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A novel and intelligent decision-making system for real-time healthcare tracking using commercial wearable data

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Abstract: Wearable health devices became popular these days and have become genuinely intertwined with society. Smartwatches and other fitness devices fulfil the consumer needs in continuously tracking human activity, which can further decode to analyse the health parameters like heart rate, blood pressure, blood glucose levels, and many more. Internet of things (IoT) enabled techniques, mobile and desktop-based applications are ameliorating the ease of using these techniques. The applications of the wearables are also transforming the quality of virtual and tele-healthcare to improve, which is a substitute for conventional medical practices. In this paper, we report a descriptive analysis on the progress in modelling the healthcare wearable sensors that impact the imminent healthcare applications in different domains. Also, we made a comparative study on consumer fitness wearable devices to analyse how the device facilitates the ease of usage with other specification comparisons. We recorded data from a consumer wearable fitness device to observe and envisage the user's effort to accomplish the activity goals each day for maintaining good health. We reported the exploratory analysis of the data obtained from the recordings. Supervised machine learning algorithms are applied to the recorded data and compared the results. Among the supervised algorithms applied, the random forest regression gave us the highest accuracy of 97.88% in predicting the subject's activity goal for the respective day.

Keywords: healthcare; wearables; smartwatches; fitness trackers; wellness activity trackers; wireless sensors; data processing; supervised machine learning; prediction; decision making system.

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1 Introduction

Healthcare services are becoming costlier day by day. As the global population is ageing, the number of chronic diseases is also rapidly rising. The technology cannot eradicate chronic diseases, nor can it stop the population from ageing. The technology can atleast make healthcare more manageable and more accessible. One of the crucial factors in the increase of hospital bills is medical diagnostics. If the accuracy of diagnosis increases, then there may be a decrease in the hospitalisation need depending on the severity of the disease. Because of technology growth, slowly, the hospital-centric (medical checks from a hospital) diagnostics move towards the patient's home (home-centric). In this generation of the internet, there is a strong need for an internet-based system that monitors health. Also, there is a need for a system that suggests the necessary precautions to follow for the respective symptoms before going to a hospital. It is also a difficult task for a doctor or hospital to continuously monitor the health of a single patient. Hence, doctors and hospitals should look for technological solutions that make their work efficient and straightforward.

To achieve this, we must make use of the Internet of Things. IoT is the collective work done by a group of sensors that collect data from different parts. All the data collected is processed using signal processing, machine learning, etc., techniques. The outcome of the applied techniques is observed by a doctors or medical practitioner to find the disorders. According to the observed infirmity and the reports, doctors can suggest a medication, respectively. The data-driven insights and the healthcare analytics allow healthcare providers to speed up decisions with fewer errors. During life-threatening circumstances, it is critical to receive an on-time alert. The devices used to record data can continuously communicate with each other.

In some cases, they make some decisions depending on the need to save lives by introducing IoT into healthcare, many advantages that significantly improve the treatment outcomes. The health practitioners may minimise the errors as they must attend to multiple patients at the same time. If the patient's criticality is less, they may reside at home and follow the physician's guidelines. All the IoT devices continuously monitor the status of the patient and send an update to the hospital staff, who may decide at necessary times. This may also reduce the movement of a patient from home to hospital and back to home. Also, IoT technology reduces healthcare costs as disease management is improved. Thus, it is good to consider the quantified technology.

2 Influence of Internet of Things on medical practices

The applicability of the Internet of Things (IoT) in all kinds of healthcare is extensively increased [1,2]. For a better treatment of patients and the competitive operation of the medical centres, the IoT paradigm helps to increase mutual hope. The quality and efficiency of the treatments could be improved by using this technology in healthcare. The aggregation of microelectronics systems, medical and health, computer science, and many other fields builds an IoT system. From the current health IoT, 2017 to 2022 stands as the growth phase of IoT healthcare and their applications that expedite healthcare and the other stakeholders involved in accelerating it [3]. IoT is transforming the healthcare sector by redefining the devices and associated people in the healthcare solutions [4]. The three main components of healthcare IoT systems are body area sensor networks, internet-connected smart gateways, cloud, and big data support [5].

Figure 1 Remote health monitoring system by tracking data recorded from different sensors connected to a human (see online version for colours)

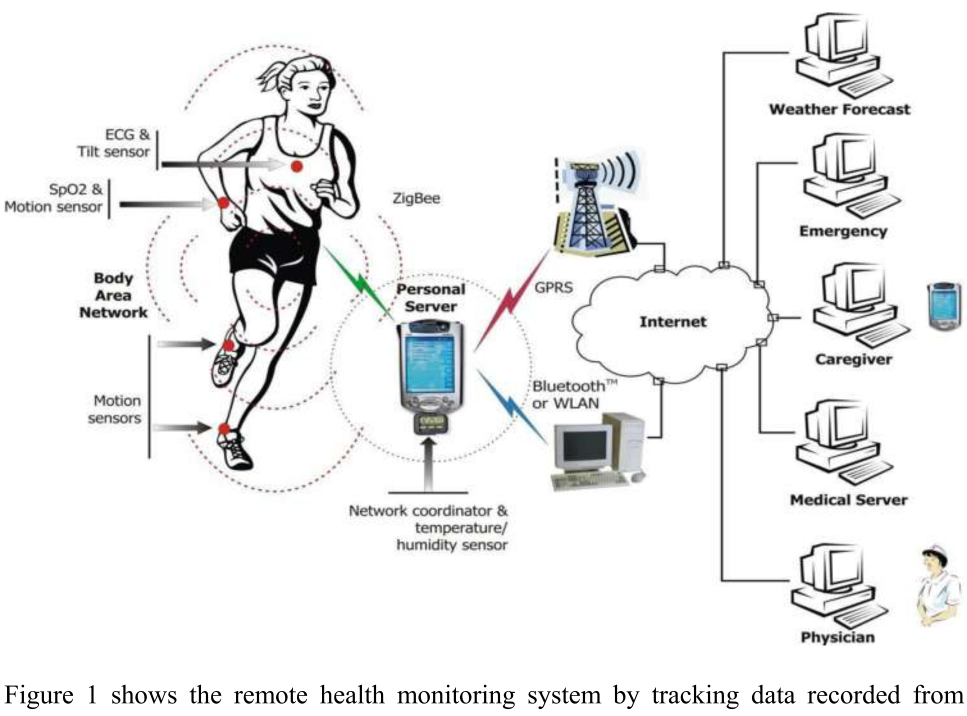
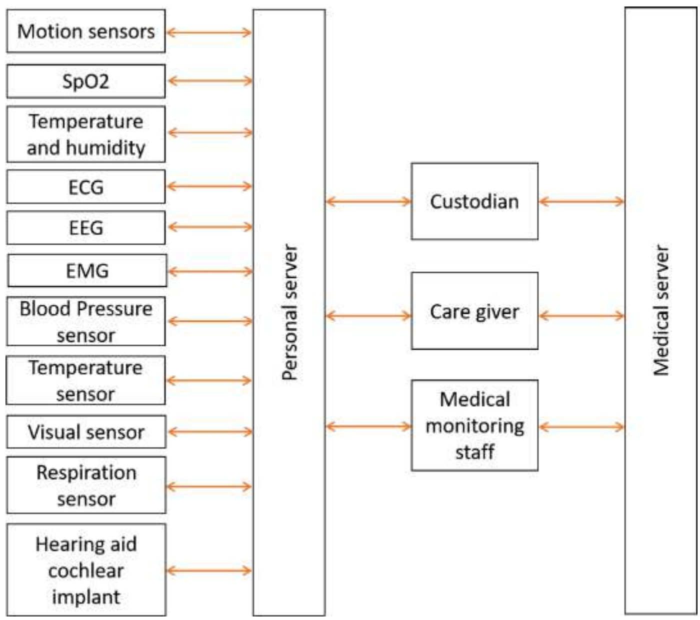


