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IoT Enabled Smart Activity Recognition using Machine Learning Methods

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Abstract— Internet of Things (IoT) enabled architecture-based devices are becoming accessible worldwide irrespective of the area. But functional settings depend on Internet facilities. In this context, the Healthcare industry took a step forward to automate Human Activity Recognition related concepts using IoT and Machine learning methods. This research used a Nodemcu ESP8266 device to track and communicate human activities acquired using ADXL345 accelerometer sensors. Three volunteers participated in this research, and data were acquired using two accelerometer sensors placed on the hand, wrist, and ankle. Data shared to the cloud- thingspeak.com. Acquired data were analyzed and trained with the Random Forest algorithm and tested with the data, achieving 100% accuracy. This model can be helpful in various applications like elderly patient monitoring, I.C.U., dementia, Alzheimer's, etc.

Keywords- IoT, Activity Recognition, Cloud, Nodemcu, Accelerometer, Activity, Random Forest

I. INTRODUCTION

The Internet of Things, shortly known as IoT, has detained recognition in numerous fields as this technology is a current trend of an expeditious segment of the internet. In the current generation, this plays an essential role. To classify the sensor data in real-time, IoT enhances stronger when combined with machine learning techniques. During the earlier days, with the evolution in the A.I. field, all the objects behind the understanding of humans into the level of practice. In numerous applications, deep learning is used as this is a subgroup of machine learning. Its extension has been shown in numerous areas like robotics, health care, colouring, entertainment, images, and videos. Under machine learning, deep learning is contemplated as one of the chief areas. It can assist in developing a model that can predict numerous real-time aspects. Using numerous medical sensors, data can be collected for analysis. For prediction, data can be input into numerous machine-learning algorithms. In the cloud, real-time data is stored. Similarly, we can benefit from both cloud computing and IoT [1–5]. To lead high efficiency to a system, we can merge cloud computing and IoT. In every equal interval of time, the severity of the parameters can be measured as we can notice frequent changes in the collected health parameters. To monitor a patient's health condition independently, in the environment of IoT, the main entities are wearables and intelligent health care sensors. To make a decision, machine learning algorithms can handle massive data. Deep learning is derived from a standard neural network with a vast number of perceptron layers that can recognize all the hidden layers. As there occurs a scarcity problem in the early stages when deep learning is launched in computing systems, but as there is a change in time, computational power has enlarged. In deep learning, massive data will be stored in cloud computing devices. Deep learning is contemplated as creating a system that grasps a concept that can be concluded through semi-supervised, supervised, or unsupervised learning techniques. Figure 1 shows numerous learning techniques [2, 6–11].

II. LITERATURE REVIEW

The conception of deep learning is growing as it evolves into a hybrid system that can predict numerous diseases that influence humanity. Deep learning techniques can investigate massive datasets and build new features rather than depending on the existing ones. In modern systems like healthcare, many better functionalities and features drive industrial community and research by producing numerous integrated solutions in the technologies of the internet. Advanced technologies like Machine learning, analytics, the Internet of Things (IoT), and big data have become an operating force to address a few challenging issues in the healthcare industry. To enhance the quality of health monitoring, the networking industry has developed numerous communication network protocols, sensing devices, and networks that can be highly deployed for the care of patients in health care monitoring.

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IoT systems will be embedded with numerous devices bridged to produce a healthier environment. In the technology of IoT, there is a lot of improvement like wearable devices, sensors, smartphones, and portable handheld devices that have led the way in the growth of much-personalized health care. Numerous tasks are challenging to provide quality services in healthcare with good financial support and limited resources.

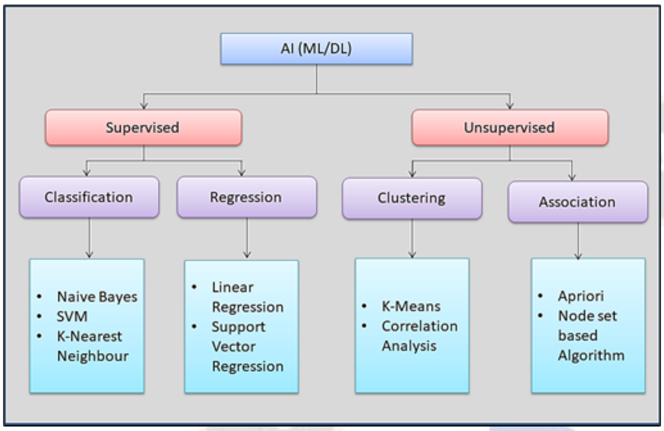

Figure 1. A.I.- ML Methods – Algorithms

Figure 2 Shows IoT and Clod Infrastructure for Healthcare services. Among the population, older patients generally have some disabilities that lead the way to assist the model as per the needs of the patient by providing care, home assistance, support, rehabilitation, etc. [12–22]

