Chapter 8
Wearable Devices and COVID-19: State of the Art, Framework, and Challenges

Rajalakshmi Krishnamurthi, Dhanalekshmi Gopinathan, and Adarsh Kumar

Abstract  In the current century, the novel coronavirus has presented itself as a serious threat to the global human population. However, constructively, with the intervention of the latest computing technology such as the Internet of Things, distributed cloud computing, and artificial intelligence, the COVID-19 pandemic can be effectively handled. From this aspect, the main objectives of this chapter are to study and present various wearable devices as part of the healthcare system toward combating the COIVD-19 pandemic. First, this work aims to review the different wearable devices and their usage to combat COVID-19 by patients, healthcare professional, frontliners, and global citizens. Hence, the major objectives of these wearable devices include device tracking, information sharing, and awareness creation to minimize the risk of coronavirus infection. Second, the chapter addresses a generalized framework toward the implementation of wearable devices to handle the COVID-19 pandemic. Next, this chapter aims to review monitoring techniques and various mechanisms used to analyze the data gathered from wearable devices in order to extract useful and critical information pertaining to users in the COVID-19 scenario. This chapter involves reviewing efficient techniques and algorithms that exist in literature for data analysis based on vital body signals from the wearable sensor devices. This effort enhances the patient/healthcare staff monitoring mechanism and helps to uncover preventive solutions in the COVID-19 scenario. Particularly, the data processing and analysis mechanisms such as data denoising, data aggregation, data outlier detection, and missing data imputation are emphasized. Finally, the chapter addresses various challenges associated with wearable devices in the COVID-19 scenario such as real-time processing, heterogeneity, interoperability, security, and privacy.
8.1 Introduction

The coronavirus disease, abbreviated as COVID-19, is a virulent disease instigated by a novel virus, nCOV, also termed severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). As of 12 April 2020, the World Health Organization (WHO) reported that approximately 1,700,000 people were infected by this coronavirus. In addition, more than 100,000 people were reported dead due to this novel virus infection. Keeping this in mind, the recent studies exhibit that efficient solutions for handling the COVID-19 pandemic can be achieved with the intervention of emerging computing technologies such as wearable devices, the Internet of Things (IoT), cloud computing, fog computing, and big data, which play vital roles in empowering the global citizens [1–3]. Hence, this work aims to explore how wearable devices can provide efficient solutions regarding identification, monitoring, collaborating, and crowdsourcing to tackle the effects of COVID-19. The wearable devices are smart sensor-based electronic devices that can be worn by a person and carried easily. These wearable devices are capable of sensing vital body signals. Additionally, these devices are able to gather, transmit, store, process, and analyze data to extract information from these sensor signals [4, 5].

Wearable devices are quite popular in critical healthcare systems due to their user-friendliness, light weight, and accuracy. In recent years, the IoT-based smart healthcare system has impacted greatly on the rising demand of wearable devices [6, 7]. The benefit of IoT-enabled wearable healthcare devices is that they provide individuals with the knowledge they need to gain greater control over their health outcomes. Wearable devices and the IoT would support and reduce the human interference in healthcare, allowing context-based automation. In many works, IoT healthcare systems have been built for various reasons, including rehabilitation, diabetes control, assisted ambient living (AAL) for elderly people, and more [8, 9]. Although these systems have been developed for many different objectives, they are each intricately connected by their use of common enabling technologies. Such applications include fall detection, quantification of physical activity, study of human habits, and monitoring elderly people care. Electrochemical accelerometer sensors are commonly used to monitor human physical activity. These sensors are capable of measuring the speed of any moving object. With respect to human physical activity monitoring, the accelerometer sensors provide information regarding individual activities and the number of footsteps for quantitative evaluation [10, 11]. Most wearable devices are non-invasive nanomaterial-based biosensors that measure the vital signs by being put on the body or near the body.
Another aspect of wearable devices is general human movement tracking or motion tracking. The human motion tracking mechanism has several useful applications in the medical field, sports, and in other domains. Wearable biological sensors include watches, shoes, bandages, glasses, contact lenses, and rings conveniently attached to the body of a person and functioning in terms of portability, ease of use, and adaptability [12–14]. A wide range of wearables have been available in recent years on the market offering rising functionalities and wear options. Several different wearable devices have been developed by various companies: fitness trackers, smart watches, headsets paired, smart glasses, wristbands, etc. Wearable devices can sense, capture, and store physiological data and improve the quality of human life. They carry out several micro-level activities such as checking incoming messages and immediate processing of urgent data. Figure 8.1 shows various wearable smart devices available for users. These wearable devices are equipped with sensors (e.g., accelerometer, gyroscope), network ports, camera, data processor, etc., which are a successful candidate for tracking the everyday behavior of users (hiking, jogging, smoking, etc.) [1]. The sensors measure temperature, humidity, motion, heart-beat, etc. Wearable devices are currently used in several domains such as healthcare, sports, and navigation systems.