Figure 1 shows the remote health monitoring system by tracking data recorded from different sensors that are connected to a human. We can record simultaneous reporting and monitoring of several cases of medical emergencies like hypertension, diabetes, heart failure, etc. We can collect health and other related medical data by using several smart medical devices. All kinds of smart medical devices can operate using the internet. Employing an application on a smartphone or a computer, we can operate smart devices. We can use these kinds of devices for real-time monitoring of patients. After the data is collected, it can be stored in the cloud. It can also be shared with the nearest or available physician [6]. By following such a kind of practice, we also can reduce the readmission rate. Figure 2 shows the block diagram of the data exchange and the process flow of a typical remote health monitoring system.

Figure 2 Block diagram of data exchange and processing flow (see online version for colours)



It is also a challenging task to analyse the data collected from different healthcare devices manually. There is a need for the cloud to store and manage the data. The IoT devices can collect, report, and analyse data. It reduces the need to store the raw data collected in realtime. The data collected in the cloud will be processed, and the final reports are obtained for access. The data-driven insights and the healthcare analytics allow healthcare providers to speed up the decisions with fewer errors. During life-threatening circumstances, it is critical to receive an on-time alert. The mobile applications and other linked devices are notified after the IoT devices are collecting the data. The doctors confirm the severity of the patient's condition after observing the reports and alerts. This helps to provide on-time treatment by making well-versed decisions even when the patient cannot reach the hospital. Thus, IoT allows a real-time alerting, tracking, and monitoring system [7,8]. Also, IoT enables better accuracy, correct intervention by doctors, better hand-on treatments that can improve the delivery results of the patient.

Also, there are few challenges while using IoT technology and associated healthcare devices [9,10]. As IoT devices capture and transmit data, the major threat they possess is data security. The data protocols and standards of the IoT devices have no proper and fixed format. Hence, they have several privacy issues regarding data ownership. There is a chance for cybercriminals to hack the system and misuse the patient's and doctor's information. By using the patient's name and other identities, they may even file a fraudulent insurance claim. To implement IoT, it needs multiple devices to be integrated. The integration of IoT devices may create an impediment during the implementation.

As there is no harmony among the device manufacturers of IoT-related products in healthcare, there are no collective and standard communication protocols. So, when we connect different devices, due to the usage of different protocols for communication, the aggregation of data will be complicated [10–12]. The scalability of IoT in healthcare is reduced due to different protocols used between the connected devices as it takes more time to process the data. However, the amount of data recorded by IoT devices is so huge that a doctor may be perplexed, which may affect the quality of making a decision. When more devices are connected, more and more data is recorded, and we may encounter this concern more often. There are some methods and techniques being implemented to overcome a few of the above challenges in several industries [13,14].

A nano data acquisition system [15] is a portable system that uses nanosensors. The system interfaces with smartphones and is portable. The components that are available commercially are used to develop this system. They are emerging portable sensing technology at a nanoscale. With the help of smart mobile applications as shown in Figure 3, patients can contact a doctor who is far away during emergencies [16]. By improving mobility solutions, healthcare providers can check the patients instantly and spot the disorders. IoT improves the patient's care in homes or hospitals during epidemics. The healthcare industry is also looking forward to building machines that help distribute drugs from the patient's prescription and the availability of data regarding the patient's infirmity via healthcare devices [17].

Mobile-powered solutions for smart and improved patient care are the need of the day. Healthcare training and innovations are slowly transforming in the healthcare industry. The usage and the requirements of healthcare devices gain momentum as technology advances [18]. The usage of smart devices is tremendously increased nowadays, which is limited to patients and other medical professionals. They are being deployed for good tracking of several functionalities of human organs.

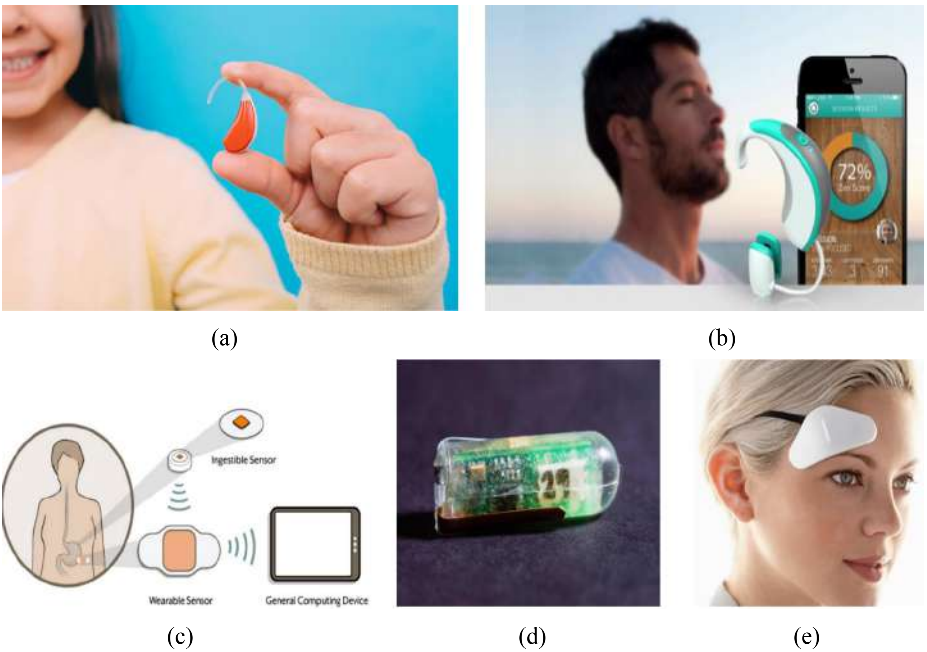
Figure 3 A glucometer add-on for mobile phones (see online version for colours)

3 Wearables

3.1 Wearable technologies

Picard [19] introduced a new field of research in 1995 called affective computing to consider human effects. Wearable technology is a type of affective computing that recognises the activity [20–23]. Wearable technologies have been evolved through continuous technological advancements [24]. These are the devices embedded by technology that can be worn by humans [25]. Recently these wearable devices became popular, even though they are available for decades, because of their functionality, popularity, and fashion [26]. Many companies are trying to boost usage by improving the design, wearability, usage, and other aesthetics of wearable devices [27]. There are even other aspects that play an essential role in wearable technologies. Wearable devices can be on the body or inside the body, which offers hands-free functionality that enables the users to perform their own tasks without any conscious observation on to the device [28].

