# HEALTH CARE ANALYTICS THROUGH FIT-BIT BAND

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**Abstract:** Thanks to new commercially available consumer-grade fitness and health equipment, it is now simple and more frequent for users to get, save, share, and learn about some of their important physiological characteristics, such as steps taken, heart rate, sleep quality, and skin temperature. These sensors are usually found built into smart watches or particular wearable wrist bands since these wearable devices may be worn for extended periods of time and do so frequently. This enables them to intelligently support users with relation to their activity levels. Doctors could be able to monitor and manage their patients' activity levels with the help of this new connected wearable device. What has been lacking is a mechanism for clinicians, especially exercise physiologists, to automate and transmit appropriate training levels and feedback in a practical way. There are several software programmers and complex Wireless Body Area Network (WBAN)-based systems for remote patient monitoring. This study proposes a software architecture that would allow users to securely record their exercise session, submit it wirelessly to a centralized data repository where physiologists would have access to it, and then know their suggested level of exercise intensity level. Here, we use machine learning algorithms like decision trees and additional tree regression approaches to analyses the data in order to forecast the health condition.

**Index Terms: - *:*** Machine learning, IOT, Artificial Intelligence, Health , Fitbit

## I Introduction

Consumer fitness equipment can assess physiological and health indicators that can assist clinicians have a better knowledge of the overall health of the patient. People of all ages have been found to benefit from exercise, and those who don't consistently exercise have a far higher chance of getting chronic illnesses. People's health is greatly improved when they lead an active lifestyle and exercise frequently. Doctors, exercise physiologists, and other medical professionals are increasingly prescribing physical activity in addition to drugs as part of treatment strategies. Examples of patients where the practice of prescribing exercise is more appropriate or required and is also very effective in the recovery include patients with fractures that render a part of the body immobile for several months, patients with traumatic brain injury (TBI), who have reduced or impaired mobility and need regular exercise to gain mobility, and especially with older people. In order to fully recover, patients who participate in physical therapy and exercise for an extended period of time during recovery and rehabilitation typically need to maintain a specific exercise routine consistently for months without supervision. With the right technology, doctors may have a much deeper understanding of their patients' health. The patient's physical activity is no longer timely, reliable, or consistent information that doctors can access. When a patient's health information is urgently needed, doctors have very few alternatives on how to obtain it. In particular, when maintaining a certain level of daily physical activity is crucial for rehabilitation, it is essential for the doctor to get ongoing feedback from the patient and to create a personalized target for the patient after studying the patient's prior activity levels in cases where any delay or break in the exercises can cause irreversible deterioration.

## 2 Literature survey

It is crucial to understand how prior efforts have been done and establish a starting point before discussing the integration of Internet of Things (IoT) and health recommender systems. In order to explore the integration of IoT and health recommender systems, the following idea is used: data, artificial intelligence (AI), internet of things (IoT), mobile health (mHealth), wearable devices, recommender system, and health recommender systems.

### 2.1 Data

Data in healthcare is generated in enormous quantities on a daily basis. With that being said, the utilization of big data in healthcare can improve healthcare treatment so the patients will decrease the medical impact on their body. Generally, big data analysis consists of 6 V's: volume, variety, velocity, veracity, validity, and volatility (Jagadeeswari et al., 2018). Among the characteristics, the three main features are volume, variety, and velocity. Volume shows the quantity of the information to attain the respective goals. Variety refers to the type of data that can be stored and analyzed. For example, variety in big data can be videos, sounds, text, etc. Velocity tells the speed of when the big data is generated or delivered to another (Kaur & Mann, 2017)

### 2.2 Artificial Intelligence (AI)

Artificial Intelligence (AI) is a technology which immerses human intelligence so that computers have perception ability, learning ability, and an ability to understand natural language through the computer programs (Kaur & Mann, 2017). AI systems rely on their input data. AI in healthcare supports the patient's health monitoring with, for example, vital checks in real time (Kaur & Mann, 2017). In addition, AI systems can explore the patients' data, and then, providing personalized health monitoring, recommendation, and treatment.