During the COVID-19 pandemic, wearable sensors and nano-biosensors have gained considerable publicity due to the contactless-based healthcare diagnosis.
The wearable sensors are capable of measuring vital signals of the human physical body such as heart rate, blood pressure, skin coloration, body temperature, respiratory rate, sleep duration, and body motion. These measured quantities are clinically important and can also be obtained through contactless processes [15–17]. Various surveys and studies have been conducted based on the usage of wearable devices to handle the COVID-19 pandemic as follows.

- **Stanford Covid-19 Detection Study** addresses the fitness of users through tracing their activities. The wearable devices considered for this study are Fitbit, Apple Watch, Garmin, and the Oura ring. The study focuses on the prediction of infectious disease onset, including COVID-19. The wearer’s vital health data is collected through wearable devices and is processed for further analysis and predictions.

- **Duke Covidentify** aims to study wearable devices and to determine the ability of wearable devices to identify COVID-19 and influenza-like symptoms. This daily-based survey aims to measure the severity of viral infection through wearable devices. The study involves wearable devices such as Fitbit and Garmin.

- **Scripps Detect Study** involves the study and analysis of various human body vital information, such as heart rate, sleep length, and fitness activities. The study uses wearable devices such as Apple Watch, Fitbit, Beditt, Oura, and Garmin, which are capable of sharing data with remote cloud servers.

- **UCSF TemPredict** works according to the principle of measuring the body temperature and identifying any changes in the temperature from the baseline threshold. The Oura ring is used as the wearable device in this study.

- **RNI Feasibility of Wearable Devices for Covid Monitoring** aims to forecast COVID-19 infection based on the body symptoms and mind signals. The Oura ring is used as the wearable device in this study.

The major objectives of this chapter are:

1. A review of several research works carried out regarding wearable devices and their applications toward handling the COVID-19 pandemic.
2. A generalized framework for wearable devices in the COVID-19 situation includes the sensor layer, network layer, processing layer, and applications layer.
3. Comprehend and study various wearable devices, sensors, and data monitoring mechanisms.
4. Data gathering, data processing, and data analysis techniques in wearable devices.
5. Address various challenges in wearable devices.

The rest of the chapter is organized as follows. Section 8.2 elaborates the various existing works related to IoT-based wearable devices for handling the COVID-19 situation. Section 8.3 presents the generalized framework on wearable devices regarding handling the COVID-19 pandemic and Sect. 8.4 discusses the sensing and monitoring mechanisms in wearable devices that involve device identification and user identification. Section 8.5 presents the detailed mechanisms such as data processing, data analysis, and artificial intelligence incorporated by IoT-based
wearable device toward handling COVID-19. Section 8.6 discusses various challenges associated with wearable devices in COVID-19. Finally, Sect. 8.7 concludes the chapter with future scope.

8.2 Related Works

The Chinese Sina-microblog [3] discussed the effect of information dynamics related to how the information regarding COVID-19 propagates among the citizens in Provinces of China. For this study, the Sina-microblog was considered. The data dissemination model permits the user to discuss topics from two different news platforms, namely CCTV and China Daily. The CCTV is a broadcasting channel based on several general topics. While China Daily aims at specific new information. The users of Sina microblog could instantiate multiple instances of microblogging picked from both CCTV and Chain daily. The data dissemination pattern from this perspective model was analyzed to provide insight regarding the multilevel diffusion of COVID-19 related information. Hence, the authors claimed that a serious lack of analysis models regarding information and fake information diffusion could lead to chaos, aggression, and serious health emergencies among citizens of China.