Figure 4 (a) Smart hearable [35], (b) smart hearable connected to a mobile app that monitors health [36], (c) operation of the ingestible sensor [37], (d) pill-shaped ingestible sensor [38] and (e) moodable [39] (see online version for colours)



Wearable devices that can be worn on the body are called wearable computers and can be defined concerning their features [29]. Wearable computers are defined as body-worn devices such as clothes, rings, etc., which provide specific features to the users [16]. There are plenty of applications available where IoT is dominantly used nowadays. Hearables are hearing aids where we can observe the enormous transformation in the design and the technology embedded [30]. Hearables are operated by a smartphone that syncs data with the help of Bluetooth. These are the new-age hearing aids. They perform many actions to the real-world sounds like filtering, equalising, etc. Figure 4(a) and (b) shows how commercial smart hearables look and connect to a mobile application that monitors health. A pill-sized sensor that monitors and broadcast the medication in the human body are called ingestible sensors [31,32]. These sensors are a modern science marvel and Figure 4(c) shows the operation of an ingestible sensor. Figure 4(d) shows a pill-shaped ingestible sensor. Moodables are also healthcare IoT devices that help in enhancing the mood [33]. These are head-mounted wearables as shown in Figure 4(e). They send currents to the brain, which are of low intensity that elevates human mood. Behaviour state analysis can also be analysed using head-mounted wearables [34].

Table 1 Comparison of smartwatches

Parameters	*Samsung Galaxy Watch 3*	*Apple Watch Series 6*	*Oppo Watch*	*Xiaomi Mi Watch Revolve*	*TicWatch Pro 2020*	*Apple watch SE*
OS	Tizen OS	WatchOS 7.0	Wear OS 5	Xiaomi's custom OS	Wear OS	watchOS 7.0, upgradable to 7.1
Compatibility	Android, iOS	iOS	iOS	Android, iOS	Android	iOS
Display	360 × 360, OLED	1.78″ OLED	1.6″/1.9″ AMOLED	1.39″ 454 × 454 AMOLED	1.39″ 400 × 400 AMOLED paired with + FSTN display	1.78″
Processor	Exynos 9110	S6 SiP with 64-bit dual-core	Snapdragon Wear 3100 & Apollo3	–	Qualcomm Snapdragon Wear 2100	S5 SiP with 64-bit dual-core processor
Band size (mm)	22	22–24	41–46	22	22	22–24
Onboard storage (GB)	4	16	8	–	4	32
Battery (hours)	48	24-48	36	168-336	48	18
Charging method	Wireless	Wireless	Wired magnetic	Proprietary	Magnetic connecting pin	Wireless
IP rating	IP68	Water-resistant to 50 m	5 ATM/2 ATM	5ATM	IP68	IPX7
Connectivity	Wi-Fi, Bluetooth	Wi-Fi, Bluetooth, NFC, LTE	Wi-Fi, Bluetooth	Wi-Fi, Bluetooth, GPS	Wi-Fi, Bluetooth 4.1, NFC	WLAN, Bluetooth, GPS, NFC

mm – millimetre, GB – giga byte.

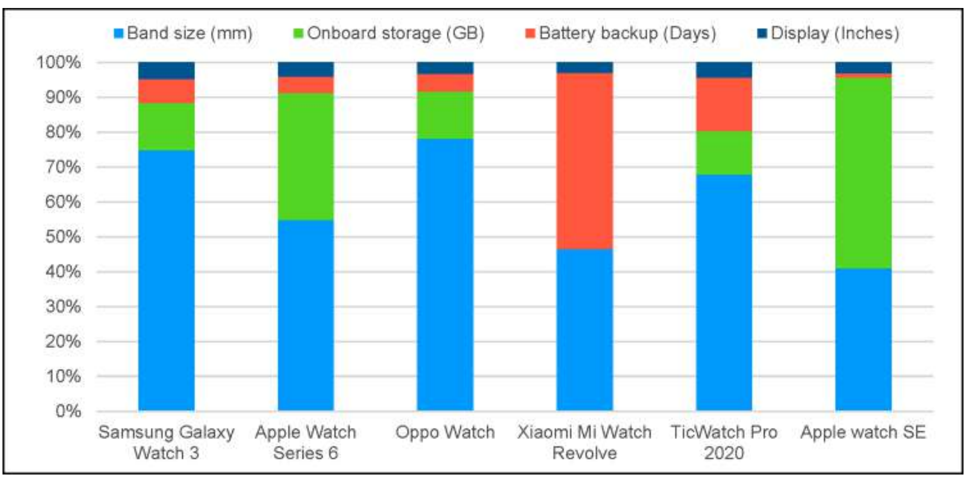
Nowadays, healthcare monitoring and activity recognition are the main two applications of wearables [35,36]. Some other important fields where wearables are being used are education [37], biometric recognition, ambient assistance living systems (AALS) in elderly people [38], gesture recognitions to authentication [39].

3.2 *Types of wrist-worn devices*

Among all the wearable devices, wrist-based or wrist-worn devices (WWD) have gained more popularity as they are easy to wear [40]. The commercial versions of WWDs are categorised into three types. They are smartwatches, fitness trackers, and armbands [41]. Table 1 gives a comparison of highly rated and used smartwatches. The comparison includes different specifications like the size of the band, display operating system (OS), connectivity, etc. Table 2 gives a comparison of different specifications of highly demanded and rated fitness trackers.

Figure 5 gives the graphical view of comparing the band size, onboard storage, battery backup, and display size of the smartwatches mentioned above in Table 1. Among all the smartwatches listed, Xiaomi Mi Watch Revolve has the highest battery backup, where Apple watch SE has the lowest. Apple watch SE has the largest onboard storage space, and Tic watch pro 2020, Samsung Galaxy watch 3 has the lowest.

Figure 5 comparison between the band size, onboard storage, battery backup, and display size of the smartwatches mentioned in Table 1 (see online version for colours)



3.3 *Bloodless wearable technology and devices*

Bloodless wearable devices are a kind of wearable device that automatically measures the capabilities in sports and other extreme environments. They are used in diagnosing and monitoring diabetes mellitus and cystic fibrosis diseases. Sweat has important metabolic biomarkers that could provide insightful physiological information. Sweat glucose, sweat sodium, sweat potassium, sweat lactate, sweat acidity, temperature, and pH, etc., can be analysed by the data collected from these devices.