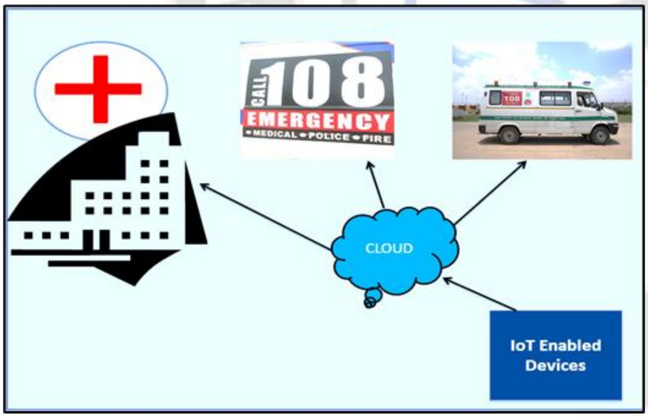

Figure 2. IoT-enabled and Cloud Infrastructure based Healthcare Services

III. METHODS

A. A.I. Techniques in Health Care

Machine learning and deep learning approaches are subcategories of A.I., abbreviated as Artificial Intelligence, as these are quick-growing fields in the current trend. Numerous layers are comprised of deep learning. It imitates the human brain as it copies the neurons of the neural network. To the system in deep learning, initial training is given so that it responds naturally based on the situation. In the case of emergencies, a perfect decision will be taken. This will be enabled in deep learning systems. The system's performance will be very high, and sometimes it surpasses the performance of humans. In many numerous fields, deep learning plays a vital role as this provides an accurate output. Massive computing data and labelled data are crucial in deep learning. For training the models of deep learning and features, a massive set of labelled data needs to be taken into account, as these can be brought out directly without any manual feature extraction.

Deep learning techniques in healthcare can improve the system with more accuracy. In the medical imaging process, deep learning helps out in the recognition and detection of melanoma. The most important features can be learned from a bunch of medical images. By utilizing the images from M.R.I. and many other sources, 3D brain building is possible. Here, other applications comprise tumor detection, brain tissue classification, etc. In the field of bioinformatics, deep learning helps in the treatment and diagnosis of terminal diseases such as cancer. In the area of predictive analysis, deep learning is enhanced [14, 23–27]. In healthcare centres, deep learning helps doctors analyze a particular disease and take quick decisions based on the disorder, leading to proper treatment. Deep learning has obtained more importance in numerous healthcare fields like cell scope, the discovery of drugs, genomics, medical imaging, and Alzheimer's disease. In the genomics field, if any patient is experiencing any treatment, deep learning can predict the genomic structure and future diseases. By using deep learning technology system process is more accurate and faster. The doctor visit in hospitals can be reduced by using cell scoping as this can monitor patients' health conditions. Injurious diseases like cancers and brain tumors can be detected using medical imaging techniques. By using deep learning techniques, in the early stage, we can predict Alzheimer's. Unstructured data in deep learning can be represented by individuals, which can be very easy to determine. A crucial relationship can be learned in the data that helps create a model. More accurate outputs are obtained at low cost using deep learning techniques [24, 25].

B. Sensors For Various Healthcare Applications

Numerous sensors play a vital role in the healthcare industry in various testing applications. Table 1 shows the Sensor types and their purpose in the Healthcare industry.

C. A.I. Methods For Human Activity Recognition System

Pattern recognition and human-computer interactions played a crucial role and obtained a lot of attention in human activity recognition. The lifestyle of any particular human being can be identified using wearable sensors. The crucial part of the system

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is recognizing and sensing feature extraction. Through raw data, the process of feature extraction can be done initially. Data collection is done by using triaxial accelerometers and gyroscope sensors. By using a low-pass Butterworth filter, noise reduction can be made. The strength is obtained by processing all the external features using linear discriminant and principal component analysis. Human activity recognition utilises a deep belief network [7, 8, 11, 19]. The DBN is divided into two main parts:

1. Pre-training phase
2. Fine-tuning algorithm

The pre-training phase is based on constricted Boltzmann machine, and following pre-training, fine-tuning algorithms are utilized to alter the network's weights.