Hence, it is critical to understand the characteristics of the coronavirus and to find efficient ways to handle the pandemic situation.

The coronavirus takes 14 days to show symptoms, and during this period, asymptomatic patients can infect large numbers of people [18–20]. Hence, it is necessary and critical to have an observation system that determines the highly infectious regions and all the people in contact with the patients who have tested positive. To obtain the direct contact of the infected person is easy, but all the other people who had contact with the infected person also have to be identified.

In Singapore, under the “Smart Nation” initiative, the government aims to enhance protection and security for its citizens through a “Contact Tracing” application on mobile devices. As of 5 June 2020, there were approximately 37,000 confirmed cases of COVID-19 among the 5.7 million population of the country. A three level care system has been developed to provide support for oneself, relatives, and the community. The contact map is generated for any COVID-19 patient within a 14-day span. The wearable device-based digital footprints are used to carry out the tracing process. The digital signature through ATM, video recordings of public spots, and private buildings are used to implement the efficient contact tracing map.

In [21], the authors propose an IoT-based solution to determine the precise paths of infected persons (exact coordinates labeled with time). The system is deployed in smartphones. The application collects the required geo-localization data along with the time and sends it to the analysis layer. The analysis layer observes both the location and health data of the infected person. The system has an authorities’ interface which offers functionalities to the authorities such as government, health officials, and other organizations who are responsible for monitoring and controlling the outbreak.
This section discusses (1) various types of sensors that exist in the literature and (2) various wearable device-based solutions for combating the COVID-19 pandemic. First, there are various healthcare monitoring sensors that can be attached to belts, clothes, and fixed on the skin [18, 20, 22–24]. Commonly used healthcare wearable sensors are temperature sensors, pressure sensors [24, 25], acoustic sensors [18, 20, 26], humidity sensors [19], oximetry sensors [27], and multimodal sensing platforms [22].

- **Temperature sensors [27]**—The temperature sensors are used in a wide variety of applications such as the human body temperature sensor, robot skin temperature measurement, and machines/appliances temperature monitoring. Regarding COVID-19, the human body temperature measurement can be obtained using LM 35, SMT 160-30, and DS 1820. Table 8.1 below shows the characteristics of these sensors.

- **Pressure sensors**—These sensors are based on the diaphragm contraction and relaxation. This sensor is designed as a belt [24] and an electromechanical film (EMFit), which is a capacitive pressure sensor that has a thin porous polypropylene film structure with a sensitivity of 30–170 pC/N. During the respiration process, the expansion of the chest exerts a force on the sensor and produces a voltage change proportional to this motion. The second type of pressure sensors is [25] designed as a facemask and used effectively during respiration when in contact with inhaled and exhaled air. The EMFit sensor performed well regarding the detection of respiratory rate. This sensor is suitable only for still or modest moving patients [24] because measurement accuracy depends on body movements.

- **Acoustic sensors**—Acoustic sensors are used to monitor lung sounds and placed near the nose, mouth, throat, and suprasternal notch [18, 20, 26] to obtain the acoustic signals related to breathing. It is a user-friendly wearable device placed next to the nose using tape [18]. It measures the respiratory rate during sleep and sends the signals through wireless communication to a smartphone. The normal and abnormal lung sounds monitored and evaluated by the sensors are used to detect asthma attacks [28].

- **Humidity sensors**—Humidity sensors for breathing analysis [19] are based on a porous graphene network, which is a chemical structure capable of detecting moisture. This sensor senses the rhythm of human respiration, apnea, speech, and whistle. The sensors are attached to the body with a facemask. The disadvantage of using this sensor is that long time use is also uncomfortable. It still needs some improvements to further commercialization.

**Table 8.1** Characteristics of temperature sensors

| Sensor   | Temperature Min (°C) | Temperature Max (°C) | Voltage (V) |
|----------|----------------------|----------------------|-------------|
| LM35     | −55                  | 150                  | 4–30        |
| SMT160   | −45                  | 130                  | 450–700     |
| DS1820   | −50                  | 125                  | 2.5–5       |
• Oximetry sensors—Oximetry sensors measure oxygen saturation [27]. This sensor can be worn on different body parts such as wrist, finger, head, ear, thigh, and ankle. It measures the absorption of light according to the levels of oxygenated and deoxygenated blood. Oximetry monitors respiratory problems and blood oxygen levels.