Table 2 Comparison of highly used fitness trackers

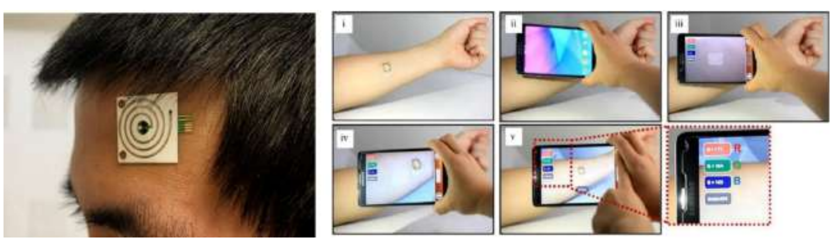
	Fitbit sense	*Fitbit inspire HR*	*Apple Watch Series 6*	*Garmin Vivosmart 4*	*Fitbit Ace 2 activity tracker*	*Mi Band 5*	*AmazfitBip U*
Company Details	Fitbit	Fitbit	Apple	Vivo	Fitbit	Mi	Huami
Product Released	August 2020	March 2019	15 September 2020	September 2018	June 2019	29 September 2020	15 October 2020
Dimension (mm)	5.03 × 10.11 × 22.86	37 × 16	44 × 38 × 10.4	15 × 10.5 × 197	36.83 × 16	46.95 × 18.15 × 12.45	40.9 × 35.5 × 11.4
Weight (g)	32 05	20	47.1	16.4	18.14	11.9	31
Battery type	Lithium polymer	Lithium polymer	Lithium-ion polymer	Lithium polymer	Lithium polymer	Lithium-ion polymer	Lithium-ion polymer
Battery life	up to 6 days	up to 5 days	up to 18 hours	up to 7 days	up to 5 days	14 days	9 days
Battery full charging time	Approximately 40 minutes	2 hours	1.5 hours	2 hours	2 hours	Less than 2 hours	2 hours
Step counting	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calories	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sleep	Tracks light deep and rem sleep time	Sleep App	Sleep app	Advanced sleep with REM sleep monitoring in Gramin mobile app	Tracks light deep and rem sleep time	24-hour sleep monitoring	Sleep quality tracker
Heart Rate	ECG app PurePulse 2.0	ECG app	ECG app	ECG sensor	Ppg sensor	PPG sensor 24 hour	24 hr monitoring
Fitness Analytics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Speed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SpO2	Red and infrared sensors used to monitor oxygen saturation (SpO2)	Red and infrared sensors used to monitor oxygen saturation (SpO2)	red and infrared light from its new sensor	IR sensor Pulse OX	–	–	Red and IR sense bio tracker

Table 2 Comparison of highly used fitness trackers (continued)

	Fitbit sense	*Fitbit inspire HR*	*Apple Watch Series 6*	*Garmin Vivosmart 4*	*Fitbit Ace 2 activity tracker*	*Mi Band 5*	*AmazfitBip U*
Goal tracking	90-day Fitbit Premium trial for new Premium users with personalized guidance	90-day Fitbit Premium trial for new Premium users with personalized guidance	daily trend of data on Activity app	walking, running, strength training, yoga, pool swimming is monitored by a dedicated activity timer	Sleep tracking/ activity tracking for kids	–	60 sports modes
Water resistance	50 m	50 m	50 m	50 m	50 m	5ATM	5 ATM
Screen type	AMOLED	Backlit OLED display	Retina LTPO OLED	OLED	OLED	AMOLED	LCD color display
Touchscreen	Capacitive	LED scroll response	Sapphire crystal	Scroll sense	backlit display	On touch button	Touch sense
Screen size (Inch)	1.58″	1	1.78″	0.26″ / 0.70″	1.3″	1.1″	1.43″
Alarm function	quiet vibration during a lighter sleep stage	silent alarms	-	Vibration alert	Silent alarm with quiet buzzing	Vibrate alert	-
Data sharing	Bluetooth® LE and internet connection.Fitbit app	The app can sync data with iPhone 4S model and, later, iPad 3rd generation.	Airdrop	Garmin Connect™ Mobile app	Bluetooth and internet to an app	Mi Fit app	Zepp App
Wearable body type	Fits wrist 139 180 mm wrists	Fits 140–180 mm	Fit 130–200 mm wrists	Fits 148–215 mm wrists	Fits 4.6″–6.6″ wrists	Free size wrist fit	Free size wrist fit
UI	OS 2.0	Fit bit OS 2.0	watchOS 7.0, upgradable to 7.1	Custom OS	Custom OS	Custom OS	Amazfit OS
Social network data sharing	Can transfer from app	Can transfer from app	ICLOUD	Fits wrist 139–180 mm wrists	Fits 140–180 mm	–	–

There is a huge progress in developing wearable sweat biosensors [42–54], which are used for measuring detailed sweat profile during several indoor and outdoor activities. These sensors are built on flexible substrate materials that can maintain a sure contact with skin as shown in Figure 6(a). It uses a significantly less volume of sweat to analyse metabolites, electrolytes, heavy metals, etc. Sweat secretion is a complex task as it involves several chemicals [55]. Soon after it was secreted on the human skin, we need a parallel detection mechanism to process and analyse. Figure 6(b) shows an example method for image capture and analysis of calorimetric sensor through mobile phone application. There are plastic-based sensors available where human skin is interfaced with silicon-based integrated circuits (ICs). As the sensors are connected to IC, signal processing techniques can be applied simultaneously after collecting sweat samples [46,47,54]. A wearable sweat ethanol sensor, which is a union of the flexible wireless circuit board and iontophoresis-based sweat extraction arrangement, gives the clear distinction of the ethanol levels in the blood before and after alcohol consumption [51]. Diabetes can be monitored from sweat samples, and feedback therapy can be offered using wearable devices [53]. A colorimetric sweat-sensing system is available with wearable technology for monitoring glucose, pH, lactate, and sweat chloride [52]. Glocowatch is a commercial wearable that works as a non-invasive glucose-monitoring device. It works on the principle of reverse iontophoresis. By using this method, a portion of interstitial fluid is analysed from transdermal extracted glucose [56]. As shown in Figure 7(b), a tattoo is used as a wearable platform to extract interstitial fluid and sense the glucose.

Figure 6 (a) Sweat fluid sensor and (b) image capture and analysis of calorimetric sensor through mobile phone application (see online version for colours)



(a) (b)

After sweat, saliva and tears are salient and complex biofluids. They contain numerous vital constituents that are noninvasively available. These biofluids contain excellent liquid integrands. Sensors with electrochemical sensing are used as part of soft contact lenses to record and monitor glucose and lactate, which are available from the analytes of tears [57–59]. Google incorporated a similar idea and built a device called Google contact lens [60] that monitors glucose levels (Figure 7 shows the google contact lens). Transducers that are made by amorphous indium gallium zinc oxide field-effect transistors are integrated into contact lenses. These contact lenses are potential and transparent sensors that sense glucose from tear fluids [61,62].

Graphene has a nanoscale nature, and it is capable of detecting sensitive analytes. The antimicrobial peptides are self-assembled onto graphene to detect bacteria at single-cell levels. The power and connectivity requirements can be eliminated by including a resonant coil. The combination of these two elements forms a new nanosensor that can be integrated into a tooth to sense saliva for monitoring respiration and for bacteria detection as shown in Figure 7(c) [63]. There are non-invasive wearables responsible for detecting salivary lactate and salivary uric acid continuously, which can communicate to a computer wirelessly [64,65]. In diabetic patients, saliva can explore as a substrate that measures glucose levels and monitor glycemic control [66,67].