Table 1. Sensors and their usage in Healthcare Applications

Sensors used in healthcare	Purpose
Force Sensor	With high-reliability measures, the force
Photo optic sensor	Suitable for medical applications
Air bubble detector	To identify the properties of fluids
E.C.G. sensor	To measure the heart rate
Position Sensor	To measure the changes in Magnetic Field
Blood glucose sensor	To find the blood glucose level
Oximetry sensor	Used to monitor oxygen saturation
Temperature Sensor	Determines body temperature
Blood Pressure	Systolic and diastolic pressure is identified
Potentiometric sensor	Sweat ion monitoring
Image sensor	Cardiology
Accelerometer	To measure acceleration
Bio-sensor	Scan during pregnancy, ultrasound, blood sugar
Gyroscope	To measure angular velocity

D. IoT Devices For Human Activity Recognition System

The occurrence of IoT has unlocked an excess of opportunities. In recent times, Human activity recognition has obtained stretched attention. IoT concepts can be experimented on living and non-living things by connecting them to an intelligent environment. Sensors are critical in any IoT-based system or application. A minor change in the system can be predicted by utilizing these sensors, and the collected data is processed and automated to work smartly for all innovative applications. Without human intermediation, IoT devices communicate with various sensors embedded in the device or application. IoT applications are primarily based on wearable sensors. Many sensors like microphones, accelerometers, and gyroscopes are used in daily life activity to predict a particular action or movement. Numerous types of research are done to determine human activity by noticing different parameters. Using intelligent devices, monitoring can be done for many age groups, such as young people, infants, disabled and older adults. Monitoring can be done by using these wearable sensors. Reports of physical or mental health patients can be sent to their families by monitoring their activities through sensors. Earlier, researchers utilized multiple sensors placed at various positions like the waist, chest, ankle, thigh, ear, knee, wrist, eyes, and many others. These are categorised into different subsets based on particular actions and applications.

A single sensor would be enough to monitor all the upper body movements. Assessment and classification of activities in day-to-day life, most H.A.R. systems use accelerometers to predict the activity. Based on the application and size, single or multiple accelerometers are used, which are attached to different body parts to monitor. Multiple sensors attached to the body are allowed to some extent as we can get more accurate output but wearing multiple sensors is not a good practice and is feasible for a human being. Wearable sensors are used to detect physical activity movements, but these also help predict and analyse stress levels, sleep patterns, and mental fitness conditions. Different data is gathered from around three individuals for predicting and analyzing physiological patterns.

These systems help in finding out the factors which are affecting the performance of academics, stress level, sleep quality, and also mental health. In H.A.R. systems, data is collected and arranged into a pre-processed dataset, and data classification is carried out. This paper represents numerous techniques and steps for H.A.R. recognition. By using wearable devices, human activities are recognized and classified into two techniques: unsupervised and supervised. A more accurate outcome is obtained from supervised techniques compared to unsupervised ones. In IoT, Sensors are varied from one application to another application. This paper represents different IoT applications and notifies the demand for intelligent applications based on the sensor type. Numerous types of wearable sensors are used to monitor human activities and areas of applications.

This paper represents a brief review of locations where the wearable sensors can be placed. It also tells us that a particular sensor is suitable in that location or not. Wearable sensor positioning along with the preference of relevant features for all the different activities challenges in this field. Regarding activity classification, the sensors have some limitations in detecting and predicting the activity based on the optimal location. Further, numerous areas are traversed in this paper so that we can predict the future and approach a good solution.

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IV. EMBEDDED – HAR MODEL IMPLEMENTATION