### 2.3 Internet of Things (IoT)

The Internet of Things (IoT) is a physical object that has a network connection (Vermesan & Friess, 2013). There can be different types of devices, such as medical instruments, home appliances, Smartwatch, industrial systems, people, buildings, vehicles, and Smartphones. These devices are connected and communicate with each other based on the required protocols to enable personal online monitoring, process administration, tracing, and positioning (Vermesan & Friess, 2014). IoT in healthcare can support health monitoring systems, wearable health monitoring, remote health monitoring, Smartphone health monitoring, etc. (Sahu et al., 2020). Patients keep monitoring their vital health conditions, for instance, body temperature, blood pressure, blood glucose, respiration rate, and pulse rate, using the sensor which is attached in the patient's body (Kumar &Gandhi, 2018). Monitored patient's vital health condition can be used for disease prediction and further treatment (Madakam et al., 2015). Moreover, the monitored data can be stored in the repository so that healthcare professionals have access to the data for future medical treatments (YIN et al., 2016)

### 2.4 Internet of Medical Things (IoMT)

The Internet of Medical Things (IoMT) is the combination of Internet of Things (IoT) with medical devices (Razdan & Sharma, 2021). IoMT is aimed to manage patients' health by using sensors implanted in medical objects and transmitting the monitored data via network so that patients can communicate with their healthcare providers (Vishnu et al., 2020). According to Figure 1, the collected data from patients goes to the healthcare professionals, and then, feedback goes back to the patients. In the near future, most medical devices could connect and be monitored through the internet by healthcare professionals. Such systems will reduce the cost of medical treatment and allow faster access to medical care. In addition, IoMT with the integration of AI, big data, and cloud computing will accelerate the IoMT usage in healthcare.

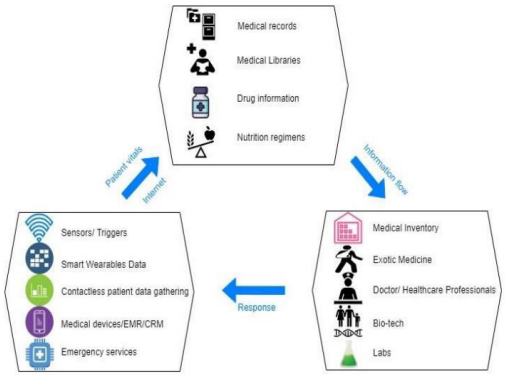


**Fig 1: - IoMT applications**

Mobile Health (mHealth) is the utilization of mobile communication with network technology for healthcare (Dutta et al., 2017). mHealth apps collect user's health information, nutrition, and wellness so that the apps can help people with chronic diseases. In addition, users can track their workout schedule and diet nutrition. Therefore, mHealth apps improve the user's overall health condition by collecting user's health related data. mHealth has been widely used for communication between healthcare providers and patients and delivery for healthcare services (Dutta et al., 2017).

### 2.5 Wearable Devices

The definition of wearable devices is the devices that can be attached to clothing and the human body with receptors and transducers (Xie et al., 2020). Wearable devices can do patient monitoring, asset monitoring, tracking, early medical interventions, and drug management (Banerjee et al., 2017). It can be used in healthcare for cardiovascular diseases, Alzheimer, Parkinson's disease and other psychological diseases, asthma, obesity, and in-hospital monitoring. Moreover, wearable devices not only support personalized health services but also individualized portable devices and sensors (Guk et al., 2019). Portable devices can be divided into wrists, body clothes, feet, heads, and body sensor controlling devices (Kamišalić et al., 2018).