• Multimodal sensing platforms—It is a monitoring platform consisting of a chest-patch, wristband, and handheld spirometer [22]. The objective of this sensor is to track health and environmental factors for respiratory diseases such as asthma. The spirometer assesses lung functionality; the chest-patch monitors ECG, skin impedance, photoplethysmography (PPG), wheezing, and motion; and the wristband measures temperature, humidity, PPG, ozone concentration, and motion.

According to the author in [29], COVID-19 has influenza-like symptoms. This includes an average increase in heartbeat rate to 8.5 beats per minute, a body temperature increase of 1 °C and shortened sleep duration. The Huami wearable device can measure the resting heart rate (RHR) and sleep duration of the user. Two types of sensors, namely photoplethysmography and accelerometer sensors, are used for this purpose. The continuous monitoring of flu-like illness is provided through Huami wearable devices. During these observation periods, the physiological anomalies such as RHR and sleep duration are further analyzed through predicting algorithms to narrow down the possibility of COVID-19 infection. Figure 8.2 illustrates the basic parameters that need to be measured from the human user through wearable devices when COVID-19 is suspected.

In 2020, the authors in [30] proposed a wearable device “EasyBand” to handle user mobility depending on the safety parameters during the COVID-19 pandemic situation. EasyBand is based on the programmable microcomputing on chips with

![Fig. 8.2 Basic parameters measured through wearable device for COVID-19](image)
IoT technology, and is also capable of performing smart functions such as identifying and establishing communication with similar peer devices. Further, the proposed device can gather information regarding the nearby contacts, and store the relevant information for almost 15 days. The device is also capable of providing users with safety alerts, with three status levels: safe zone, moderate safe zone, and high infectious zones.

In [31], the authors proposed a smart helmet to combat the exposure effect of COVID-19 in public places. This wearable smart helmet has two inbuilt types of sensing cameras: optical and thermal camera. First, the thermal camera senses the body temperature of passerby within the detection zone. If any passerby body temperature exceeds the minimal threshold temperature, the optical camera captures an image and performs digital image processing to fetch the information regarding the person. Further, the details of the person such as image and temperature are recorded and intimated to the concerned health care officials through mobile GSM communication module.

The authors in [32] discuss the nano material-based biosensor for healthcare monitoring and diagnosis of COVID-19 in suspected patients. The nano biosensors include the geno sensor and immuno sensor that are embedded on-chip to perform assessment of COVID-19 patients. The data gathered from the sensors are further analyzed through AI supported data processing and analysis algorithms. Interfacing of nano sensor-based bio chip with the IoT is known as the Internet of Bio-Nano Things (IoBNT). This IoBNT can be used in several ways such as data sharing with other medical and healthcare centers across the globe, faster assessment of COIVD-19 infection, contact tracing, quarantine management, and targeted COIVD-19 patient sensing.

The authors in [33] proposed a wearable bracelet named iBand that performs information exchange between users and the persons in their close contact. Whenever the iBand user comes in close contact with their relatives, the handshake and proximity are detected through the infrared detector. The iBand functionality is similar to the social media and networking platforms, where the main objective is to connect humans and share information. However, in the case of iBand, the added advantage is that the users can use their bio vital signals and senses such as touch. Google Glass promises to be efficient and the most popular wearable computing device. The advantages of Google Glass include being lightweight, user friendly, all day wearable, and supporting virtual display through augmented reality. Table 8.2 illustrates the summary of various wearable devices that have proved popular during the COVID-19 pandemic.

