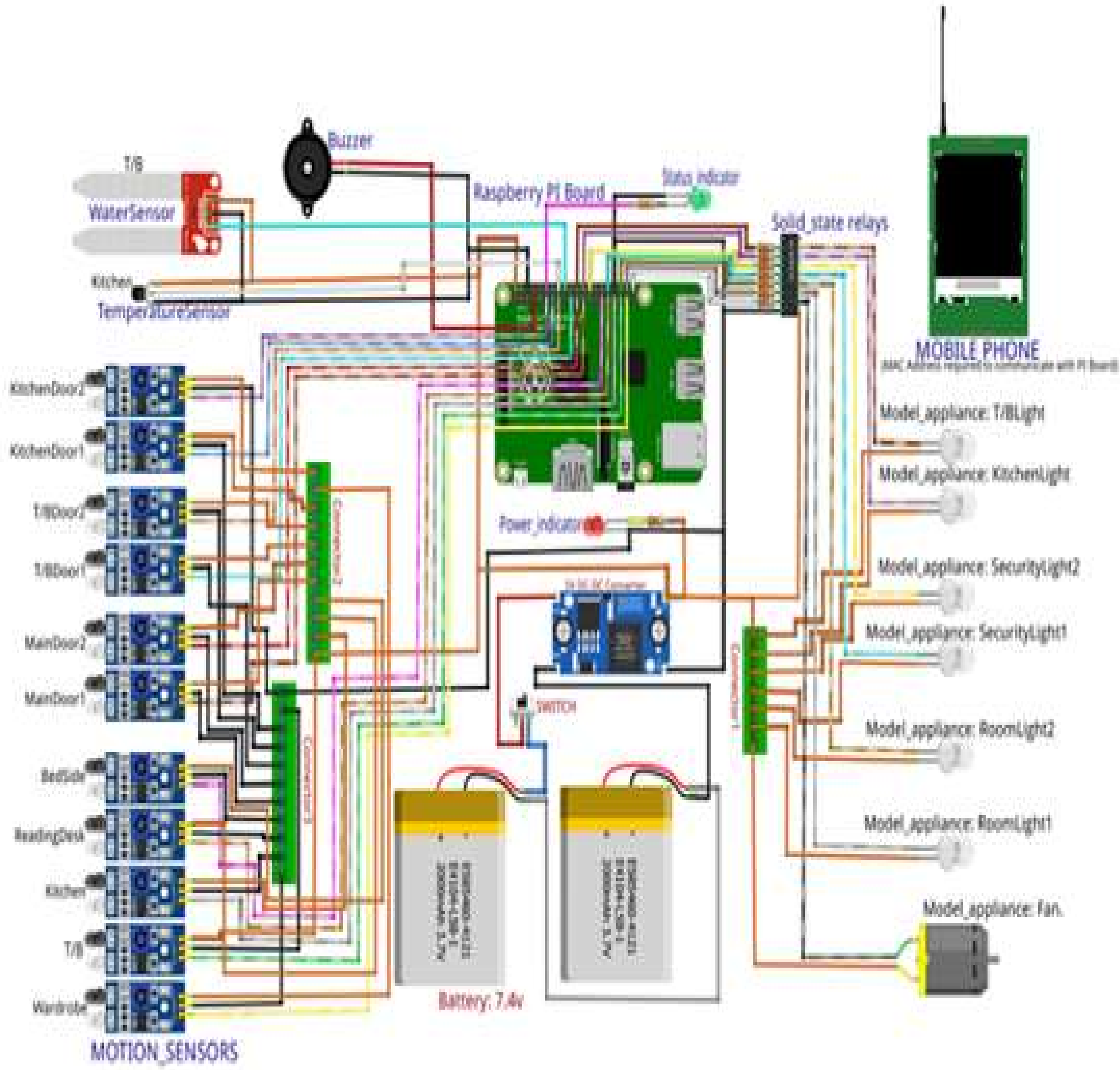

Figure 4: The System Circuit Diagram.

The circuit above is built around the Raspberry Pi 4 board with 40 general purpose Input/Output (GPIO) pins. Based on system architecture, the sensors are needed to take inputs for the Machine Learning Algorithms via the GPIO's of the Pi board.

The circuit representation of the system is according to the following

1. Power Supply
2. Sensors (Input devices)
3. Actuators (Output devices)

Power supply section provides electrical power needed for the system to carry out its functionalities. The electronics components that make up the system power supply are the Batteries (or a 12V DC power adapter), power switch, DC-DC Buck converter and Power Indicator LED. The batteries are voltage sources to the system while the power switch provides means to control (On/Off) the flow of power. Voltage supplied by the batteries is higher than is required by system, hence the inclusion of the Dc-Dc buck converter to step down the voltage from batteries to 5v which is sufficient for the Pi board and other components. The power indicator LED lights up to show the presence of power in our system.