### 2.6 Recommender System

Recommender System is a decision-making system used to filter information depending on user's preferences, interest, and previous activity (Isinkaye et al., 2015). Therefore, it is helpful for users to make their choice by giving out suitable options in the information overloaded world (Sahoo et al., 2019). Recommender System can be divided into seven different systems, such as content-based filtering, collaborative-based filtering, knowledge-based filtering, hybrid filtering, context-aware based filtering, demographic-based filtering, and social-based filtering (Ertuğrul & Elçi, 2019)

**2.7 Health Recommender Systems**

The Health Recommender System (HRS) is a system that applies the Recommender System in healthcare. Health Recommender Systems provide medical information that is related to the patient's medical history (Archenaa & Anita, 2017). Health Recommender Systems can provide patients personalized guidance into Clinical Diagnosis Systems (CDS) and provide personalrecommendations, for example, diet recommendations, follow-up alerts, list of diagnosis, preventative care alerts, etc (Archenaa & Anita, 2017). The Quantified Self (QS) is a concept of self-tracking of personal health conditions in physical, biological, behavioral, or environmental information (Erdeniz et al., 2019). In addition, the QS system will include more recommendation systems to support the users using wearable devices, mobile phones, biosensors, and cloud services. In the basis of Quantified-Self (QS), Virtual Coach, Virtual Nurse, and Virtual Sleep Regulator can be used for improving personal health conditions. Virtual Coach helps to schedule a workout plan and Virtual Nurse supports a physical activity plan depending on the user's medical history and Virtual Sleep Regulator assists insomnia users to improve their sleep quality by recommending their sleep plan and physical activity. For example, collaborative filtering-based recommender systems use K-Nearest Neighbors (KNN) approach to find similarities among the population and recommend a topic that might be interesting and helpful for the targeted users by high chances (Erdeniz et al., 2019).

In this chapter, Data, Artificial Intelligence (AI), Internet of Things (IoT), Internet of Medical Things (IoMT), Mobile Health (mHealth), Wearable devices, Recommender System, and Health Recommender Systems have been reviewed. The literature review helps to understand how various technologies can come together to help monitoring personal health conditions. It also gives an insight to develop an idea which is an integration of IoT and Health Recommender Systems. Therefore, this study is focused on highlighting how can integration of IoT and Health Recommender Systems help responsiveness and affordability in healthcare.

## 3 Implementation Study

Recent studies have analyzed accelerometer data and have investigated the data for physical activity recognition. Nevertheless, few of them have undertaken the difficult task of performing experiments out-of-the-lab. The conditions to perform experiments out-of-the-lab create the need to build easy to use and easy to wear systems to free the testers from the expensive task of labeling the activities they perform. This study attempts to address this challenge and afford the ability to generate and analyze data outside the lab in an open and free environment using data recorded by the accelerometer on wearable devices or cell phones. Data generated in such a format can be used to train models using machine learning algorithms and use the models to test new data. support vector machine, C4.5 and k-nearest neighbor methods were used in the existing system

**Disadvantages**

1) They have a less accuracy

2)They do not perform better in prediction system

3)They are not interpretable

**3.1 Proposed Methodology**

Data preparation and preprocessing using decision tree and extra tree involves feature selection, a process which we have used in our case and described in section 4 below. Feature selection algorithms fall into three categories: filters, wrappers, and embedded techniques. The extra tree algorithm fits into the embedded techniques category. Embedded methods combine the qualities of filter and wrapper methods. They are implemented by algorithms that have their own built-in feature selection methods.

