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GUASSIAN NAÏVE SENSOR-BASED APPROACH FOR ACTIVITY RECOGNITION.

Musa Martha Ozohu
Department of Computer Science
University of Port Harcourt
Port Harcourt, Nigeria
martha.musa@uniport.edu.ng

Prof. Ugwu Chidiebere
Department of Computer Science
University of Port Harcourt
Port Harcourt, Nigeria
chidiebere.ugwu@uniport.edu.ng

Prof. Onyejegbu Laeticia Nneka
Department of Computer Science
University of Port Harcourt
Port Harcourt, Nigeria
laeticia.onyejegbu@uniport.edu.ng

ABSTRACT

A smart home is a standard residence that is equipped with sensors and actuators in order to provide services to occupants. One of the key aspects of smart home is the identification of activities performed by residents. In this paper, a wooden smart home prototype was constructed with sensors and actuators in order to capture activities in the home. The motion sensors in the smart home are interfaced with the Human Activity Recognition (HAR) model which was developed using Gaussian Naïve Bayes algorithm. The solution is built around the raspberry pi 4 computer board running the linux-based Raspbian Operating System. The sensors water, temperature and motion and actuators light bulb, sound alarm or buzzer and door motor were interfaced with the processor via the GPIO pins on the Raspberry Pi board. The HAR model is also integrated into the Pi board. The system was implemented with python programming language with tools from Scikit-Learn library. Experiments were performed on the developed system to test its ability to predict activities and the results of its predictions were evaluated using the confusion matrix.

KEYWORDS

Activity Recognition, Smart Home, Sensors, Actuators, Internet of Things(IoT).

1.1 INTRODUCTION

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 the environmental conditions.

One of the prominent applications of the IoT is the smart home. Smart homes are buildings and homes which are automated and can be controlled from a remote site. Lights, AC and Fans and other household equipment can be controlled from a far distance location via the internet. This leads to energy optimization as lights or resources which were accidentally leave on can be switched using the IoT technology. In this paper, we define the smart home as one that is context aware, provides home automation, is intelligently controlled and can be controlled remotely to assist the occupant carry out his or her activities of daily living.

Data capturing from the so called "things' is essential to make home automation and control realizable, these captured data is processed into meaningful information which eventually control the 'things'. This is where Activity Recognition comes into play in smart homes.

We can think about data generated by an IoT device as going through three separate phases. The first phase is the data creation itself. This phase takes place on the level of the IoT device from where the data is transmitted over a network. The second phase of the journey of IoT data is that of collection and organization. The third phase involves the actual use of the data. This is the process of making the data valuable for different uses such as research, modelling of data for making predictions etc.

To achieve this, we developed a smart home prototype with sensors and actuators mounted on it. These sensors and actuators capture data which are mapped to some predefined activity labels. This is the goal of activity recognition. We achieved this using the supervised machine learning approach, we trained our model with the sensor data as input features and the labelled activities as expected outputs. This has to do with the first two phases mentioned above.

A secure smart home is valuable for monitoring the state of the home when the resident has left. An activity-aware smart home can recognize when the resident has left and when a person enters the home. For this type of security monitoring, a camera can also be used to perform face recognition on individuals who enter the residence. However, many residents do not want a camera monitoring them continuously. Additionally, face recognition techniques encounter difficulties when the person is obstructed, wearing a face mask or there are poor lighting conditions. Hence the need for recognizing human activities from sensor readings which are can be used to secure the home, which is relatively cheap to implement.

Gaussian Naive Bayes is based on Bayes' Theorem and has a strong assumption that predictors should be independent of each other. This assumption is called class conditional independence. It is a simple but powerful algorithm for predictive modeling under supervised learning algorithms. It is simple, fast in processing, and effective in predicting the class of test dataset. So it is useful in making real-time predictions, as it is required in smart homes, hence the reason why it is chosen for this research. It does well with few samples for training when compared to other models like Logistic Regression.

2.1 RELATED WORK

The following papers were reviewed in the course of this paper and are streamlined as follows;

Akram et. al., (2014), in their paper titled 'A Study on Human Activity Recognition Using Accelerometer Data from Smartphones' described how to recognize certain types of human physical activities using acceleration data generated by a user's cell phone. They proposed a recognition system in which a new digital low-pass filter is designed in order to isolate the component of gravity acceleration from that of body acceleration in the raw data. The system was trained and tested in an experiment with multiple human subjects in real-world conditions. Several classifiers were tested using various statistical features. High-frequency and low-frequency components of the data were taken into account. They selected five classifiers each offering good performance for recognizing their set of activities and investigated how to combine them into an optimal set of classifiers. They found that using the average of probabilities as the fusion method could reach an overall accuracy rate of 91.15%.