To operate a smart environment, there are numerous challenges in operating and implementing these applications. Feasibility, efficiency, and reliability are needed in advanced smart applications. Energy usage and current environment condition are controlled by various kinds of sensors in a smart environment. Observations and measurements are obtained by the sensors to control the system and intelligent algorithms are utilized to implement the control system in the network. In vast areas, sensors are implemented for monitoring and surveillance purpose. Numerous examples are listing as follows: electric toll collection system, traffic signal monitoring, highway data collection, traffic management system and structural health monitoring, etc. The figure presents IoT major applications where IoT creates a smart environment. In Health care and medical applications, sensors solve numerous issues that are related to incurable diseases in medical discoveries. By using wearable devices sensors are connected without using wires in health care applications or devices. For Identification Management IoT is used in the medical sector. In the Identification Management system, everything should be unique to ensure information safety and identity. I.D.M. is dependent on sensors. NightC is one of the platforms that detect every activity overnight of the patient in the health care centre. In this application, sensors are attached to the clothes of the patient. A low-cost e-health monitoring system is modelled to predict and detect human activities. The authors model a similar innovative system to monitor all the physiological parameters of the patients. An intelligent health care application is also modelled to monitor and detect human temperature and patient s body humidity. For this detection technique, the sensors are placed in the patient's shoe.

A. Human Activity Recognition (Har) System

By noticing numerous parameters, Human Activity Recognition is detected using various sensors that are joined to the human body using different wearables. Numerous H.A.R. systems are designed in various fields for analyzing purposes. By noticing different parameters, many researchers have designed many models as the system is small to monitor and the device is wearable. Monitoring can be done on any age group, such as infants, middle age, or old age. In patients' health care, numerous physiological parameters are monitored by using these wearable devices. The information is shared with the respective relative or a doctor in the form of alerts or notifications. Sensors are tagged to the body parts like the Hand, wrist, and Ankle – A total of 2 accelerometer sensors have been used to acquire data. As there will be technological advancements, some have proposed intelligent rooms, innovative education, and bright rooms in a university so that parents or teachers can track and predict what students undergo on a campus. Using variable sensors, academic performances can also be detected and analyzed by the patient's stress, sleeping patterns, and mental health. Data is collected from around three individuals, predicting all the physiological patterns and analysing the behaviour. The performed activities are shown in Figure 3.

B. Hardware Implementation

Nodemcu – ESP8266

IoT applications utilize NodeMCU ESP8266, mainly quarried, open-source Lua-based development and firmware boards. This incorporates firmware that runs on ESP8266 Wi-Fi Soc from Express if systems and on E.S.P. – 12 module hardware is based. In Figure 4 Nodemcu device is shown.

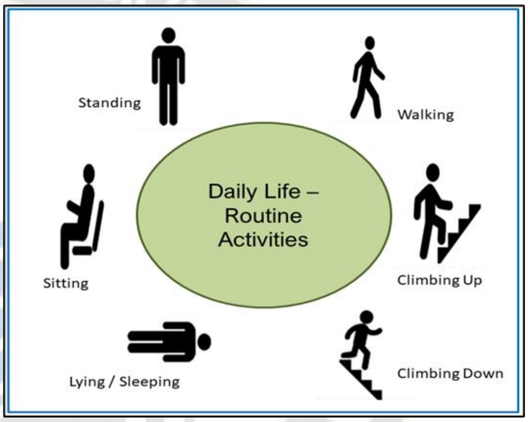

Figure 3. Activities performed in this research, shown in pictorial representation

Nodemcu – ESP8266 board consists of Control Pins – R.S.T. and EN for getting RESET using pins and buttons. Analog Pin -A0 – used Within the range of 0-3.3V analogue voltage is measured. GPIO pins - GPIO1-GPIO16 16 general-purpose pins in and out pins are there on the NodeMCU board. UART pins TXD0, RXD0, TXD2, RXD2 - Two UART interfaces are present in NodeMCU. RXD0 & TXD0 represents UART0 and RXD1 & TXD1 represents UART1. This UART1 is utilized to upload the program. S.P.I. Pins - SD1, C.M.D. SD0, CLK - To S.P.I. communication, four pins are available to NodeMCU.

Figure 4. Nodemcu – ESP 8266

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I2C Pins - NodeMCU supports I2C functionality, but we need to find which pin is I2C due to some internal functionalities. This Nodemcu power connection- Micro-USB, GND,3.3V, V_{in} - Micro-USB: NodeMCU is powered by the USB port. GND: Ground Pin, 3.3V: To power the board, 3.3V regulated voltage is supplied; V_{in}: External power supply. Nodemcu operates with Voltage 3.3 V, consists of A.D.C., S.P.I., UART, I2C, 16 Digital I/O pins, 64KB SRAM, 4 M.B. Flash memory, and it works on 80MHz Clock Speed, consists of Antenna. USB – TTL-based CP2102 enabled onboard used to plug and play easily.

