

IoT Based Human Activity Recognition and Classification Using Machine Learning

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Abstract— For a variety of reasons, human activity recognition is currently a hot study issue. The basic purpose is to use Several methods are used to recognise a person's activities, including orientation detectors, motion sensors, position sensors, and chronology. Pervasive computing, artificial intelligence, humancomputer interface, health care, health outcomes, rehabilitation engineering, occupational science, and social sciences are some of the domains where human activity recognition is used. Human behaviour contains a lot of context information and aids systems in achieving context awareness. It aids in the functional diagnosis of patients and the proper assessment of health outcomes in the rehabilitation field. Recognition of human activity is a key performance metric for participation, quality of life, and lifestyle.

Keywords - Internet of things, MPU6050 Sensor, ATMega328, ADXL334 Accelerometer

I. INTRODUCTION

The most critical and necessary feedback required to build smart internet of things (IoT) applications is the results of the procedure of recognising human activities and their bodily interaction with the surrounding environment. It was critical to combine the inferring and sensing components in the Human Activity Recognition (HAR) study field in obtaining accurate and correct input about humans actions and experiences. Most researchers nowadays are drawn to this scientific topic. However, this interest arises from a desire to acquire contextaware data, which is then utilised to give tailored support to customers across a range of application sets, including security, medical, military, and lifestyle applications. The practise of properly distinguishing everyday behaviours like walking, standing, and running benefits both the user and the caregiver. Everyday monitored assessments of person actions, for example, may be incredibly valuable in stopping him/her from engaging in specific behaviours that may be various incidents or hazardous to his/her health due to his/her sickness or disease history status. Furthermore, such everyday recognized insights may help a user's health by offering comments, ideas, and warnings

depending on the input research of their everyday actions' efficiency, thus assisting the user in enhancing her/his living condition.

A. Existing System

Yang [65] experimented with apps that employed movement detection from a device's sensor to track physical activity. Yang samples the gyroscope at 36,000 Hz with a Nokia N95 for movements such as resting, moving, running, jogging, riding, and bicycling. The data were then stored to a database and annotated before being analyzed. Yang examined the estimation accuracy of C5.0 Trees, Nave Bayes, k-Nearest Neighbor, and Support Vector Machine (svm)using the WEKA training toolkit. Vertical and horizontal features had a bigger impact on recognition rates than magnitude features alone, according to the study. This feature set and the Proposed method obtained 90.6 percent accuracy using ten 10-fold cross validation. Bieber et al. [66] used Sony Registered agent on file devices, including w715 to recognise each other.

B. Aim of project

Aim of the project to make a device which will be independently used for human activity recognition using IOT and sensors giving acceleration and gyroscopic position. The final result will be predicted using MATLAB based program.

II. PROBLEM DEFINITION Problem statement

We will design a freestanding gadget based on the two aspects below.

- The smartphone-based HAR system is heavily on on the sensors, characteristics, and classification algorithm chosen to meet the device's constraints and adapt to changing conditions.
- The criteria for choosing the methods to use are determined by the application's specific requirements, which can include response time, recognition accuracy, and energy usage.

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III. LITERATURE SURVEY

Experts have been studying human activity recognition for years and have proposed numerous solutions. Vision sensors, inertial sensors, or a mix of the two are commonly used in existing approaches. Machine learning and threshold-based algorithms are frequently used. Machine learning algorithms are more accurate and dependable, whereas threshold-based methods are faster and easier to use. Body posture has been captured and identified using one or more cameras [8]. The most popular solutions [10] are multiple accelerometers and gyroscopes coupled to various body locations. There have also been approaches that integrate vision and inertial sensors [14]. Data processing is an important component of all of these methods. The input characteristics' quality has a significant impact on performance. Previous study [15] centred on obtaining the most valuable characteristics from a time series data source Both the temporal and frequency domains of the signal are frequently examined. The active learning method has been used to handle a number of machine learning problems where labelling samples takes a long time and effort. Speech recognition, information extraction, and handwritten character recognition are some of the uses [18]. However, this method has never been used to solve the problem of human activity.

IV. PROPOSED SYSTEM

Human activity recognition has been the subject of various scientific projects. This area has been studied for at least three decades. In the literature, several terminology linked to human activities are utilised In this section, we'll go over some of the key words in use in gesture recognition research. We also go through how to classify human behaviours and how to recognise them using cutting-edge approaches. We also go over the taxonomy of HAR research methodologies and explore each one briefly.

• Action: An action is a gesture or movement made by a person.

• The Oxford dictionary defines activity as "whatever a person or group does or has done."

• Physical Activity: The World Health Organization (WHO) recommends that people engage in physical activity.