Samaneh *et al.*, (2019), in their paper titled 'Enhancing activity recognition using CPD-based activity segmentation' recognized that learning human activity model from streaming sensor data is an important problem for the successful realization of intelligent environments. Activity learning encompasses valuable capabilities such as activity recognition, activity detection, activity segmentation and activity forecasting. They tried to enhance activity recognition by identifying activity transitions, by introducing a change point detection-based activity segmentation model which partitions behaviour-driven sensor data into non-overlapping activities in real time. Results of their analysis indicates that the method provides useful information about activity boundaries and transitions between the activities and also increases recognition accuracy by 7.59% and f measure by 6.69% in comparison with the traditional window-based methods.

Mohammed *et al*., (2018), in their paper titled 'A robust human activity recognition system using smartphone sensors and deep learning' presented a smartphone inertial sensors-based approach for human activity recognition. Their proposed system consists basically of three main parts: sensing, feature extraction and recognition. The sensing part collects sensor data as input, feature extraction starts with the removal of noise to isolate relevant signals after which it does statistical analysis on fixed-size sliding windows over the time-sequential inertial sensor signals to generate robust features. The activity modelling was done from the extracted features with deep learning and Deep Belief Network(DBN). Their system was compared with traditional expression recognition approaches such as support vector machine and Artificial Neural Network (ANN) where it outperformed them.

Abubaker *et al*., (2019), in their paper ' The human behavior indicator: A measure of Daily Working' recognized that understanding progressive changes in human behaviour is very important in formulating an effective intelligent environment. By inspecting the trends in multiple activities, it is possible to identify and predict human behavioural changes. They refereed to trends in people's behaviour as behavioural evolution. Behavioural evolution of a participant in an ambient intelligent environment (AmI) is an indicator of a person's social and health status. The aim of their paper is to assess the Activities of Daily Living (ADLs) or Activities of Daily Working (ADWs) of a person who lives or works independently in his or her own home or office and present it as a single value for each day which is used to provide a holistic view of the behaviour of the person being monitored and is used to forecast the behaviour changes of the participant. They collected real datasets from wireless sensor networks with which they performed experiments on their proposed system and the experimental results demonstrated that the approach can identify and distinguish normal and abnormal behaviours.

Darpan *et al*., (2019), in their paper titled 'A semantic-based approach to sensor data segmentation in real-time activity recognition' proposed Semiotic theory inspired ontological model, capturing generic knowledge and inhabitant-specific preferences for conducting ADLs to support the segmentation process. They developed a multithreaded decision algorithm and system prototype and evaluated against 30 use case scenarios where each event was simulated at 10sec interval. The results suggested that all sensor events were adequately segmented with 100% accuracy for a single ADL scenario and 97.8% accuracy for composite ADL scenario.

Sang et al., (2015), in their paper titled 'Human Activity Recognition and Monitoring Using Smartphones' noted that unexpected illness can result from the sedimentary lifestyle of most workers. Their paper presents an effective way of monitoring the daily activities of workers with sedimentary lifestyle using accelerator and gyroscope sensors embedded in a smartphone. Signals were recorded by the sensors while a user performing different activities (walking, sitting, driving etc) wore the phone. K-nearestneighbhor (KNN) and artificial neural network (ANN) were applied to recognize user activities. The overall accuracy of recognizing five activities is 74% for KNN and 75.3% for ANN respectively.

Henry et al, (2020), in their paper titled "Development of a Human Activity Recognition System for Ballet Tasks" mentioned that accurate and detailed measurement of a dancer's training volume is a key requirement to understanding the relationship between a dancer's pain and training volume and that currently, no system capable of quantifying a dancer's training volume with respect to specific movement activities, exists. They tried to address this by determining if machine learning can accurately identify key ballet movements during dance training. They also tried to find out how location and number of sensors influence accuracy. They used convolutional neural networks to develop two models for every combination of six sensors with and without the inclusion of transition movements. At the first level of classification, including data from all sensors, without transitions, the model performed with 97.8% accuracy. The degree of accuracy reduced at the second (83.0%) and third (75.1%) levels of classification. The degree of accuracy reduced with inclusion of transitions, reduction in the number of sensors and various sensor combinations. The models developed were robust enough to identify jumping and leg lifting tasks in real-world exposures in dancers.