Sensors in this circuit includes motion sensors, water sensor and temperature sensor. The motion sensors are situated at entrance doors and other strategic points within the apartment. For motion sensing at the entrance doors, each door has two motion sensors to enable direction of motion detection. As shown in the wire connections, output pins from the motion sensors are connected to GPIO pins of the Raspberry Pi (GPIO2, GPIO3, GPIO9, GPIO11, GPIO22, GPIO10, GPIO17, GPIO0, GPIO6, and GPIO27). The water sensor which has 3 pins is installed in the bathroom to sense water presence on the flow. Output pin from the water sensor is connected to GPIO5 of the Raspberry Pi. This pin would turn to 5V (HIGH) whenever water gets in contact with the sensing surface. The temperature sensor is installed in the kitchen to monitor heat and is connected through wires as shown with the GPIO4 pin of the raspberry Pi.

Actuators or output devices in this circuit are Lights, status LED and buzzer. The solid state relay shown enables the Raspberry pi to conveniently control these home appliance representations by meeting the current requirements of these devices. With the solid state relay, the Raspberry pi GPIO pin associated with an appliance only provides the control signal needed for switching while the solid state relay provides the current. The appliances are connected with wires to the Raspberry Pi board on GPIO7, GPIO8, GPIO12, GPIO16, GPIO20, GPIO21, and GPIO25. The buzzer which is connected to GPIO15 provides sound alert as would be required in security situations. While the status LED connected to GPIO19 of the Pi board shows system activity in progress or completion.

4. EXPERIMENTATIONS AND RESULTS

Experiments were carried out to test the functionalities of the smart home prototype. This was done by triggering the sensors with life objects, for example, the human hand. The results generated are shown in Table 5.

Table 5: Experimental Results

S/N	PREVIOUS ACTIVITY 2	PREVIOUS ACTIVITY 1	CURRENT ACTIVITY	EXPECTED OUTPUT	PREDICTION	ALERT	NOTIFICATION
1	REN	LNG	SNG	YES	YES	MOVEMENT UPDATE	HOME IN GOOD CONDITION
SENSORS TRIGGERED	MS05	MS03	MS08				
2	LNG	SNG	KEX	YES	YES	MOVEMENT UPDATE	HOME IN GOOD CONDITION
SENSORS TRIGGERED	MS03	MS08	MS06				
3	SNG	KEX	CAY	NO	NO	SECURITY ALERT	ANOMALY CONDITION DETECTED
SENSORS TRIGGERED	MS08	MS06	MS11				
4	KEX	CAY	HEX	YES	NO	SECURITY ALERT	ANOMALY CONDITION DETECTED
SENSORS TRIGGERED	MS06	MS11	MS00				
5	CAY	HEX	KEX	NO	NO	SECURITY ALERT	ANOMALY CONDITION DETECTED
SENSORS TRIGGERED	MS11	MS00	MS06				
6	HEX	KEX	HEX	NO	NO	SECURITY ALERT	ANOMALY CONDITION DETECTED
SENSORS TRIGGERED	MS00	MS06	MS00				
7	KEX	HEX	HEN	YES	YES	MOVEMENT UPDATE	HOME IN GOOD CONDITION
SENSORS TRIGGERED	MS06	MS00	MS01				
8	HEX	HEN	KEN	YES	YES	MOVEMENT UPDATE	HOME IN GOOD CONDITION
SENSORS TRIGGERED	MS00	MS01	MS07				
9	HEN	KEN	KEX	YES	YES	MOVEMENT UPDATE	HOME IN GOOD CONDITION
SENSORS TRIGGERED	MS01	MS07	MS06				
10	KEN	KEX	ENG	YES	YES	MOVEMENT UPDATE	HOME IN GOOD CONDITION
SENSORS TRIGGERED	MS07	MS06	MS02				
11	KEX	ENG	HEN	NO	NO	SECURITY ALERT	ANOMALY CONDITION DETECTED
SENSORS TRIGGERED	MS06	MS02	MS01				
12	ENG	HEN	DNG	NO	NO	SECURITY ALERT	ANOMALY CONDITION DETECTED
SENSORS TRIGGERED	MS02	MS01	MS02				
13	HEN	DNG	KEX	YES	YES	MOVEMENT UPDATE	HOME IN GOOD CONDITION
SENSORS TRIGGERED	MS01	MS02	MS06				
14	DNG	KEX	REN	NO	NO	SECURITY ALERT	ANOMALY CONDITION DETECTED
SENSORS TRIGGERED	MS02	MS06	MS05				
15	KEX	REN	LNG	YES	YES		
SENSORS TRIGGERED	MS06	MS05	MS03			MOVEMENT UPDATE	HOME IN GOOD CONDITION
16	REN	LNG	REX	YES	YES	MOVEMENT UPDATE	HOME IN GOOD CONDITION
SENSORS TRIGGERED	MS05	MS03	MS04				
17	LNG	REX	CAY	YES	YES	MOVEMENT UPDATE	HOME IN GOOD CONDITION
SENSORS TRIGGERED	MS03	MS04	MS11				
18	REX	CAY	DNG	YES	YES	MOVEMENT UPDATE	HOME IN GOOD CONDITION
SENSORS TRIGGERED	MS04	MS11	MS02				
19	CAY	DNG	BNG	NO	NO	SECURITY ALERT	ANOMALY CONDITION DETECTED
SENSORS TRIGGERED	MS11	MS02	WS10				
20	DNG	BNG	REX	NO	NO	SECURITY ALERT	ANOMALY CONDITION DETECTED
SENSORS TRIGGERED	MS02	WS10	MS04				

