**Analysis of Activity Recognition Data using IoT Smart-Watch and Personalised Recommendation by Applying Machine Learning Algorithm**

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***Abstract-- In this smart emerging world, modern day equipment, like wearable devices, not only provides functionality or advancements in lifestyles but also becoming a trending fashion choice. Most of the devices which are wearable provides basic functionalities like display time or date. But implementation of more smart features like displaying message, phone call or even medical activity recognition can lead the productivity in dense and holds a potential to create a product demanded by huge number of customers. Smart wearable devices connected to internet approaches the methodology and required application and implementation of secure IoT environment and cloud infrastructure. Compared to other internet connected devices wearable devices like smart watches are designed to be capable of monitoring activity for 24 hours a day. Mostly they are designed as durable and water resistance with addition of appropriate sensors for required functionalities and detection. In this paper we are proposing a model for identifying requirements of activity and inactivity recognition by implementing on a secure and smartly designed cloud infrastructure. Here we are also defining a new measurement of heart-rate data applying various machine learning methods.***

***Key Words:*** *IoT, Smart-Wearable-Devices, Cloud, Machine Learning, Web Application, Activity Recognition, Personalized Recommendation*

**1. Introduction**

21st century wearable devices like smart watches not only offer visual display of time and date, but also gives us several other feature rich functionalities which helps to create advancement in day to day human life. Most recognised feature for smart watch is health monitoring. Wearable technology introduced the methodology of continuous monitoring of medical and personal data. This not only gives us productivity and efficiency, but also provide us a better way to live our life- A smart life.

Adding sensors to wearable device enhance the functionalities for collecting data about user activity. By collecting and storing the data into a database or secure storage we can provide a platform of innovation for third party vendors. There is various availability of application of accelerometer and gyroscope application to recognise activity of a particular user. Activity and inactivity recognition of individuals have become a current development scenario for wearable devices. But we can do lot of enhancements and predictive approach by applying machine learning to those data set.

In this paper we will discuss about possible futuristic implementation of personalised activity recommendation based on the data collected through smart watch. Besides we will present the scenario of collecting heart rate data from test cases and predicting upcoming health issues by applying available machine learning model into it. Which does not only add valuable medical functionality, but also gives a boost to the existing scenario and an upgraded technical application.

**2. Related Work**

**2.1 Smart Watch**

In the era of 90’s watches had been designed to be connected to modern computers by integrating light sensors in. After the invention of modern wireless technologies connectivity for smart devices has been redesigned [].

Smart watches are wearable in hands and is placed in a particular place to get stable data. Consisting with screen a smart watch is designed to capable of displaying communication services like SMS, Facebook Feed, WhatsApp and even incoming calls. Some watches are enabled to control music and attached with camera module to capture details in stealth.

Smart watches are classified into two separate genre based on the implementation and design -

The first type is known as autarkical watch. The type which comes out with a built-in computational power and dedicated wireless connection for synchronization over the internet. Thus the processing unit directly process the data with the watch itself. Which undoubtedly demands more power for running [].

The Second type consist of a dedicated terminal for event listening and transmitting the records to a hub like a smart-phone device. The heavy work of processing data and transmit back the events to the smart watch. In this way the smart-watch is able to save battery and no extra requirement for computational power [].

**2.2 Activity Recognition**

Research into the field of activity recognition based on the fact of presence of various sensors in a smart-phone, is being conducted for past few years []. But it’s been depicted that a smart-phone is not a good choice for tracking daily activity of a person as they keep their phone inside pockets at idle state. Which places the sensors for tracking near the thigh area and definitely not a suitable place to track activity data from a human body. Mostly people keep their phones aside after usage. In other way, the major functionality of sensor trackers can be void by the inference of other important usage purpose of a mobile phone.

Compared to a smart-phone it’s more suitable to use a smart-wearable device for tracking activity, as it is kept in a particular place of our body and track data for hours without any interruption. Smart-watch is most ideal because it is usually placed in our wrist and an individual mostly use his hand to commit most of the daily works like eating, drinking, writing or even exercise. It’s been studied that a smart-watch is capable of identifying drinking activity by an accuracy of 93.3% compared to a smart-phone with a recorded accuracy of 77.3%[].

**2.3 Activity Unit**

The activity recognition unit identifies the activity mainly based on two sensor units which are accelerometer and gyroscope. Now the accelerometer captures the motion and positioning based on the Cartesian coordinate measurement system. It measures the three axis sensor values as x, y and z which are perpendicular to each other. The sensor values will give a similar output as gravitation force ‘g’ (9.81 m/s2). Which is calculated by the equation –

gl = ∑(x2 + y2 + z2)0,5

Gravitational force (g) influence every object present on earth. Though the gravitational force is not constant everywhere on earth, keeping that in mind a new algorithm has been developed which defines the mean acceleration of the sensor in the 3D space in each second. This feature was deliberately given a name as “Activity Unit (AU)” and is defined by the international unit for measurement by m/s3. Regardless of the unconditional influence of gravitational force on each and every material, the AU is designed to take note only on the change of acceleration occurrence.

A physical jerk is accompanied to the system for the occurrence of rate of changes [], which can represent the derivative of acceleration w.r.t time. Despite of the consideration of the acceleration being zero, low or high it detect the changes regarded. Contrasting with the jerk, the Activity Unit declare the current level of acceleration which is being occurred. As an example the jerk will give similar result as zero when the sensor is motion less even when the device is being transferred in a constant acceleration value. In other case the AU value is zero when it is motionless but output different value when the outcome is the case of the device being accelerated in a unchanged condition. We can define the activity unit value by the following equation-

Here the recorded variables are –

* x, y, z are the sensor values in m/s2
* xn, yn, zn are the values received by the sensor in each readout cycle n.
* xmean, ymean, zmean are the mean of the sensor values for each axis.

During the sensors are motionless the gravity is affecting the output of those sensors. After a certain amount of time the algorithm will be unable to detect any force because of the moving average. While the sensors are rotating they will detect different readings of ‘g’ for each axis. According to previous research implementations, assuming the sensor reading as 32 Hz and sensor rotation by 90 degree, it is required that the force of acceleration on one axis, which had no gravity influence, will be able the acquire the gravity force of one tau, which is about 63.2%, within 2 seconds. This small amount period will provide 64 data triples converted as a usable window frame for activity recognition []. The requirement for time leads to an average of 0.95 as a value for ‘a’ using the following equation, where the provided average is analogous to the values of ymean and zmean.

Here the recorded variables are –

* X(n)= current sensor value
* a= absolute term
* xmean(n)= calculated average
* n=readout cycle
* xmean(n-1)= calculated average for (n-1)

The calculated estimation is being measured up by the consideration of using mean acceleration values for each axis. To determine an estimation for the user activity the summed up values of AU can depict desired output. The summation of the activity unit values can roughly determine how active the user was throughout the day. The prior can also be useful for the determination of noise for the sensor values.