**Advantages**

1 They have a high accuracy

2 They generalize better

3 They are interpretable

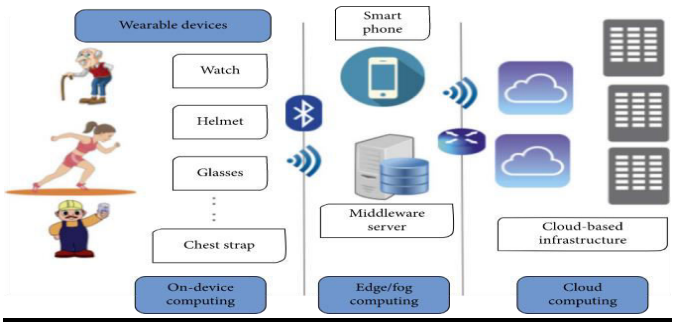


**Fig1: System Architecture**

## 4. Methodology

**MODULES:**

**4.1 Description of Data**

The dataset consisting of uncalibrated accelerometer data with a sampling frequency of 30 Hz, is collected from 8 participants using their wearable devices (mobile phones) performing six activities. These activities are referred to as labels and are codified as follows 1: Working at a computer 2: Standing and walking 3: Standing 4: Walking 5: Walking up and down stairs 6: Talking while standing For each participant, the corresponding csv file which can be downloaded containsthe following information: sequential number, x acceleration, y acceleration, z acceleration and activity label. The activity label is codified as numbers 1 to 6 where each activity has a corresponding number associated with it. Working at the computer has a code of 1, Standing has a code of 3, etc. Note: In the data tables and plots in this paper, the classes are labelled

according to the above list of activities

**4.2 Data Preparation and Preprocessing**

Data presented below provides a list of variables for which raw data were collected from the wearable device corresponding to the activity - sitting at a computer. From this list, a set of values for the following fields were used for the prediction of the activity. These include

Logging Time,

Logging Sample,

Accelerometer AccelerationX(G),

Accelerometer AccelerationY(G),

Accelerometer AccelerationZ(G).

Acceleration data recorded in the dataset are coded according to the following mapping: [0; +30] = [-1.5g; +1.5g]. Ehatisham-ul-Haq, Azam, Naeem, Rehman and Khalid (2017) observed that the time series generated by smartphones generally contains noise generated by the participants and by the smartphones. So, the coded data is smoothed by Holt Winter exponential smoothing model. It is to be noted that data obtained under carefully controlled conditions may contain much less noise and yield much better accuracy (Tillis 2016). As suggested by Pierluigi et al. (2011), features have been extracted by windowing of 75 samples, corresponding to 2.5 seconds of accelerometer data, with 50% of overlapping between windows. From each window, fifteen features have been extracted corresponding to means, standard deviations, minimum, maximum and median values for the three axes x, y, and z. As stated earlier, R language software was utilized for generating these new set of features.

**4.3 Classification and Prediction of Activities**

In order to classify and predict the individual's activity based on the newly derived features, the decision tree and extra tree machine learning model was utilized. For fitting software programs were developed using the python programing

