Design and Implementation of Tracking a user’s Behavior in a Smart Home

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Abstract. A smart home is automated structures with control contraptions and presented area; it comes with advanced sensing and automation systems to supply the inhabitants with monitoring and management no matter if they are in the home or outside. In light of the developments that are taking place in the smart home, machine learning, and the needs of the home, which makes the appropriate decisions based on the user’s behavior of the smart home, and the use of development in technology to facilitate the general requirements of people. Modern smart home systems tend to be standalone solutions that focus on lifestyle needs using a smart control system, such as lighting and temperature control. Ubiquitous home expects the emergence where sophisticated (Ambient intelligent) systems monitor and learn user’s behavior and lifestyles and enable the home to predict and respond to all the needs and activities of home occupants. During perception, residents perform their daily routine while the in-house embedded sensors transmit and store the readings in a database. By doing so, the intelligent agent uses these readings to generate knowledge, such as patterns and trends. Thus, it can predict based on the built knowledge to enable the smart home to identify and automate the action that meets the occupants’ aims.

Keywords. Smart home, Ambient intelligent, Advanced sensing, Automation systems.

1. Introduction

Many systems focus on the process of devices operation using mobile phones or via the Internet, such as controlling the home lights and the air conditioning (cooling and warming ) systems; this is a smart home [1]. We may move our imagination further, such as that the air conditioner operates before arriving home by a certain period so that the room temperature becomes at the required degree, or making the water heater works to heat the water before arriving home, or that the TV set operates automatically according to the typical system behavior. These can be done by studying the people’s vital daily activities and turning them into device commands [2]. The smart home is mostly designed from microcontrollers, sensors, and actuators. Sensor data are inherently carrying the behavioral data, the purpose of which is to infer health and wellness visions, reduce energy, or facilitate a way of life [3]. Satpathy proposed a smart home concept that focuses more on helping the home user to live independently and comfortably with the help of electrical, digital, and mechanical devices [4]. Gavin Chand presented a system that uses machine learning techniques to predict the behavior of the person by using ultrasonic sensors in a single room, such as to monitor the position and the status of a person (sitting, standing, or lying down). The proposed system is only for one permanent occupancy for a
single house, and one a caregiver who can intervene occasionally. The system used an ESP32 microcontroller, ultrasonic sensors, and a local MQTT server (Mosquito); it was proposed to monitor the behavior of the resident, including pressure, ultrasonic, electricity flow, and water flow. Data mining algorithms are applied by using Weka to determine the behaviors [5]. There are different types of user’s behaviors, but the everyday basis for each of them is that they must be recognized. If human activities are correctly and automatically identified, it will become possible to implement a wide range of applications and services, such as turn on the music or TV device on time or cooling the room before the homeowner come back. In this paper, the proposed system is to follow user behavior and make the appropriate decision from home itself to facilitate the way to live inside the home. A complete structure of the proposed system is presented with the used algorithm for analyzing the behavioral data, determining the process of collecting data, and then leveraging the deep learning techniques to extract the complex and multivariate patterns from the daily sensor data. The proposed system could be beneficial for building efficient and appropriate monitoring services to facilitate living in a smart home while reducing energy. A supervised learning algorithm analyzes the training data and produces an inferred function to map new examples. It depends on a set of tagged training data called labeled training data, which consists of realistic examples such as sensor cases at a specific time. Each case represents a pair that consists of an input object (typically a vector) and the desired output value (supervisory signal). The algorithm analyzes the training data and produces the inference function used to map the new examples. An optimal scenario allows us to correctly identify sample classes or unseen instances, which are entirely new and not used in the training phase. This requires generalizing the learning algorithm using the new sample training data cases reasonably [6].

2. Smart home and machine learning
Since microprocessors have been miniaturized, computing power has been incorporated into familiar objects such as mobile and home devices; however, this technology is gradually entering all the fields of society. Pervasive computing technologies and machine learning have matured to provide automated contextual support in our everyday environments. A smart home is the physical embodiment of this system [7]. Environmental sensors are used for many applications in smart homes. Sensor data implicitly include behavioral data that could be helpful to infer the wellness and health insights [3] indirectly. In the home environment, the computer program plays the role of the intelligent agent that understands the physical environment, the resident’s behavior, and the reasons for this behavior through sensors using the artificial intelligence (AI) techniques and then takes decisions to implement specific goals. In machine learning and AI, supervised learning refers to a part of systems and algorithms that define a predictive model with known outcomes using data points. The model is learned through training, which usually works through some improvement measures to reduce error or error function. The first phase in the supervised learning process is the collection of the labeled training data. The label data is the output and provides the algorithm with feedback. The next phase is to divide the labeled data into three sets after having enough data: training, testing, and validation. The algorithm uses a training data package to change the model to reduce the error.

2.1. Decision tree (DT) learning
Decision tree learning is an algorithm commonly used in data mining. It is so easy to understand the level of this algorithm compared with other classification algorithms by using the tree representation to solve the problem. An internal node of the tree can represent each feature or attribute, and each node corresponds to a class label. The goal of this algorithm is to create a model that predicts the value of the output variable based on multiple input variables. The DT algorithm is used for classification problems and solving regression too. DT is a simple and effective classification algorithm. One of its most important advantages is that it provides human-readable classification rules [8][6].

3. System design
The architecture of the proposed system is shown in Figure (1). This system contains a Raspberry Pi microcomputer connected to an ESP32 microcontroller via the serial port, a device is interfaced to the ESP32 using a relay, and also, a switch control device is connected to the ESP32.
Figure 1. Architecture model of the proposed system.