A. Proposed System Architecture

Walking, standing, sitting, bending, and sleeping are all examples of common actions that could be investigated. Sensors attached to various regions of the body were used to collect data (the chest, left hip, left wrist, left thigh, left foot and lower back). Data from a sensor worn around the waist can be used to track a variety of activities, including sitting, standing, walking, sleeping in various positions, and jogging. The hand, shoulder, waist, bottom back, thigh, and trunk have all been used as accelerometer placement locations to distinguish between sleeping, sitting, walking, standing, and bending.

One of the most crucial processes in the data collection and analysis is data pre-processing. Analysis of the data, missing and outlier value restoration, and obtaining features are all covered. Windowing techniques, which divide sensor signals into small time segments, are frequently used to extract features from raw data. After that, segmentation and classification techniques are used to each window. Sliding windows, in which preproceeded is required to identify many happenings, which are then used to determine further dataset segmentation; and task window frames, in which data segmentation is based on change of activity.

There are 14 digital input/output pins and 6 analogue input pins on this board. It has a 5 volt operating voltage and a 7 to 12 volt input voltage range. You'll need the Arduino IDE to programme it. In order to programme the Arduino Uno using the USB to serial converter, it must be connected to the computer via USB. It features a serial port that allows it to communicate with a computer [16].



Figure 1: Proposed basic systems for Human activity detection



Figure 2: Human body with joints and position of mobile phone

When compared to other devices that require an external chip programmer, uploading programs to the on-chip non-volatile storage is much easier. This simplifies the use of an Arduino by allowing for the use of a regular computer as the programmer. Opti boot loader is currently the default boot loader on Arduino UNO. The role of machine learning improvises the results or prediction of activities.

V. HARDWARE DISCRIPTION

A. Microcontroller

Microcontrollers are small, low-cost computers built to do specialized jobs in embedded systems such as displaying microwave information, receiving remote signals, and so on. A generic microcontroller is made up of the CPU, memory (RAM, ROM, EPROM), serial ports, peripherals (timers, counters), and other components.

B. ESP (WI-FI) Module

This project made use of the ESP8266 WI-FI module. It is a low-cost microprocessor that runs on the TCP/IP stack. The microcontroller can connect to a wireless network via Hayes style commands or TCP/IP connections thanks to this microchip. The ESP8266 is a Wi-Fi-capable singlechip device with 1MB of built-in flash. Espress if Systems created this module, which is a 32-bit microprocessor. There are 16 GPIO pins on this module. This module comes after the RISC processor. It has a DAC with a resolution of 10 bits. Later, Espress if Systems published a software development kit (SDK) that allows users to program directly on the device, eliminating the need for a separate microcontroller. Node MCU, Arduino, and Microchip are just a few of the SDKs available.

C. Accelerometer

The ADXL334 Accelerometer is simple to use with this breakout board. ADXL334 Accelerometer is a 12-bit resolution, low-power three-axis capacitive MEMS accelerometer. With two interrupt pins to pick from, this accelerometer is jam-packed with embedded functionalities and user-programmable options. Embedded interrupt functions save energy by eliminating the need for the host CPU to poll data on a regular basis.

The ADXL334 Accelerometer includes user selectable full scales of 2g, 4g, and 8g, as well as high pass filtered and info that is not filtered and is easily accessible The ADXL334 Accelerometer can be designed to generate gyroscope wake- up interrupt signals from a variety of customisable integrated algorithms, permitting it to detect events while remaining power-efficient when not in use.

VI.TECHNOLOGY DETAILS

A. Internet of things

The Internet of Things (IoT) is a technology that allows objects to communicate with one another over the internet. In the same way, connected devices communicate with one another or with people. Finally, they upload the acquired data to the cloud. The data can reveal information about the data. As a result, regular monitoring, automation, predictive maintenance, and commercial tracking are just a few of the uses for smart linked devices. The cloud, or information aggregators, is linked to the smart devices..

B. Thingspeak in Matlab Toolkit

Thingspeak is a MathWorks-hosted web service that makes it simple to gather, analyse, and act on sensor data, as well as build Internet of Things applications. The ThingSpeak Support Toolbox uses MATLAB to read data from ThingSpeak and write data to the ThingSpeak platform. It also has functionality for visualising and accessing data saved on ThingSpeak.com. It displays data, timestamps, and channel information for the selected public channel on ThingSpeak.com. The sensor values will be obtained from ThingSpeak's channel data. thingSpeakRead= [data, time stamps, chInfo] (chId, Name, Value)

VII.METHODOLOGY

A. Methodology

Hardware implementation

1. The user does something (Walking, Standing, Sitting, Bending, Sleeping)

2. Using a hardware application to collect data.

Description: We will create a hardware application that will be able to record data for various human activities and then use that data for recognition and analysis.

Recognized activities

We will select a random sample of collected data by browsing the excel sheets, and the selected data will then be identified or detected as walking, sitting, or jogging activity.

Data selection and filtering

The Gaussian Filter is being used for filtering purposes. Filtering is used to reduce the amount of noise in the data.

Visualization and modification of signals

RMS stands for Root Mean Square and is primarily defined as the square root of.