The wearable devices such as Lovegety, groupwear, Synchro.beat, Digital Proxies, and Smart-Its Friends disseminate the information of similar interested groups of people [37–40]. These wearable devices initiate communication within wireless range and exchange sensor readings. Similarly, SwissMarte SpotMe is a secure wearable RFID-based device used in event organization and provides enhanced security and privacy solutions to event control worldwide. It provides solutions to analyze audience performance and behavior, and to understand the audience’s intent to buy, participate, learn, or perform their activities.
Under “Future Travelling,” a leading initiative project called Guide2Wear deals with various public transportation services through wearable devices based on different user mobility types. The main objective of Guide2Wear is to enhance and optimize the intermodal behaviors of passengers based on their mobility pattern. The passengers are provided with fast, accurate, and suitable services and information based on those mobility patterns and recommended an appropriate environment friendly mode of transportation. The information dissemination involves representation of data about mobility pattern, driver supportive or traffic information regarding a specific transportation mode.

### 8.3 Framework for Wearable Devices as a Monitoring Mechanism for COVID-19

Wearable devices are gaining popularity because of their lightweight design and their continuous tracking capabilities to improve the quality of life of users. These devices are the basic building block of the Wearable IoT (WIoT). A wearable IoT device collects data from the sensors, processes and analyses the data using some intelligent algorithms and sends valuable information to the wearers. A robust technological framework offered by IoT facilitates data collection and storage by integrating the prominent technologies such as cloud computing [41] and big data [42].

---

**Table 8.2** Summary of wearable device during the COVID-19 pandemic in literature

| S.n | Authors | Products | Measuring parameters | Focus |
|-----|---------|----------|----------------------|-------|
| 1   | Tripathy et al. (2020) [30] | EasyBand | • Proximity  
• Peer device networking and communications  
• Alert system | Mobility during COVID-19 |
| 2   | Mohammed et al. (2020) [31] | IOT based smart helmet | • Body temperature  
• Facial recognition | COVID-19 |
| 3   | Mujawar et al. (2020) [32] | Nano-enabling biosensing systems | • Glucose, coagulation, blood gas, electrolytes, cholesterol | COVID-19 |
| 4   | Chamberlain et al. (2020) [34] | Smart thermometers | Body temperatures | COVID-19 |
| 5   | Nittas et al. (2020) [35] | Healthcare device | • Audiovisual cues  
• Skin color changes using video recordings  
• Vital signs using wearable device | Telehealth |
| 6   | Tayal, et al. (2020) [36] | Remote monitoring device | Body vital signals | Fitness during COVID-19 |
| 7   | Kanis et al. (2020) [33] | iBand | Body vital signals | Social networking during COVID-19 |
The WIoT framework connects the medical infrastructure, including doctors and hospitals, to assess the patient’s condition regardless of their location [43].

The framework for WIoT as a monitoring mechanism for COVID-19 consists of (1) data collection and monitoring from remote locations (2) virtual management of the collected data (3) analyzing the collected data and controlling data (4) following up the report obtained. The overall impact of this framework includes a better tracing of contacts, identification of clusters, and acquiescence of isolation. The devices in this framework use various applications to meet the important requirement of lessening the effects of the COVID-19 pandemic. It predicts the forthcoming condition with the help of appropriate collected data. The tracking of bio-vital signs such as heart beat rate, blood pressure, glucometer, and other activities improves the personalized attention.

The wearable devices perform tasks such as to sense, analyze, store, transmit, and apply. The processing may happen either on the wearer or at a distant location. Personalized information processing is required for each scenario, which transforms the sensory data to knowledge to respond to the situation efficiently. A prominent area where the wearables are used is the health sector, which enables doctors to capture the activity of long-term patients and exercising compliance, provide efficient delivery of pharmaceutical items for chronic patients, and provide availability of tools for evaluating and recommending their ability to carry out complex motor tasks using remedial approaches.

The basic processes involved in wearable device-based health monitor systems can be divided into three layers, namely perception, service, and API layer as shown in Fig. 8.3. The perception layer contains various sensors to collect data in real time.

The service layer contains various application programs to analyze the data and suggest a method to improve the activity. The API layer contains various APIs that store a new profile of the wearer or retrieve the existing information of previously registered wearers.

The wearable devices can be placed inside the body, on the body, and around the body. Inside-body wearable devices are placed inside the human body (for example, a Pacemaker). On the body wearable devices are worn on the body and include accessories such as smart watch, smart band, smart jewelries, and smart clothing. Around the body devices work within proximity of the users. These devices collect data around the users such as environment data. The two devices involved in the wearable device framework are (1) wearable device and (2) host device. Wearable

![Wearable Device Monitoring Architecture](image_url)

**Fig. 8.3** Wearable device-based health monitoring process
devices sense data for the activity generation, and they have limited storage, low computation, and low battery power, whereas the host device has more computation power, larger storage capacity, and larger battery power.