Continuous glucose monitoring (CGM) systems use interstitial fluids (ISF) of the skin to measure glucose. Figure 8(a) shows the testing kit, which uses a blood drop to capture blood glucose levels in a glucose monitor [68]. Though this is the accurate method in identifying blood glucose concentration, patients are unwilling to follow the process due to pain and a need to dump the used lancets. In the current era, the CGM technology enables to use a wearable as shown in Figure 8(b) that monitors the glucose concentration in the skin ISF, which is proportionate to the blood glucose concentration. These values are transmitted to a smartphone or cloud for storage and analysis purposes. CGMs with alarms automatically notify the user when their glucose level is above or below a preset threshold. CGMs also measure the rate of change of this analyte [69].

Figure 7 (a) Google contact lens [60] (Copyright 2017, Alphabet) (top left), (b) transdermal alcohol sensing device using iontophoretic-sensing tattoo (top right) and (c) bacteria monitoringdental tattoo sensor (bottom left) (see online version for colours)

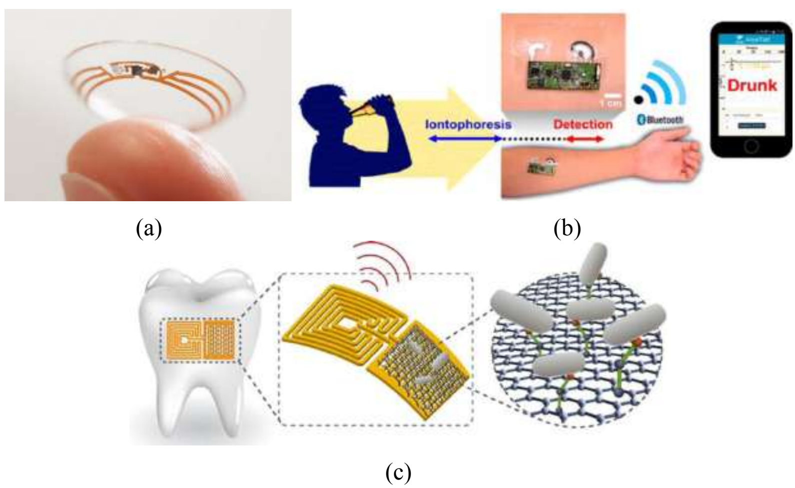


Figure 8 (a) Blood glucose levels test for diabetes patients and (b) continuous glucose monitoring product (see online version for colours)

3.4 Wearable technology for sports

The other potential application of wearable technology where it positively influences the practice is sports. In sports, wearable technology benefits monitoring, overcoming injuries, and further strengthen performance. Traditionally, optical motion capture technology is used as a gold standard reference to monitor the movements in swimming [70], rowing [71], baseball [72]. These systems use a camera that tracks passive or active markers. These markers are placed at the anatomical landmarks of the human body to capture the movements. For the sports like football [73,74], rugby [73], athletics [75], and netball [76], the Vicon motion capture system were used as a gold standard reference to wearable technology. The current wearable technology for sports uses inertial measurement units (IMU), microelectromechanical sensors (MEMS), flex sensors, magnetic fields, and angular rate sensors embedded in the devices to calibrate motion. Sensors that are used in these devices to record data have added features and are susceptible to extreme environments that withstand cold temperatures and are also waterproof [77–82]. There is a drawback with ferromagnetic objects inside wearable devices, which may misreport the measurements from inertial-based systems [74]. Due to the precise positioning of the sensors, data obtained may not be extrapolated to attain any other related results out of the wearable system [83,84].

These wearable systems can provide real-time feedback, which should validate with the optical systems, which are widely considered a gold-standard method for motion capture [85]. Concurrent data validation establishes the resemblance of the data procured from wearable system technology and a gold-standard reference. While rating the sensor performance with reference to the subjects, testing-retesting and intra-subject reliability are also important factors. The sensitivity of the sensors is also crucial to track the data according to changes of parameters with respect to time [86].

The studies [72,73,77,87–95] describe different applications of wearable technology into sports that elucidate the prevention of injuries, computing skill level thereof expertise, how the technique can be improved and characterising the movements and gaits. Sensors are used for movement recognition and are explored in cricket, football, rugby, badminton, rowing, swimming, and table-tennis [70,71,74,90,96–100]. Acceleration values are significant in recognising the movement after sensors record and process data in non-laboratory sports applications. By comparing the standard deviation in acceleration, block movement can be characterised in table tennis, and athlete levels can also be discriminated [96]. Characterisation of Nordic walking (NW) can be achieved by acceleration and force values [101]. It would be an attractive and safe form to have regular NW training to have a positive influence on kinematic parameters [102].

3.5 Factors affecting WWDs

There are several factors that affect the use of WWDs. The user interface is a big challenge [103–106] of physical limitations and other parameters of usage. A micro-interaction technique is proposed in Motti and Caine [107], where the user spends less than four seconds to complete the task. Also, it explains the ease of smaller tasks to minimise the effort needed. Many wearable devices have respective user interfaces that are clear and simple to navigate, allowing users to feel comfortable while using [108]. But this can be a little difficult with all the WWDs, as there are very small in size. So, they need a computer-based or mobile-based application, where the data is stored, processed, and then analysed to meet the user’s needs. The companion application should also be user-friendly.

Table 3 Comparison of android-based health and fitness, mobile applications (Top nine editor's choice) (see online version for colours)

S. No.	*Name of the application*	*HealthifyMe*	*Pacer*	*Step counter*	*Home workout*	*MyFitnessPal*	*Headspace*	*Calm.com*	*Lifesum*	*Runtastic*
1	Logo									
2	No. of downloads (in millions)	10+	10+	10+	100+	50+	10+	10+	10+	50+
3	Free/Paid version available	Both	Both	Both	Both	Both	Paid only	Paid only	Both	Both
4	Diet tracking available	Yes	No	No	No	Yes	No	No	Yes	No
5	Water tracking available	Yes	No	Yes	No	Yes	No	No	Yes	No
6	Steps tracking available	Yes	Yes	Yes	No	Yes	No	No	Yes	Yes
7	Nutrition calculator available	Yes	No	No	No	Yes	No	No	Yes	No
8	Sync with other health/fitness apps	Samsung health, Google fit, Garmin, Fitbit	MyFitnessPal, Fitbit, Garmin (only premium users)	Samsung health, Google fit	No	Fitbit, Google fit, Samsung health	No	No	Fitbit, Google fit, Samsung health	Polar, Gramin,
9	What permissions are required	Location, Read/write storage, Camera	Camera, contacts, location, phone, storage	Location, storage	Storage	Camera, contacts, location, phone, storage	Calendar, Phone, storage	No permissions required	Camera, storage	Camera, contacts, location, Microphone, storage

Table 3 Comparison of android-based health and fitness, mobile applications (Top nine editor's choice) (see online version for colours) (continued)