Huichen and Neil (2016), surveyed existing solutions for enhancing security in IoT, they identified key future requirements for trusted smart home systems. They also suggested the gateway architecture as the most appropriate for resource constrained-devices and for high system availability. Support for system auto-configuration and automatic update of system software and firmware were two key technologies they identified for system auto-management. They summarized the existing network techniques that can be used to secure the smart home and also presented two areas of particular concern: system auto-configuration and security updates.

Serge and Younghwan (2015), discussed the possibility of recognizing and predicting user activities in two steps: activity pattern clustering and activity type decision. For the first step, classifying so varied and complex user activities, they used the k-pattern clustering algorithm, an efficient unsupervised learning method. Activity type decision was done by utilizing 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 data mining classification algorithms. This accuracy is achieved at the cost of run time. They however suggested the additional use of an efficient feature selection approach called the J48 decision tree to improve the average accuracy and run time performance.

Dahmen *et al.*, (2017), proposed an activity aware approach to security monitoring and threat detection in smart homes. Their approach is unique because it requires knowledge of the current activities to determine deviations from normal behavioral patterns in the home. Activity awareness in the secure smart home is formed by activity recognition and discovery algorithms. Activity Learning involved Activity recognition, activity discovery, anomaly detection, and evaluation. Their work demonstrated that smart homes can be automated for security threat detection.

Wang *et al.,* (2009), designed a smart home monitoring and control system. The system 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 are adequate to be used in this scenario, the researchers proposed a new protocol with a new command format.

Rashidi *et al., (*2008*)*, developed Centre for Advanced Studies in Adaptive Systems (CASAS) at Washington State University. CASAS is an adaptive smart home that uses machine learning techniques to discover user behavior patterns and automatically mimic these patterns. The user can modify the automation policies, provide feedback on the proposed automation activities, and introduce new requests. CASAS can automatically identify changes in resident behavior. The Frequent and Periodic Activity Miner (FPAM) algorithm identifies frequent and periodic activity patterns after Z processing activity information.

Noguchi *et al., (*2002*)*, designed an intelligent room to support the daily life of an inhabitant. The system has three main components: data acquisition, data processing, and integration of processed data. It learns the current state of an environment from the sensors attached to beds, floors, tables, and switches. A summarization algorithm is used to track any change in the system. The algorithm segments the collected sensory data at points where the sensor output changes drastically (i.e., switch sensors are changed or pressure data appear suddenly). The segments are labeled as "room states." The algorithm joins the state of each segment to quantize the collected data and ties up the changed situation. Their proposed summarization algorithm was able to detect user activities.

3.1 GUASSIAN NAÏVE SENSOR-BASED MODEL

A desktop smart home prototype was constructed with sensors and actuators mounted on it for activity recognition in the home. The Smart Home System processes sensor information for Human Activity Recognition (HAR).

In this paper, a Supervised Machine Learning Model was developed to process sensor information into valid Human Activities. For a supervised machine learning model, it is necessary to determine the valid activities for the system with their respective unique identifications. Table 1 shows the activities for the smart home system in figure 1.

The sensor labels in Table 2 represent the features while the Activity column represents the class labels in our HAR model. The model would then read processed binary data from system sensors which generate the input features and fit it into the trained HAR classifier to determine a predicted output which represents the recognized activity. The Gaussian Naïve Bayes algorithm was used in achieving this.

In all, there are twelve sensors installed in the home and these sensors are responsible for generating twelve different activities in the home. Actuators include the buzzer or alarm, the light bulbs. The picture of the smart home system is shown in figure 2.