The wearable device collects the sensor data and can apply some pre-processing techniques to reduce the volume of data that can be transmitted to the host or can directly send the raw data to the host depending on the design of the device. It then sends the desired data to the host device. In [9], the authors propose a daily activity monitoring wearable IoT device where some computation is performed at the wearable device before sending data to the host device. User’s activities are collected using a 9-axis wristband. The data is pre-processed and segmented at the device level prior to sending to the host. However, the potential problem that needs to be addressed here is that it requires strong authentication and access control mechanisms to support the wearable devices and the data associated with them. An authentication is required to identify the authorized user of the device. An authentication based on the biometric parameters can provide an efficient solution to this.

Thus, a generalized WIoT framework with four functional layers includes a sensing layer, networking layer, processing layer, and applications layer.

- **Sensing layer:** The first layer collects the monitored data from the wearable sensors such as on-body and near-body sensors, which capture physical parameters such as heart activity, blood pressures, respiratory rate, and physical movement. These data are preprocessed to prepare it for analysis [44–46]. In general, the wearable devices are application dependent. Most of these devices are integrated with communication abilities, limited on-board power management, and embedded computing facilities with a small storage support. The limited storage and computing facilities in the sensing devices and the limitations in communication bandwidth and battery power makes the wearable devices insufficient to work in an independent manner. Hence, the integration of these sensing devices with the IoT infrastructure provides a better platform for data aggregation, storage, and transmission, which provides a better analysis framework.

- **Networking Layer:** The network layer configures the wearable devices using a standard or hybrid topology to provide interoperability, energy efficiency, network management, and QoS requirement. In addition, it should also maintain security and privacy of the user data from the personalized healthcare applications [8, 47, 48].

- **Processing layer:** The data processing layers suggested in [29, 43, 45, 49] use different intelligent algorithms, such as the supervised, unsupervised, semi-supervised approaches; knowledge-based approaches, which includes semantic reasoning and modeling; or using hybrid approaches.

- **Application layer:** The application layer of the WIoT architecture provides high quality services to healthcare providers as well as individuals [50, 51]. A user-friendly interface provides a better way to access these solutions to people who are typically not familiar with using intricate technological interfaces.

Figure 8.4 illustrates the general framework of various layers involved in the WIoT for the COVID-19 scenario. The main challenge in developing applications is
that they should abstract the details that are irrelevant to patients or users and summarize the details appropriately to healthcare professionals to help them make appropriate decisions from their end. Data fusion is involved in monitoring mechanisms for wearable devices.

8.4 Sensing and Monitoring Mechanisms in Wearable Device Made for COVID-19

The IoT on a day-to-day basis is viewed as the utility of products or apps serving people’s real-life requirements in different ways, such as home protection, intelligent lighting, and other tasks that are easily controllable with devices such as smartphones and smart voice recognizers. In the current pandemic situation, every country battling against COVID-19 is looking for a genuine and productive solution to face the multiple complications arising. The number of infected persons increases daily globally; the technology behind the IoT well supports data exchange and collection, especially because it is already used in various domains of healthcare.

The major benefits of the IoT for the COVID-19 pandemic is that it guarantees effective control, better diagnostics, and better treatment with lower cost and fewer mistakes. During quarantine, the infected persons can be monitored better. The IoT network can track high-risk patients using vital signs such as blood pressure, heartbeat, and glucose level [31, 52].

In general, the WIoT personal healthcare can be broadly classified as (1) physical activity monitoring, which monitors physical parameters such as motion, breathing, and heart activity; (2) self-monitoring application, which concentrates on improving the quality of life of an individual; (3) clinical decision support for diagnosis and
treatment, and emergency health services. This application works according to health data of the individual. It automatically analyzes the data and should be able to predict the diseases, monitor the responses of the treatment provided by the patient, and (4) provide assisted living solutions for the elderly and differently abled [44, 53]. For patients suffering from disorders such as stroke, chronic pain, and heart failure, it gives assistance to the elderly people who live independently.