Accelerometer – ADXL 345

Acceleration is a tool that measures appropriately. Proper acceleration is the rate of change of velocity of a body on its own in an instance's rest frame. This acceleration is different from coordinate acceleration as this has a fixed coordinate system. Due to the earth's gravity, acceleration is measured at rest on the earth's surface, which g=9.81 m/s2 defines. In contrast, accelerometers in free fall will measure zero. An accelerometer has numerous uses in both science and industry. In an inertial navigation system, more sensitive accelerometers are used for missiles and aircraft. Accelerometers monitor vibrations in rotating machines. Accelerometers are utilized in digital cameras and tablet computers to display images correctly on the big screen. Accelerometers help in-flight stabilization in uncrewed aerial vehicles.

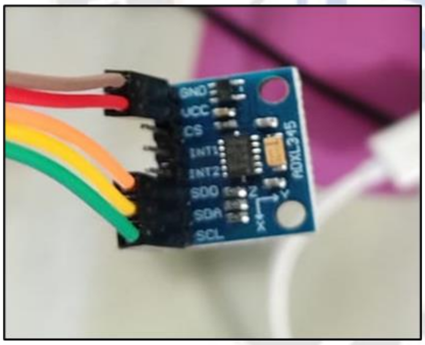

Figure 5. ADXL345 Accelerometer

When two accelerometers coordinate with one another in space, we can measure gravity and acceleration contractions. A gravity gradiometer is utilized because its absolute gravity is a weak effect that depends on the local density of the earth, which is variable. We can detect the magnitude and direction of proper acceleration by using a single and multi-axis accelerometer as we can sense the orientation. In portable electronic devices and video game controllers, MEMS accelerometers are growing to recognize the changes in the position of the devices.

In this research, we use an ADXL345 accelerometer sensor. Figure 5 shows the ADXL345 accelerometer sensor. This is 3-axis MEMS accelerometer with modules with S.P.I. interfaces and I2C, which is low power. This module, a feature of onboard 3.3v voltage regulation and interfacing the device with 5v microcontrollers, makes it easy as this has a level shifting feature. This sensor can be easily connected to an Arduino board. This sensor has a four-sensitivity range from +/- 2G to +/_ 16G, and output data is supported from 10Hz to 3200Hz. This ADXL345 sensor has three axial accelerometer MEMS – Micro-Electro-Mechanical Systems. A silicon wafer is available that consists of a micro-machined structure. The structure of ADXL345 is hung by polysilicon springs that allow it to divert smoothly in any direction when it is subjected to acceleration in all three axes. Diversion causes a variation in capacitance between plates affixed to the suspended structure and the fixed plates. When there is a variation in capacitance on every axis, that is converted into output voltage proportional to the axis of acceleration.

C. Working Principle of Accelerometer

To control numerous physical quantities, we need to monitor our device; we use sensors along with the device. A device embedded with a sensor interacts with all surroundings respectively and sends an alert to the corresponding. We have many sensors in analogue and digital forms to measure physical quantities like direction, pressure, temperature, etc. Similar to sensors, we have an accelerometer sensor to measure the acceleration and speed of any device. An accelerometer's basic fundamental working principle is a dumped mass on a string. When a device experiences an acceleration, the mass will supplant until the string can simply move the weight at a similar rate, equal to the acceleration it sense. The measure of displacement value gives the acceleration. These accelerometers are accessible in both analogue devices and digital devices. Some different methods are used to design accelerometers. The mechanical motion caused by accelerometers can be easily converted to an electrical signal by utilizing capacitive components, piezoelectric, and piezoresistive. To measure the acceleration of any device, we can utilize the piezoelectric effect that is made up of using single crystals. To determine the device's orientation and velocity, which are interpreted by these crystals when we apply any stress on the device. A silicon micromachined element is utilized in capacitive accelerometers. When a device is sensed by acceleration, capacitance is generated and converted into voltage to measure the velocity values. The smallest MEMS are modern accelerometers available in both 2-dimensional and 3-dimensional forms to measure the orientation of the velocity. Accelerometer sensors are used in various applications; In mobiles and laptops, accelerometers detect the device's position. To measure the depth of C.P.R. chest compressions, an accelerometer is used in rotator machines to detect faults, Health monitoring in machinery and Inertial navigation systems.

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D. Interfacing Accelerometer with NodeMCU

To interface the Accelerometer sensor with NodeMCU, we require the following:

Hardware Requirement: ADXL345 accelerometer sensor, Connecting wires., NodeMCU, Micro USB. Bread Board.