Table 4 shows the results obtained from the experiments conducted on the smart home prototype. In serial number 1, the first activity carried out was REN (Rest Room Entry), and the sensor responsible for this activity is MS05, which was triggered. The home owner receives a 'Movement Update' alert on his/her mobile device and on the notification details he or she receives a 'Home in good condition'. The second activity carried out is LNG (Stooling). This was done by triggering the sensor MS03 which is responsible for the stooling activity. REN becomes previous activity1 while LNG becomes Current Activity. The home owner receives a 'Home in good condition' alert. MS08 was triggered next to carry out the third activity, SNG (Sleeping). This sequence of activities: REN, LNG, SNG (i.e. Previous activity2, previous activity1, current activity) form a recognized pattern which is referred to as a behavior. Based on the training dataset, the expected output is a YES (meaning that the behavior is normal and the home is safe).

The experimental result which is a UBA prediction is also a YES, which means the prediction is correct. The home owner receives an alert of 'movement update' on his or her mobile device and a 'home in good condition' notification. This notification is same for all instances of the experiment where the user behavior is normal and there are no security threats. For serial number 3, MS11 was triggered representing CAY and it became the current activity, KEX which was the initial current activity became previous activity1 and SNG which was the initial previous activity1 became previous activity2 and LNG which was the initial previous activity2 was automatically discarded. The expected output for the series of activities SNG, KEX, CAY forming a behavior is a NO. The classifier predicted correctly, indicating that an anomaly is detected. A message is sent instantly to the home owner alerting him or her of security threats. In serial number 4, MS00 representing HEX (Home Exit) was triggered. HEX is the current activity, CAY became previous activity1 and KEX became previous activity2. The expected output is YES according to the training dataset but the prediction resulted in a NO, which is a wrong prediction. However, a security alert is sent to the home owner. Same explanation is applicable to the other rows of table 4.

Using the confusion matrix as a performance metrics, of the 20 experiments that were performed, the True Negative (TN) were 8, the False Negatives (FN) was 1, False positive (FP) was 0 and True Positives (TP) was 11. This resulted in the prediction accuracy of 95%, precision of 100%, Recall of 92% and F1_Score of 96%. This obviously proved that the developed system can provide security to about 95% in smart home which is good and will be acceptable in all standards.

5. CONCLUSION

In this research, a smart home based approach to home security was implemented in the smart home prototype, where the smart home makes use of activity recognition in order to transform the system into one that is activity aware. These activities are further categorized into behaviors which form the basis of whether the home is safe or not. This is a cost effective solution with the design of Human activity recognition (HAR) and User behavior analysis (UBA) models. The research developed two models, one that is capable of capturing sensor data and translating into human activities and the other which is able to predict if the grouped activities which is referred to as a behavior is normal or abnormal which stands as a measure to identify the security state of the home.

REFERENCES

1. Abubaker Elbayoudi, Ahmad Lotfi and Caroline Langensiepen (2018). The Human Behaviour Indicator: A Measure of Behavioural Evolution. *Expert Systems with Applications.* 118. 493-505.
2. Aminikhanghahi S. and Cook D. J. (2019). Enhancing Activity Recognition using CPD-based Activity Segmentation. *Pervasive and Mobile Computing.* 53. 75-89.
3. Amira Ben Mabrouk and Ezzeddine Zagrouba (2018). Abnormal Behaviour Recognition for Intelligence Video Surveillance Systems: A Review. *Expert Systems with Applications.* 91. 480-491.
4. Dahmen Jessamyn, Brian L. Thomas, Diane J. Cook and Xiaobo Wang (2017). Activity Learning as a Foundation for Security Monitoring in Smart Homes. *Sensors.* 17(737). 1-17.
5. Darpan Triboan, Liming Chen, Feng Chen and Zumin Wang (2019). A Semantics-based Approach to Sensor Data Segmentation in Real-time Activity Recognition. *Future Generation Computer Systems.* 93. 224-236.
6. Musa M. O., Ugwu C. and Onyejegbu L. N. (2021). Guassian Naïve Sensor-Based Approach for Activity Recognition. *Global Scientific Journals.* 9(8). 882-894.
7. Serge Thomas Mickala Bourobou and Younghwan Yoo (2015). User Activity Recognition in Smart Homes Using Pattern Clustering Applied to Temporal ANN Algorithm. *Sensors.* 11953-11971. doi:10.3390/s150511953.
8. Wang Z., Wei S., Shi L., (2009). The Analysis and Implementation of Smart Home Control System. *Proc. Conf. Information Management and Engineering.* 546-549.