The types of sensors depend on the output signals they generate that include the underlying concepts and technological capabilities. There are multiple types of sensors, such as contact sensors, accelerometers, audio and motion detectors, available for activity monitoring. They are generally classified into two categories as per the way in which they are placed all through status monitoring, namely action tracking sensors and sensors for mobility monitoring.

- **Action monitoring sensors:** The action monitoring sensors are wearable sensors [4–6] that are attached directly or indirectly to the monitored person or object. These sensors produce a signal when some form of action is performed by the monitored entity. The sensors can be placed in clothing, footwear, heels, mobile devices, etc. They can also be placed directly onto the body. To monitor various temperature, sound, vibration, light, pressure, pollutants, etc., different sensors, such as thermal, acoustic, vibration, and pressure, should be implemented [2].

- **Mobility monitoring sensors:** The second type of wearable sensors are GPS sensors. These types of sensors are useful when monitoring activities are in mobile environments or when involved in location changes [7].

Recent advances in sensor technology, wearable computing, the IoT, and wireless networking have led to research in healthcare and remote monitoring of the health and behaviors of people. Wearable device monitoring such as health monitoring systems encompass data processing and analysis of data that is retrieved from wearable devices such as smartphones, smart watches, wristbands, along with the various connected devices [8]. These systems continuously monitor the patient’s health conditions and activities by sensing and transmitting different parameters such as heart rate, ECG, body temperature, blood pressure, and respiratory rate. The data collected are then fused and analyzed for the diagnosis and treatment of patients with chronic diseases such as hypertension and diabetes.

The monitoring function is helpful for health officials to remotely monitor in-home patients. It also provides innovative methods regarding the quarantine of infected patients, which will dramatically reduce the high risk of mortality and improve the treatment process and care. In addition, it also guarantees better crowd management, transportation management, and safety for the public. Hence, the important objective of the monitoring mechanism in wearable devices is pattern identification of users.

The patterns of interactions between individuals play an important role in determining potential routes for infectious transmission pathways. Hence, awareness of these patterns is very much relevant to identify infectious pathways, to inform about the epidemic spread, and to take effective control measures to adopt prevention
strategies or interventions [54–58]. The common methods for pattern identification are contact-based pattern and spatiotemporal-based pattern identification of individuals.

Contact Pattern: In the monitoring mechanism of wearable devices, the contact pattern plays a vital role in the spread of infection among the people in the population. The relationship between the disease spread and contact pattern information is useful to identify the activities such as where the disease is most likely to be transmitted and to take most effective interventions such as wearing a mask, vaccination, hand-wash, etc.

Spatiotemporal Pattern: Recent technological developments such as mobile and wearable sensors have made it likely to be able to measure human beings with high spatiotemporal resolutions in a variety of contexts. It is believed that transmission of disease involves the spatiotemporal proximity of people regarding several infectious diseases, including some of the diseases with the greatest pandemic potential, such as influenza and COVID-19. Spatiotemporal proximity is usually approximated by social relations where social interactions (family, friends, colleagues, etc.) are assumed to catch most of the potential disease transmission.

In [59], the authors describe the infrastructure for data collection from wearable devices. These devices exchange radio-packets in peer-to-peer fashion to track the location and proximity of individuals. The radio-packets are exchanged between the devices located within 1–1.5 m of one another. The sensors are also calibrated while the face-to-face closeness of two people carrying them can be measured over a period of 20 s with a likelihood approaching 99%. Therefore, contact data is obtained in a temporal resolution of 20 s: two persons are considered to be in contact over a 20 s time period if at least one packet is exchanged between their sensors within that time; and the contact event is considered completed, if the sensors do not exchange packets during a 20 s interval as described in (see http://www.sociopatterns.org) [59, 60]. The machine senses the close-up experiences through which an infectious disease transmission may be communicated, e.g., by coughing, sneezing, or handshaking [60].

8.5 Data Gathering, Data Processing, and Data Analytics for Wearable Devices in COVID-19

The monitoring functions of IoT includes data collection, data transfer, data analytics, and data storage.