S. No.	*Name of the application*	*HealthifyMe*	*Pacer*	*Step counter*	*Home workout*	*MyFitnessPal*	*Headspace*	*Calm.com*	*Lifesum*	*Runtastic*
10	Option to enter activity information manually	Yes	No	No	No	Yes	No	No	Yes	Yes
11	Fitness monitoring/ training app	Both	Both	Monitoring app	Training app	Both	Training app	Training app	Both	Both
12	Live interaction available	Yes	No	No	No	Yes	No	No	No	No
13	Customer rating in play store (Out of 5)	4.5	4.6	4.8	4.9	4.4	4.7	4.2	4.4	4.6
14	No of user reviews (in 1000's)	163+	765+	458+	1517+	2368+	169+	327+	259+	1059+
15	24*7 chatbot assistance available	yes	No	No	No	Yes	No	No	No	No
16	Human assistance available	Yes, but limited	No	No	No	Yes	No	No	No	No
17	Additional bands required for tracking	No	No	No	No	No	No	No	No	No

3.6 Consumer health, training, fitness mobile applications

Mobile applications are also the trend in current consumer healthcare approaches. The smartphones are embedded with plenty of sensors that can track the data like a wearable device. The computational power of smartphones is an advantage to process the real-time data and project the suggestions, respectively. The comparison of the different available options of the top nine most used health and fitness Android-based mobile applications taken from the editor's choice is given in Table 3.

Figure 9 compares the customer ratings that were given by the consumers who are using the respective apps. The home workout app has the highest user ratings among the nine apps, i.e., 4.9, where the calm app has the lowest user ratings, i.e., 4.2.

Figure 9 Graphical comparison of the user ratings for apps mentioned in Table 3 taken from the play store (see online version for colours)

4 Experiment, data, and analysis

To analyse how wearable technology is influencing humans in maintaining individual health respectively, we have taken an activity database of a healthy 25-year-old male subject. The data was recorded by a consumer wearable fitness device, i.e., Fitbit Charge HT fitness tracker. The data consists of calories, steps, distance in metres, floors, minutes sitting, minutes of moderate activity, minutes of intense activity, and the calories burned for the activities. The data taken for analysis has 365 rows and 10 columns. Rows include details about the day, month, and year, where columns give information about calories, steps, distance in metres, floors, minutes sitting, minutes of moderate activity, minutes of intense activity, and the calories burned for the activities.

From Figure 10(a), an overlap of the curves can be observed. It means that the number of steps moved in a day is directly proportional to the total activity time of that respective day. In Figure 10(b), the graph is plotted to observe the relation between distance and number of steps moved. Like plot (a), in the plot (b) also, there is a strong relationship between the distance covered and steps moved. Hence, they are directly related.

In Figure 10(c), the plot shows no proper relation between calories burnt and sedentary activity time in a day. In Figure 10(d), there is more overlap between calories burnt and distance moved. It means, if the distance moved is more, the number of calories burnt is more, and both are directly related. Figure 10(e) shows the plot between time spent on all types of activity in a day, sedentary activity, light activity, moderate activity, and intense activity vs. the number of calories burnt on that respective day. We can find that more time is spent in sedentary activity in the whole day. Hence, more area on the plot is occupied by sedentary data points. Though more time in a day is spent doing a sedentary activity, there is a linear distribution observed on the plot. After the sedentary activity, the subject spent more time doing a light activity, which is also linearly distributed. After the light activity, the subject has spent intense active and moderate activity in equal time. This is because the subject is performing some health fitness activity daily for some time. If the subject is not a fitness enthusiast, we would not have got an almost overlap between these two activities.

In both cases, the plots followed almost linearity. In Figure 10(f), the graph is plotted between total activity time and the number of calories burnt, which has a linear movement. In Figure 10(g), the amount of time spent performing an intense activity is linearly related to the number of calories burnt. In Figure 10(h), the graph is plotted between average activity time in a month and normalised average calories burnt. As the average calories burnt in a month is far higher than the average activity time, the average calories burnt is normalised. We can observe that the highest average activity time is 391.62 min, and the least is 207.6 min. The highest normalised average calories burnt is 329.78 calories, and the least is 281 calories.

Figure 10 Plots showing graphical relation between: (a) steps and total activity time, (b) steps and distance, (c) calories burnt and minutes of sedentary activity, (d) calories burnt and distance, (e) calories burnt vs. time, (f) total activity time vs. calories burnt, (g) minutes of intense activity vs. calories burnt and (h) average activity time and normalised average calories burnt for each month (see online version for colours)

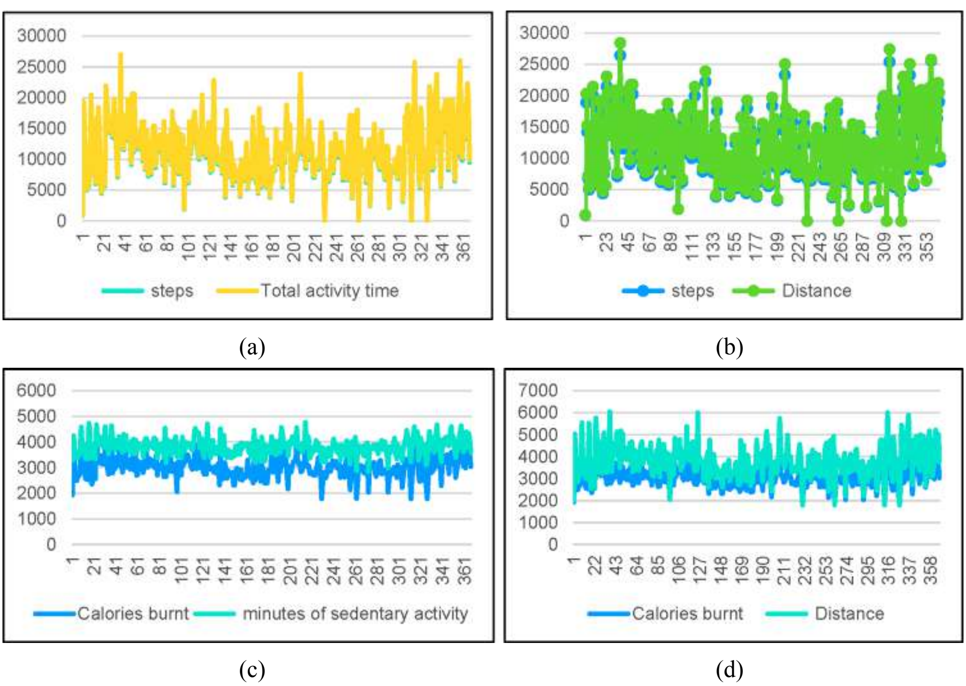
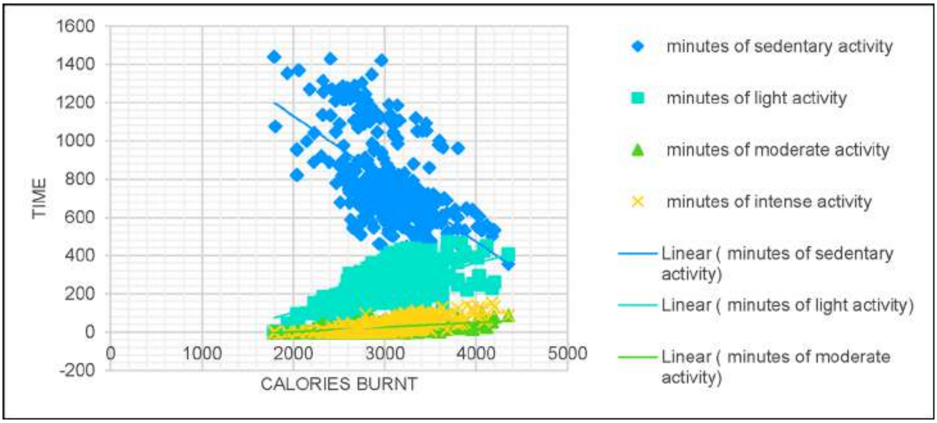
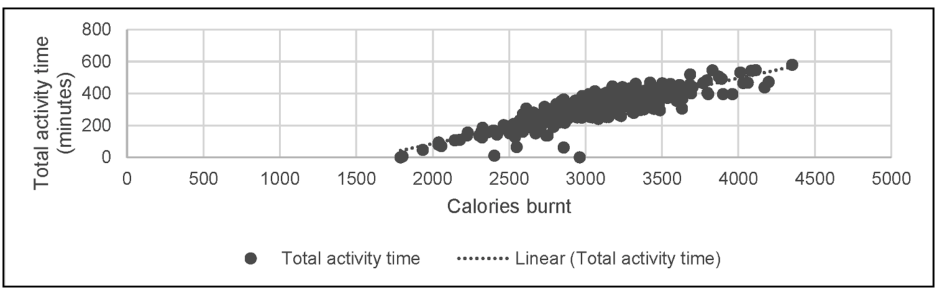