Software Requirement: Arduino IDE- ADXL345, Nodemcu packages.

Connections: Connect Nodemcu – D1, D2 to Sensors S.D.A., S.C.L., From Nodemcu Vcc, Gnd to Sensor Vcc, Gnd and Sensor S.D.O. to Nodemcu GND. Hardware connections are shown in Figure 6.

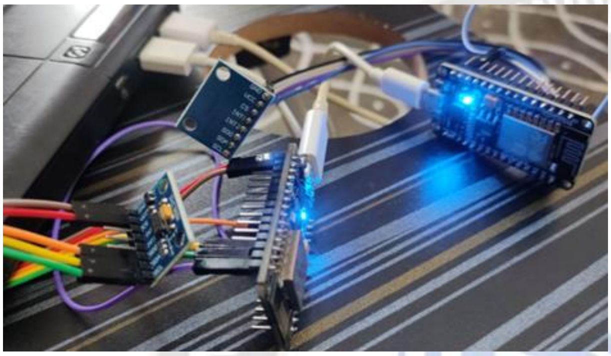

Figure 6. Hardware Connections – Nodemcu and Accelerometer sensor.

E. Data Acquisition: Thingspeak.com – Cloud Infrastructure

Two accelerometer sensors are placed on the Human subject's Hand, Wrist, and Right leg Ankle positions. Data Acquisition was started once the subject completely fixed the sensors on the body and was approved to start the body movements recording. Accelerometer sensor Data shared to the Cloud Infrastructure – Thingspeak.com https://thingspeak.com/channels For two sensors, two separate channels were created to acquire data from Wrist and Ankle movements. Channels are shown in Figure 7.

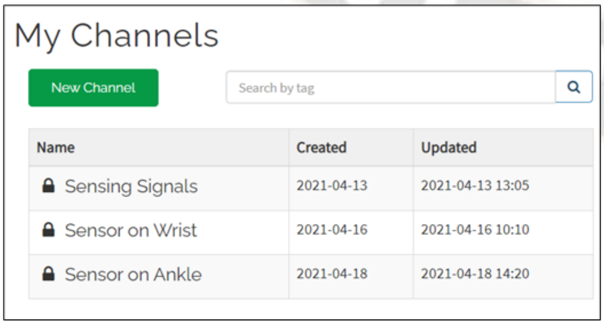

Figure 7. Thingspeak.com – Sensors Data Shared to Cloud

V. RESULTS AND DISCUSSIONS

A. Datasets

In this research, data were acquired from two accelerometer sensors. Three subjects performed six different tasks: *Standing, Walking, Climbing Up Stairs, Climbing down Stairs, Sleeping on a flat surface,* and *Sitting on a chair.* These six tasks were performed by the subjects for each task subject performed for 2 minutes. Each subject spent 12 minutes on average for six tasks for each iteration. Three iterations were performed, by each subject, to maintain qualitative and quantitative data. Table 2 represents the subject's physical attributes and research data attributes.

B. Data Modeling and Classification using Random Forest Algorithm

Random forest is a popular algorithm in the supervised learning technique. This can be utilized for both regression and classification problems in machine learning. In this algorithm, we can solve all the complex problems by combining all the multiple classifiers to improve the model performance. Random forest is one of the classifiers containing numerous decision trees for the given dataset, so it takes an average to improve the predictive accuracy of the dataset. As this algorithm consists of many decision trees, it considers every tree output based on the accuracy of the final output is predicted. The overfitting problem is overcome by considering more trees in the forest to attain higher accuracy. Compared to other algorithms, it takes less time to generate the output. To large datasets, it works very efficiently and predicts highly accurate output. When a large amount of data is missing from the input dataset, it can maintain high accuracy and generate a highly accurate output. It has been used in many applications like banking, land use, medicine, and marketing.

Table 2. Physical Attributes of the subjects and Research data Attributes

No of Subjects	3
Each Subject Performed Iterations	3
No of Tasks – Activities	6
Time for Each Activity	2 mins/task
Age of the Subject	+ / - 33.5
Gender	Male – 3
Body Weight	+ / - 76.9 Kgs
Height	+ / - 1.52 inches

C. Data Visualization

Data samples were visualized after pre-processing, combined X.Y.Z.- axes of accelerometer sensor data merged concerning sensors positions of six different tasks. Figure 8 shows the data of the sensor placed on the Hand Wrist. Simultaneously, Figure 9 shows the sensor data samples placed on the ankle.