4. Components information

4.1. ESP32 NodeMCU
It is one of the most popular board; it can be used as a complete standalone system or a slave to a host MCU. It is a low-cost device that supports both Wi-Fi functionality via a single-chip 2.4 GHz Wi-Fi. It has 34 programmable General Purpose Input/output pins (GPIOs), as shown in Figure 2, which can be used for interfacing different sensors and devices. It is characterized by its ability to work in an industrial environment within a temperature range from -40 °C to + 125 °C [9]. Figure 2 shows the ESP32 module used in this system.

4.2. Raspberry Pi
Raspberry Pi is a very cheap single-board computer that can be run based on Linux. In the proposed system, it has been used to store the data and implement the proposed machine-learning algorithm to predict the behavior of the user through data readings from the ESP32 by serial port.

4.3. Henge 8A UBEC
It is used to convert power from 7-25.5V to 5V/8A and from 6V/8A to 7.4V/8A. The main objective of the Henge 8A UBEC is to provide the sensors and ESP32 NodeMCU with the necessary power. Figure (3) shows the Henge 8A UBEC.

Figure 2. ESP32.

Figure 3. UBEC.
5. **Hardware aspect**

After the initialization of the ESP32 and Raspberry Pi, the ESP32 will read the status of the push button to turn on or off the device and send the result to the Raspberry Pi each minute. The system will control the device with the user behavior. Figure 4 shows the block diagram of the proposed system. Figure 5 a picture of the proposed system.

![Block diagram](image1)

**Figure 4.** Block diagram.

![Picture of proposed system](image2)

**Figure 5.** A picture of the proposed system.

6. **Software aspect**

Arduino IDE is used for programming the ESP32 MCU, Python programming language to programming the algorithm on the Raspberry Pi, and Orange for data visualization, exploration, pre-
processing, and modeling. Orange is a component-based data-mining program. It includes a set of technologies for data visualization, exploration, pre-processing, and modeling. It has a friendly and intuitive user interface. It focuses on simplicity and interactivity through scripting and component-based design.

- **Python code**
  After collecting the data, the DT machine learning algorithm is applied to analyze the results using Orange to get better and accurate classification results. The proposed work can help in identifying the device status, classifying the results into their class, and take the appropriate decision.
  
  # Group Python code:
  Step 1: Import the libraries (time, Orange, sys)
  Step 2: Device listener: The ESP32 send the value of the device status after reading it each minute.
  Step 3: Calculate the sequence of the data every 15 minutes.
  Step 4: Distributed the values to the specified times for the time of the week.
  Step 5: Classification of the data and use DT algorithms.
  Step 6: Learn the network.
  Step 7: Prediction, after testing the network with training data, update the data with new data, and add the data to the previous data.
  Step 8: Device control, by sending value to the ESP32 by serial port.

- **Orange tools design**
  By inserting two training data files, and a prediction data file, which was empty for the first time, the first data file goes for selecting time data sequence and status for the device (TV as an example) then applying the decision tree algorithm, the output data is the new prediction data, as shown in Figure (6). The training file is updated each time with the new data input and previous prediction data.

*Figure 6. Orange design for The decision to turn on the device.*
7. The decision to turn on/off the device
The proposed system can control several home devices, such as music devices and TV using machine learning algorithms. It monitors the status of a device using the Python language and uploads it to the Raspberry Pi for one week for the first time. Then, the program collects the state of the device every minute for a week (10080 minutes per week); it classifies these data for period (fifteen minutes as an example) and by using the decision tree learning algorithm to get the predicted data. After that, it controls the device (on or off) at a specific time and according to the previous behavior.

8. Results
As shown previously, the system mainly contains an embedded system. The embedded system was tested in real-life assumptions to be accurate in sending results and controlling the device in real-time and real-time notifications. The adaptive, lightweight home prototype system has been tested in natural climate to be compatible with the climate and natural climate change, by using a TV device as an example. Moreover, the system will display real-time values for the status of the TV device. The algorithm was applied to the TV device, which can be replaced by any other home device (music device, light, etc.). The system read the user behavior for one week, and then the system predicted what will happen in the next week and in the case of if there is not any change in the user’s behavior after running the system, as shown in Figure (7). The system will read the device value in real-time. The system will be updated according to the case, and the results are according to Orange, as shown in Figure (8), shows that the user turns on the TV each Sunday from 7:15 to 7:44 while he/she turns on the TV at the same time on 00:00 to 00:15 on that day.

![Figure 7. Read the device value on time running.](image)
9. Conclusions
We have introduced a smart home user behavior tracking system that is part of building a smart home system to provide services designed to facilitate the living in smart homes. This review aims to facilitate the creation of developers and service providers for smart homes. To achieve this, the proposed system allows the classification of activities for users with the possibility to update them daily as we tracked user behavior every minute and every day, which makes the development of the system and its use for several purposes and several devices such as heating and cooling devices, water drainage, and tracking the mechanism of entry and exit of teenage children to the home. It is possible to add some modifications to the system in some instances, such as tracking children, their exit to school and their return from them, and sending an alert message to the parents if they get delayed to return home. For example, we also addressed the shortcomings of other systems through real deployments and updating the system by the daily data. Moreover, the correct identification of activities related to a particular activity may significantly enhance the accuracy of its discovery. The system is also distinguished by its ease of setup and installation and cheapness compared to other systems.

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11. Conflict of interest
The publication of this article causes no conflict of interest.

| Abbreviations      | Description                          |
|--------------------|--------------------------------------|
| TV                 | Television                           |
| DT                 | Decision tree learning               |
| GPIO               | General Purpose Input/output pins    |
| MQTT               | Message Queue Telemetry Transport    |
| AI                 | Artificial Intelligence              |
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