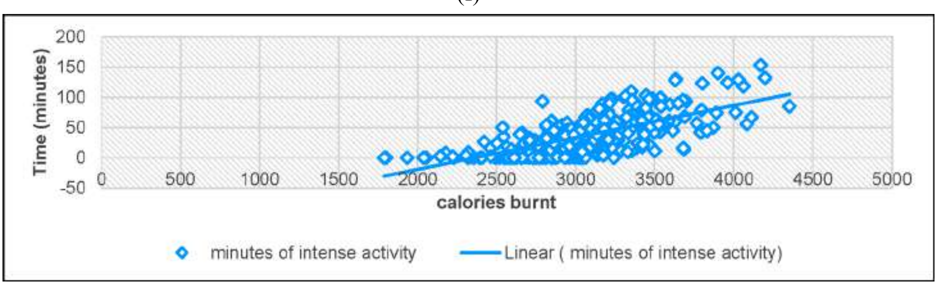
Figure 10 Plots showing graphical relation between: (a) steps and total activity time, (b) steps and distance, (c) calories burnt and minutes of sedentary activity, (d) calories burnt and distance, (e) calories burnt vs. time, (f) total activity time vs. calories burnt, (g) minutes of intense activity vs. calories burnt and (h) average activity time and normalised average calories burnt for each month (see online version for colours) (continued)



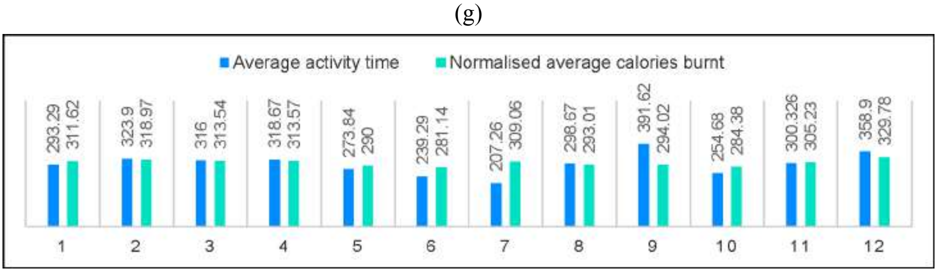
(e)



(f)



(g)



(h)

5 Decision-making system

Machine learning has evolved into teaching computers to learn and imitate humans. They use fundamental statistics and computational theories in the learning process. While learning, the machine finds a pattern among the given data, like humans do [109]. There are different learning mechanisms to work for different input data. Supervised learning is used to build a model when the given data is labelled. Unsupervised learning is used to build a model when the given data does not have any labels. Machine learning models are satisfactorily improving the efficiency of health systems [110–117]. This section proposed a decision-making system that can be used as a model for health and fitness monitoring applications. The data used in Section 4 is labelled data, and hence, supervised machine learning is adopted in building the system.

5.1 Decision tree

A decision tree algorithm is a supervised machine learning algorithm that has broad application areas. The decision tree algorithm is primarily used in biomedical applications as they are free of ambiguity and can look after the missing values efficiently. They can be used for both classification and regression to classify and predict data. The nodes of the decision tree represent features or attributes. Nodes are of three types- root node, internal node, and leaf node. The root node is a decision node that subdivides the records, where the internal node is a chance node where the top edge is connected to the parent node. The bottom edge is connected to the child or leaf node, and the leaf node is an end node that gives the event's decision. Branches represent outcomes from the root nodes and internal nodes. The optimal number of splits in the data will be decided by the algorithm only. Decision trees are of two types:

1 A classification tree is used with categorical data that predicts the class's outcome to which the data belongs. Among the core algorithms, ID3 is used to create a decision tree that uses top-down, greedy search through the given columns. It selects the attribute that is best for the classification of a given set using entropy and information gain. Entropy [118] is the measure of uncertainty in the data. Information gain (IG) [119] measures the relative change (decrease) in entropy for the independent variables. The state S is the effective change in entropy after deciding on a particular attribute A

$$\text{Entropy}(S) = -\sum P(I)\log_2\left(P(I)\right)$$

$$\text{Information Gain}(S, A) = \text{Entropy}(S) - \sum P(S|A)\,\text{Entropy}(S|A)$$

ID3 follows the rule, a branch with an entropy of 0 is a leaf node (endpoint). A branch with an entropy of more than 0 needs further splitting.

2 A regression tree is used with continuous data to predict the outcome is a real number. CART in regression cases uses least squares, intuitively splits are chosen to minimise the residual sum of squares between the observation and the mean in each node.