Table 1: Smart Home Activity Construction

S/N	ACTIVITY NAME	ASSOCIATED SENSORS	HAR IDENTITY
1.	Home Entry	MS00, **MS01**	HEN
2.	Kitchen Entry	MS06, **MS07**	KEN
3.	Rest Room Entry	MS04, **MS05**	REN
4.	Home Exit	**MS00**, MS01	HEX
5.	Kitchen Exit	**MS06**, MS07	KEX
6.	Rest Room Exit	**MS04**, MS05	REX
7.	Sleeping	MS00, MS01, MS04, MS05, MS06, MS07, **MS08**	SNG
8.	Eating	TS09, MS06, M507, **MS02**	ENG
9.	Bathing	MS04, MS05, **WS10**	BNG
10.	Studying	MS00, MS01, MS04, MS05, MS06, MS07, **MS02**	DNG
11.	Stooling	MS04, MS05, **MS03**	LNG
12.	Clothing Activity (Dressing up or undressing).	MS00, MS01, MS04, MS05, MS06, MS07, **MS11**	CAY

Table 1 has 4 columns, serial number, Activity Name, sensors associated with each activity, and n the HAR identity which is the name with which the activity will be referenced or identified in the HAR model. The table was constructed from the map of the floor plan layout of the Smart Home prototype as shown in figure 1.

In all, there are 12 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 must be outputting 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 must be outputting 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 it must output 1 for the sleeping activity to take place.

For the eating activity (ENG), associated sensors are TS09, MS06, MS07 and MS02, however, MS02 is highlighted because eating is done on the table where MS02 is located. TS09 is also highlighted because it is assumed that there should be temperature rise in the kitchen due to cooking which precedes eating.

For the studying activity DNG, associated sensors include MS00, MS01, MS08, MS11 and MS02. MS02 is highlighted because it must be active (i.e. outputting 1) for studying to take place.

The ‘Kitchen Entry’ activity (KEN) has the associated sensors MS06 and MS07 as seen on the floor plan in figure 1, they are the sensors located close to the door of the kitchen. However, MS07 must be outputting a 1 for a Kitchen entry activity to occur and it is therefore highlighted.

For the ‘Rest Room Entry’ activity (REN), associated sensors are MS04 and MS05 as seen on the floor plan in figure 1, however, MS05 is highlighted and must output 1 for this activity to occur.

The ‘Home Exit’ activity (HEX), has the associated sensors MS00 and MS01, MS00 is highlighted because it is expected to output 1 for this activity to occur.

The ‘Kitchen Exit’ activity (KEX) is associated with the sensors MS06 and MS07 and MS06 is highlighted as it must output 1 for this activity to occur.

Sensors associated with ‘Rest Room Exit’ activity are MS04 and MS05 as seen on the map in figure 1, MS04 is highlighted and must output 1 for this activity to occur.

The Bathing activity (BNG) is associated with MS04, MS05 and WS01, WS01 is highlighted because it is a water sensor close to the shower as seen in figure 1 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 figure 1.