Detected and Analyzed Activities

Here all five activities are detected according to three classifiers.

B. Algorithms



Figure 5: basic Flow chart for human activity recognition

In the following discussion, we will concentrate on supervised learning because it is by far the most popular type of machine learning in materials science. Figure 1 depicts the workflow utilised in supervised learning. A subset of the relevant population with known values of the desired property is usually chosen, or data is developed if necessary. The next step is to choose a machine learning algorithm that will fit the desired goal amount. The majority of the job comprises creating, locating, and purifying data to ensure consistency, accuracy, and other factors. Second, you must decide how to consistently map the system's properties, i.e. the model's input. This involves transforming raw data into specified qualities that will be utilised as algorithm inputs. Following this, the model is trained by maximising its performance, which is often measured using a cost function. Adjusting hyperparameters that alter the model's training process, structure, and properties is frequently required. The data is divided into several groups. A validation dataset independent from the test and training sets should be used to optimise the hyperparameters.

VIII. IMPLEMENTATION

System Design



Figure 6: basic Flow chart for human activity recognition

Above is the wiring diagram of our hardware device for connecting the ESP8266 to Thingspeak. The Arduino UNO Board is only used to send data between the computer and the ESP8266, i.e., it is not used to control the ESP8266. it acts as an USB-to-UART Converter.

The front-end sensing component of the ADXL345 senses acceleration, and the electric signal sensing component converts it to an analogue electric signal. The analogue signal is then converted to digital by the AD adapter built inside the module. This device will provide an input to MATLAB via thingspeak based upon the position of this device in X, Y and Z axis. When you rotate the ADXL345 module, three values will change.

For Wi-Fi access to the system, we have given commands in Arduino IDE software also we have given commands in MATLAB to access the continuous data in thingspeak channel that we have created.

Using machine learning we have trained the system to recognize a specific activity by providing an excel sheet of data having x,y,z value sets different for different activities. Also we have created three Graphical User Interface (GUI) . In first GUI, graphical movement of the device can be seen in X, Y and Z axis separately. In second GUI, comparative classification of activities can be seen, given by three algorithms namely SVM, KNN and decision tree. Also, the efficiency of each algorithm can be checked in MATLAB. The last GUI is the visual appearance of the front-end display that that will be accessed by the user.

Alt. Terr and Validation		Pridicted Activities			
UPLOAD TRAINING DATA		Access Test Data	SVM Daved Activity	KHK Based Activity	TREE Based Activity
			WALKING WALKING WALKING SELECTING SELECTING	 WALKING WALKING WALKING SEEPING SEEPING 	A WALKING WALKING WALKING SLEEPING
	-		BENDING SITTING BENDING SITTING	STANDING STANDING STANDING STANDING	WWA,KING STANDING STANDING STANDING STANDING
SVM Classifier	SVM PLOTS	SVM Prediction	STING BENDING STING STING EENDING STING STING	STADING STADING STADING STADING STADING STADING STADING	STANDING STANDING STANDING STANDING STANDING STANDING
KNN Classifier	KNN PLOTS	KNN Prediction	SITTING SITTING BENDING BENDING BENDING SITADBIG SITANG SITTING SITANG	STADING STADING STADING STADING STADING STADING STADING STADING STADING	STAURIS STAURIG STAURIG STAURIG STAURIG STAURIG STAURIG SLEEPING
TREE Classifier	TREE PLOTS	TREE Prediction	EESADNIG STAADENIG WAAXANG WAAXANG WAAXANG WAAXANG WAAXANG	STANDING STANDING BENDING BENDING KENDING WALKING VALUNIG	STANDING STANDING STANDING BENDING BENDING WALKING WALKING WALKING
Manual Training	Fitness Box	Activity Plots	WALKING WALKING WALKING WALKING WALKING BENDING SITING	WADONG WADONG WADONG WADONG WADONG BERGING GTTPug	WALKING WALKING WALKING WALKING WALKING WALKING

Figure 6: Second Graphical User Interface

IX.RESULT



Figure 7: Visual Display for user

The hardware implementation for human activity will reduce excess data processing and continuous monitoring on mobile phone which in terms also effectively increases the efficiency of system. The accuracy as compare to SVM, KNN and Tree algorithm we achieved more in SVM of 99.00 percentage which shows comparatively we can choose the SVM for human activity prediction. The results also shows that the present-day activity we can easily monitor and we can use this for prediction in or assisting in prescribed activity by physiotherapist or doctor and we made it possible using our project GUI. The activity of human can also be compared with graphical system available and also by listing we provided for last 50 samples or we can select today's values of human activity. The human activity detection assisting and also a hardware unit is enough to continuously monitor the human activity. The feature included in this project of IoT made it possible for access of activity monitoring from anywhere and obviously continuously, the hospitals can take this data in their central monitoring stations, even doctors can also monitor using mobile phone and caretaker will also can check the activity performed by person.

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