Mathematically, we can write residual as

$$\varepsilon_i = y_i - \hat{y}_i$$

and the residual sum of squares (RSS) [120] as

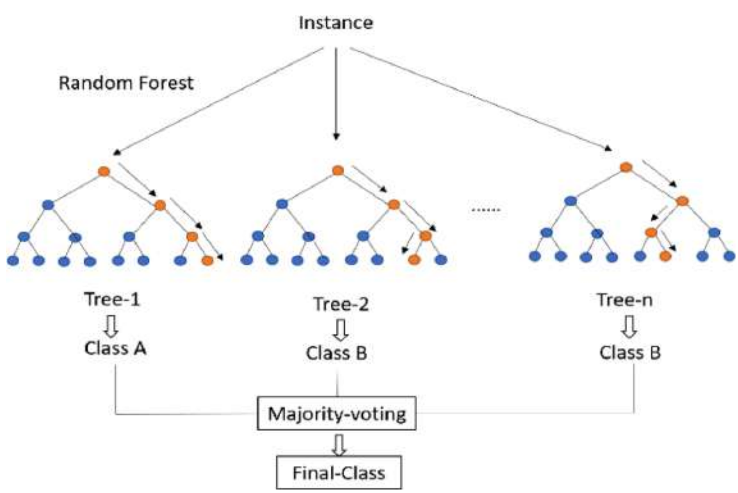
$$\text{RSS} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2, \quad \text{RSS} = \varepsilon_1^2 + \varepsilon_2^2 + \cdots + \varepsilon_n^2$$

To find out the 'best' split, we must minimise the RSS.

5.2 *Random forest*

Random forest performs regression and classification [121,122] tasks by decision tree as a base (shown in Figure 11). It is an ensemble learning technique that uses bootstrap aggregation or bagging. The idea behind random forest is to merge multiple decision trees to direct the final output.

Figure 11 Random forest structure (see online version for colours)



Base learners (k) and variance are inversely proportional to each other, i.e., as base learners increase, the variance decreases and vice versa. 'k' can be found using cross-validation, where bias remains consoptant.

$$\text{Random forest} = \text{Base learner} + \text{Bagging} + \text{Feature bagging} + \text{Aggregation}$$

The standard scaler assumes your data is normally distributed within each feature and will scale them such that the distribution is now centred around 0, with a standard deviation of 1. The mean and standard deviation are calculated for the feature, and then the feature is scaled based on:

$$x_i = \frac{(x_i - \text{mean}(x))}{\text{stdev}(x)}$$

5.3 Support vector regression

Support vector regression (SVR) [123] is a supervised learning model used to perform linear and nonlinear regressions. The goal of applying linear regression is to minimise the error between the prediction and data. However, the goal of applying SVR to a dataset is to make sure that the errors do not exceed the threshold. In SVR, we fit as many instances as possible between the lines while limiting the margin violation. This is done by finding an appropriate line or hyperplane to fit the data. In contrast, in the least-squares method where we try to find accurate coefficients, we try to minimise coefficients, i.e., the 12-norm of the coefficient vector, not the squared error. The error term is instead handled in the constraints, where we set the absolute error less than or equal to a specified margin, called the maximum error, ε (epsilon). We can tune epsilon to gain the desired accuracy of our model. Our new objective function and constraints are,

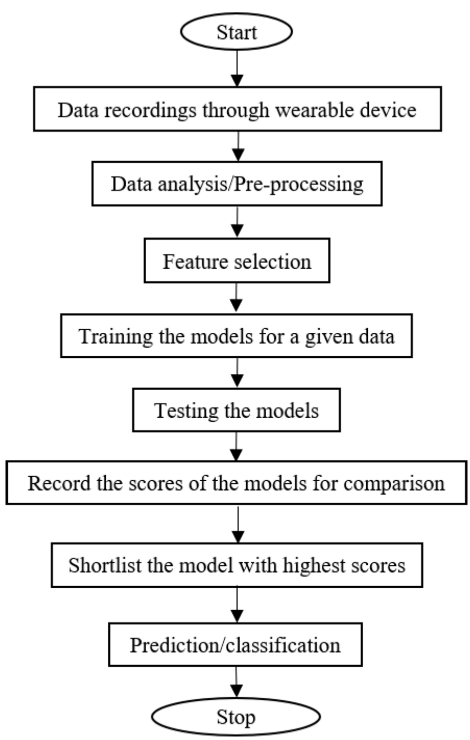
$$\text{minimise} = \text{MIN}\frac{1}{2}w^2 \text{ and}$$

$$\text{constraints} = |y_i - w_i x_i| \leq \varepsilon$$

5.4 Flowchart for a decision-making system

The following flowchart shows the process flow for the proposed decision-making system (Figure 12).

Figure 12 A flow chart of the proposed decision-making system



The data is recorded using a wearable device, i.e., Fitbit Charge HT fitness tracker. As the available data is recorded without any noise, no preprocessing is required. The data analysis can be performed to understand the organisation of data. As we have few columns of data with different features of the activity given for the respective day, we must carefully select the features while building the model.

In this experiment, steps, distance in metres, floors, minutes sitting, minutes of moderate activity, minutes of intense activity are considered as the input features to train the model. We have divided the whole dataset into 75 : 25 randomly, where the earlier is used for training, and the latter is used for testing. The machine learning techniques used here are decision trees, random forest, and support vector machines. After testing the machine learning techniques, scores are evaluated and recorded. One of the applied techniques, recording the highest score, is considered and used for prediction or classification. R-squared (R^2) is measured to represent the proportion of the variance for a dependent variable that is explained by an independent variable or variables in the regression models. As the data recorded from the experiment is continuous, regression techniques can predict the number of calories burnt in a day. Among the three algorithms applied, random forest regression gave the highest score of 97.88%, where SVR and decision tree reported 91.22% and 96.88%, respectively. The top three trail scores are reported in the table for the above techniques (Table 4).

Table 4 Comparison of the top three trails between support vector regression, random forest regression, and decision tree

	Support vector regression	*Random forest regression*	*Decision tree*
Trial-1	0.9122	0.9788	0.9522
Trial-2	0.8871	0.9732	0.9329
Trial-3	0.8821	0.9553	0.9688

6 Conclusion

This paper provided an overview of different wearable technologies-hearables, ingestible sensors, moodables, wrist-worn devices-smartwatches, fitness trackers, armbands, bloodless wearable devices-interstitial fluid sensors, sweat, saliva and tear sensors, sports wearables-IMU, MEMS, flex sensors, magnetic field, and angular rate sensors. Some factors affect wearable technologies; one of them is the user interface. There is a need for a robust user interface, which can be a computer or mobile-based application, that makes the consumer effortlessly use the device and access the data recorded. A comparison is provided among the features of highly rated smartwatches and fitness trackers in the current consumer market. At present, there is an adequate number of prospective computer and mobile applications available for consumers to track some of the health and fitness activity and its respective data. Comparing the editor's choice on android based mobile applications may give the potential mobile application for respective user interests. The analysis of the data collected from a consumer fitness tracker may give a broad comparison and connection between the level of the activity and the number of calories burnt in a respective day. The application of machine learning algorithms to the data may automate the whole system of collection of data for analysis. The proposed decision-making system, which included a few regressive algorithms of supervised machine learning, may help quickly identify whether the user can reach the daily goal of the activity or not to maintain good health. The future perspective is to build a user interface for the decision-making system and can release into the consumer market. Ultimately, a new paradigm of healthcare monitoring systems can implement with wearable sensor technology embedded with machine learning, which can alert the subject in an unmanned way to reach the goal. This can also be further extended to monitor patients from their own houses, transforming hospital-centric medication to home-centric, which is much needed during pandemic situations.

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