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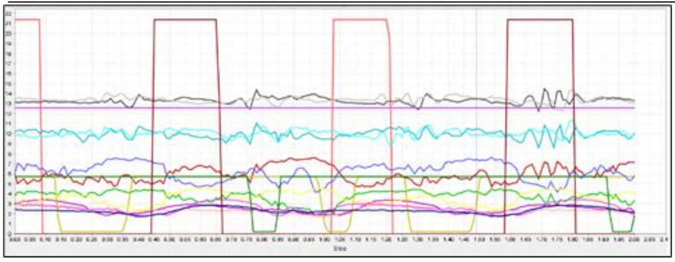

Figure 8. Hand Wrist-worn sensor data samples for six different tasks of 3 subjects

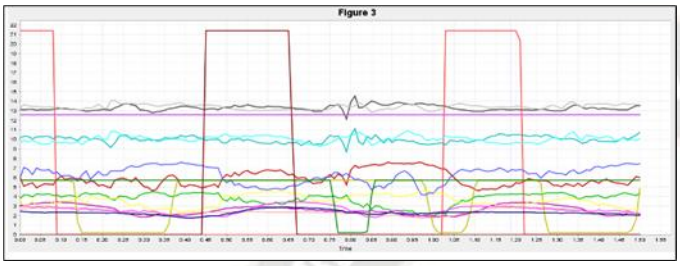

Figure 9. Ankle-worn sensor data samples for six different tasks of 3 subjects

D. Human Activity Recognition using Random Forest

While building the decision trees of random forests, two boundaries should be resolved: the original data set and the estimation of K (the number of choice tree classifiers). We decide the number of decision tree classifiers by the exploratory outcomes. In the preparation cycle of random decision tree classifiers, we select K by {5,15,25,35,45,55,60} individually, and the acknowledgement results of classifiers to the approval set have appeared in Figure 10.

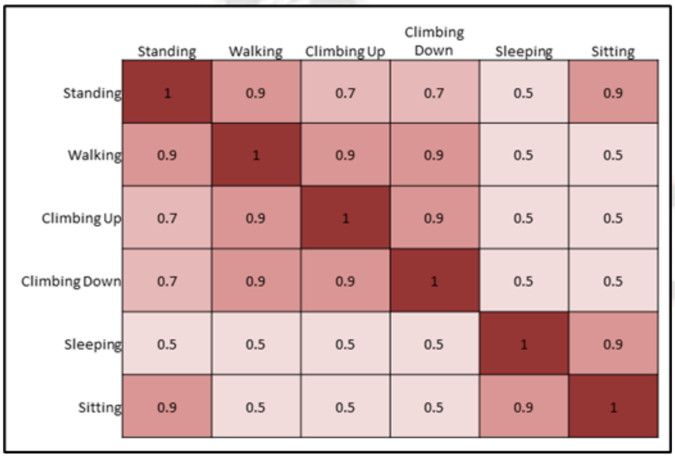

Figure 10. Confusion matrix for six activities performed by three subjects.

The results show the significance of this research; activities – *Standing, Walking, Climbing Up Stairs, Climbing down Stairs, Sleeping on a flat surface,* and *Sitting on a chair*, recognized by the Random Forest algorithm with 100% accuracy, signify the research efficiency. The algorithm recognized the best performance obtained by subjects during the research. Nodemcu hardware device is best suitable for data acquisition, and ADXL345 captured accurate data and transmitted it to the cloud without any drop in the data. Finally, the random forest algorithm was trained and tested with the activity datasets and achieved 100% accuracy in the activity recognition

VI. CONCLUSION

This research work mainly focused on utilizing the Internet of Things - IoT-enabled electronic devices for healthcare applications. From this objective, we focused on Human Activity Recognition. In this context, wearable-size, Accelerometer sensors have been used in this research for tracking human movements. These movement data are shared to cloud infrastructure – Thingspeak. We proposed an activity recognition framework for data acquired in a systematic and analyzed. And we established the activity recognition models with random forests algorithm to identify human activities. We defined the classifiers as activity models. Finally, we achieved an accuracy of 100% for six different activities Standing, Walking, Climbing Up Stairs, Climbing down Stairs, Sleeping on a flat surface, and Sitting on a chair; all activities are recognized

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