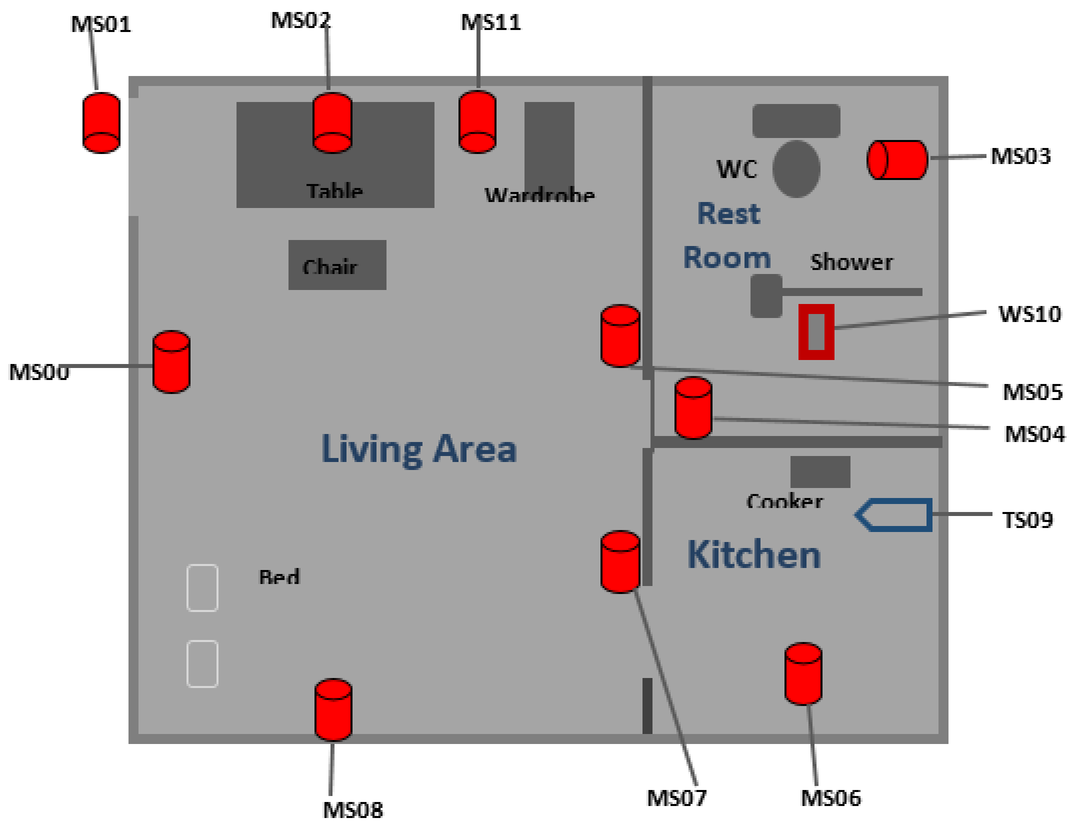

Figure 1: Smart Home Floor Plan with Associated Sensors.

The Smart Home prototype is made up of the living area, the kitchen and the rest room. MS represents the Motion Sensor, WS represents the Water Sensor and TS represents the Temperature Sensor. The picture of the system installed on the desktop wooden modeled home is shown in figure 2.

The motion sensors MS00, MS01, MS02, MS08 and MS11 are installed in the living area to track the movement activities that occur there and also to track the sleeping activity as the motion sensor MS08 is by the bed side. Entrance and Exit into the home can only be through the living area as shown in figure 1 with the associated motion sensors MS00 and MS01. The motion sensor MS02 tracks the Eating activity as it is just by the dining table and chair. The Studying activity can also be tracked by MS02 as studying is done on the same table with Eating. Activities associated with the living room are Home Entry, Home Exit, Sleeping, Eating, Studying and Clothing.

The motion sensors found in the Kitchen are MS06 and MS07. The temperature sensor TS09 is also in found in the kitchen as seen in figure 1. The activities associated with the Kitchen are Kitchen Entry, Kitchen Exit and Cooking.

The rest room is another area in the Smart Home as seen on the plan. Motion sensors found in the rest room are MS03, MS04 and MS05. The water sensor WS10 is also found in the rest room. The activities associated with the rest room are Rest Room Entry, Rest Room Exit, Bathing and Stooling.

Table 2 is the constructed training data for the HAR classifier or model.

Table 2: Human Activity Recognition 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	0	0	0	0	1	0	Bng
0	0	0	0	0	0	0	0	0	1	0	0	Eng
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

Sensors detect events or changes in the environment, these events are physical quantities which are non-electrical phenomena that are converted to electrical signals. Whenever a change is detected, the output pin of the sensor changes state from a digital low to a digital high. Digital high is represented as 1 and digital low is represented as 0. The training dataset is therefore a set of binary digits of 0s and 1s as seen in table 2.

When all the inputs from a row are combined, the output is the corresponding activity on that row. For example, on the third row, all sensor inputs are digitally low with the value 0 except for Motion Senor 06 (MS06) which is digitally high with the value 1. The corresponding activity on this row is Kex, which means Kitchen Exit. As seen on the floor plan of the home in figure 1, MS06 is the motion sensor at the Kitchen Door which signifies an Exit. The same thing follows for all the rows on the dataset as they can be traced to particular sensors in the smart home. An activity or event is generated by triggering the corresponding sensor.

The training dataset in Table 2 contains all sensor output information that translates into valid activities which is run on the Raspberry Pi board. Code is developed to monitor sensors and retrieve required information that is fed into the HAR classifier. The columns MS00, MS01, MS06, MS07, MS04, MS05, MS02, MS03, MS08, TS09, WS10 and MS11 are the features which represent the input into the model while the column 'Activity' are the classes or outcome of our classification which are the activities.

The Gaussian Naive Bayes Algorithm is used in building the model.

The Scikit-Learn is a free software machine learning library for Python programming language. Using the Scikit-learn library, a Gaussian Naïve Bayes classifier was developed to predict an activity given sensor inputs.