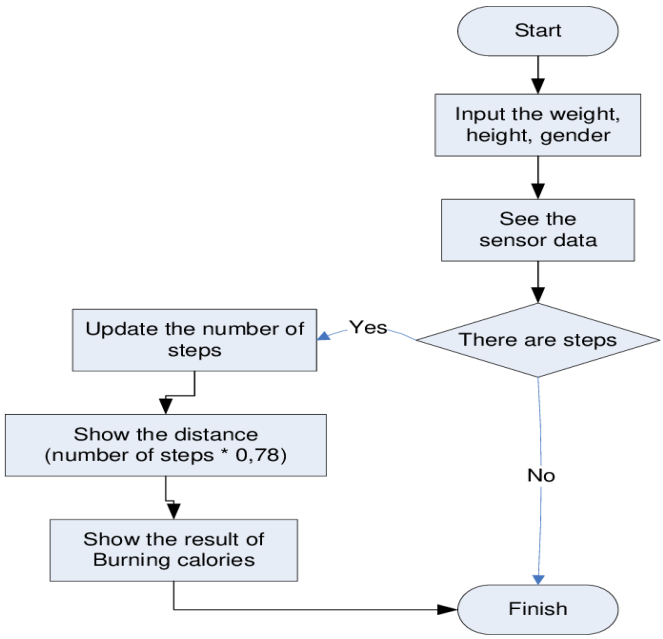


Fig 2: - flow diagram of proposed system

**5 Results and Evolution Metrices**

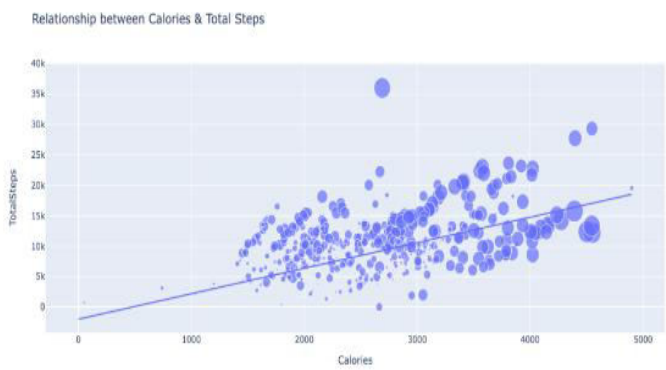


**Fig 3: -** There is a column called "Calories" in the dataset. It contains data about how many calories were burned each day. Let's take a look at how calories are related to the number of steps taken in a given day

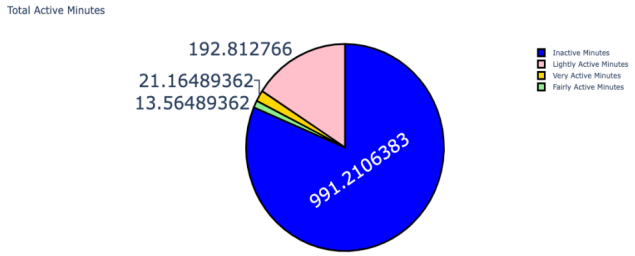


**Fig4:-** It is evident that the daily average of steps and calories burned per day has a linear relationship. Let's now look at the average number of minutes active per day.

**Observations:**

1. 81.3% of Total inactive minutes in a day
2. 15.8% of Lightly active minutes in a day
3. On an average, only 21 minutes (1.74%) were very active
4. and 1.11% (13 minutes) of fairly active minutes in a day

We transformed the data type of the Activity Date column to the datetime column above. Let's use it to find the weekdays of the records and add a new column to this dataset as "Day":

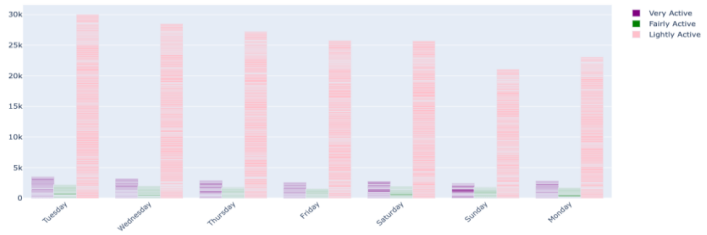


**Fig 5:-** Now let's have a look at the number of inactive minutes on each day of the week:

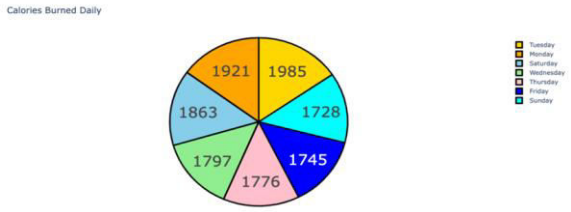


**Fig 6:-** Tuesday is, therefore, one of the most active days for all individuals in the dataset, as the highest number of calories were burned on Tuesdays. So this is how you can analyze smartwatch data using the Python programming language. There is a lot more you can do with this dataset. You can also use it for predicting the number of calories burned in a day.

## 6 Conclusion

An attempt is made in this study to predict the activity of the individual by utilizing the accelerometer data obtained from smartphones. The Decision tree and extra tree classifier Machine Learning algorithm was utilized to predict the activities utilizing the data. 80% of the randomly selected data was utilized as a training set and the remaining 20% of the data was utilized for testing the model. Extra tree model has identified the activities with 88.33% accuracy in the training dataset and 85.94% accuracy in the test dataset. So, this is how we can analyze the data collected by a smartwatch about fitness using Python. Smartwatches are preferred by people who like to take care of their fitness. Analyzing the data collected on your fitness is one of the use cases of Data Science in healthcare.

## 7 References

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