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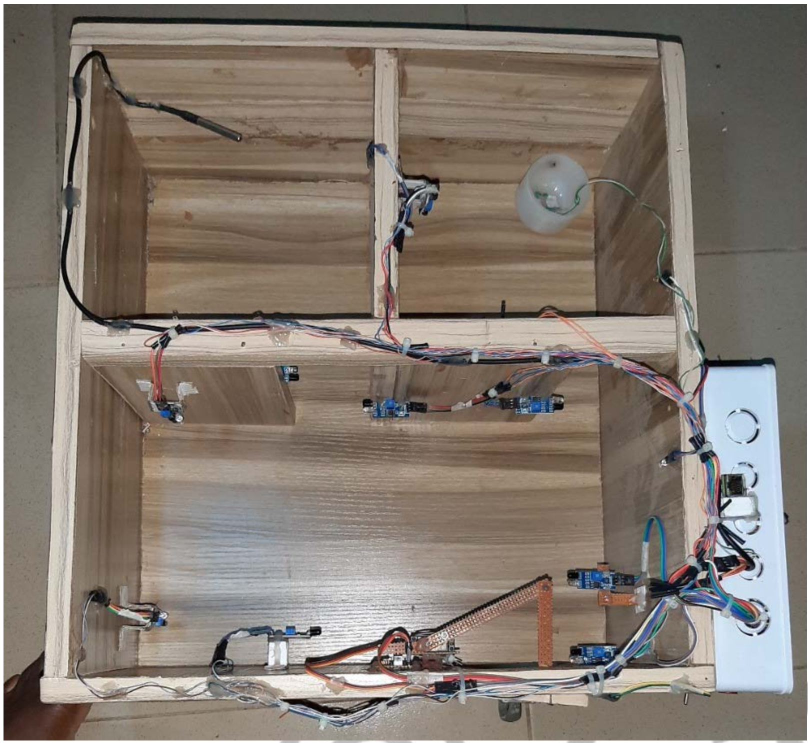

Fig 2; Complete system installed on the desktop wooden modeled home.

4.0 EXPERIMENTATION AND RESULTS

The testing or predictions are performed by triggering the sensors in the smart home. This is achieved by simply moving a life object around the sensor (for the motion sensor) or some water droplets on the sensor (for the water sensor) or applying heat to the sensor (for the temperature sensor) and the expected output is the activity which corresponds to the triggered sensor.

A series of experiments were carried out by triggering the sensors in the smart home. Table 3 show the details of the results obtained from the experiments. The predicted outcome is printed on the serial of the IDE.

Table 3: Experimental Results for Activity Recognition.

S/N	SENSOR TRIGGERED	EXPECTED OUTPUT	PREDICTION
1.	MS 00	Hex	Predicted Activity is: hex
2.	MS 01	Hen	Predicted Activity is: hen
3.	MS 06	Kex	Predicted Activity is: kex
4.	MS 07	Ken	Predicted Activity is: ken
5.	MS 04	Ren	Predicted Activity is: ren
6.	MS 05	Rex	Predicted Activity is: rex
7.	MS 02	Dng	Predicted Activity is: dng
8.	MS 03	Lng	Predicted Activity is: lng
9.	MS 08	Sng	Predicted Activity is: sng
10.	MS 11	Cay	Predicted Activity is: cay
11.	WS 10	Bng	Predicted Activity is: bng
12.	TS 09	Eng	Predicted Activity is: eng

5.0 DISCUSSION OF RESULTS

As seen on table 3, all the sensors triggered predicted correctly as all the expected outputs were the same with the predictions made, there was no wrong prediction. This could be due to the fact that the dataset for training the model is small as it is restricted to the number of sensors in the smart home built, leading to overfitting of the model. In serial No. 1, MS00 was triggered, the expected output based on the training dataset is HEX and the prediction is HEX, meaning that the model prediction is correct. In serial No 2, MS01 was triggered, the expected output is HEN and the prediction is HEN which is correct. This is same for all the other rows of the table.

6.0 CONCLUSION

In this paper, we built a smart home prototype with sensors and actuators mounted on it. A Gaussian naïve Bayes classifier that predicts or classifies the input received from the triggered sensors into some pre-labeled activities was also developed. All sensors that were triggered predicted correctly. These predicted activities can be used for further investigations and analysis regarding the home and its users.

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