- **Data Gathering**: The data is collected through various sensors, smartphones, etc.
- **Data transfer**: The collected data is then transferred for analytics to the central cloud server for decision-making. In the current COVID-19 pandemic situation, the IoT is immensely helpful. This technology uses drones for surveillance to confirm the implementation of isolation and mask wearing.
• **Data Analytics**: It is used to trace the contact patterns in the social network and is helpful to trace the outbreak; and track the patients who break the quarantine.

### 8.5.1 Data Gathering Mechanisms for Wearable Devices

The wearable devices have a receiver, a signal processor, and battery power that enables them to work as a microcomputer. They can also connect to other smart devices and communicate through Bluetooth, infrared, RFID, etc. Furthermore, the data generated from the sensors can be handled either by the platform of dedicated servers that is responsible for collecting and processing the information from the sensors or rely on cloud computing services [3]. In general, most IoT applications bank on cloud computing services that provide remote access through the internet.

Physical parameters include movement, stress, vibration, temperature, heart rate and acceleration, neurological or cardiovascular diseases such as seizures or hypotensions, and pulmonary diseases such as asthma or chronic pulmonary obstructive disease. Temperature measurements on the human body can provide a lot of useful information regarding health conditions such as stroke, heart attack, pulmonary shock, and infections.

To achieve the objective of effective monitoring, first it is necessary to monitor the quality of movement and detect reduced or weakened movement and also estimate the important physical parameters that affect movement. Accelerometers are commonly used sensors for activity tracking, which is used to detect falls, motion, and analysis of body movement and orientation of posture.

### 8.5.2 Data Processing Mechanisms for Wearable Devices

The unprecedented growth of wearable devices, including smart bands, wristwatches, smartphones, has resulted in the collection of a massive amount of sensor data regarding people’s daily life activities. These collected data can be used in various applications in activity tracking, remote monitoring of health, location tracking, etc. The increase in the volume of heterogeneous data necessitates a stronger data processing ability. The conventional methods of data processing will not meet the requirements of new applications. For this scenario, artificial intelligence (AI) technologies have been applied to the data processing with wearable devices. In the current pandemic health crisis of COVID-19, the medical community is seeking new technology to control and monitor COVID-19’s spread. AI is one such technology that can easily monitor the virus spread and identify high-risk persons and thus control infections in real-time. It helps predict the probability of mortality by examining prior patient data. It also helps counter this virus by screening individuals and providing warnings and recommendations to contain the infection [61–63].

The main advantage of using AI during the COVID-19 pandemic includes
1. **Primary detection and diagnostics**—a physician can identify and match a COVID-19 symptom with AI support. Samples can be taken from the infected person to confirm the infection and can be analyzed to provide faster decision-making that is cost-effective and diagnostic.

2. **Treatment monitoring**—An automated monitoring and prediction of the virus spread can be established. A neural network algorithm can be used to extract the features that provide help to monitor and treat the affected persons. In addition, it can provide a daily count of the patients and the steps to be implemented during the COVID-19 pandemic situation.

3. **Contact pattern detection**—AI can help assess infection rates by recognizing clusters and “hot spots” with this virus, and can effectively track and control the contacts of individuals. One can predict the future course of this disease and its likely reappearance.

4. **Predict the cases and mortality**—It can trace and predict the type, risk, and likely spread of infection from the available data. In addition, it helps to identify the most susceptible areas, individuals, and nations and take actions accordingly.

5. **Minimizing the workload of healthcare employees**—The AI techniques can also reduce the heavy workload of healthcare professionals. The significant rise in the number of COVID-19 patients also can be reduce by employing AI techniques [64–69].

There are different data processing models for processing the sensor data from the wearable devices. The unprecedented and continued growth of wearable devices has generated and continues to generate a huge volume of data. The data collected from these wearable devices needs to be properly analyzed to provide an insight to users to make an appropriate decision. Because of the wearable devices’ limited processing and storage space, the big data analysis and storage is done in remote locations such as the cloud. In [70], the authors propose a model that uses big data analysis to update the knowledge base to provide a tailored recommendation based on the analysis of the data. They propose a three-layer data analysis model. The first layer is data collection and management, the second layer is a customized adaptive analysis layer, and the third layer is a personalized adaptive service layer. The first layer collects the raw data from the sensors attached in the wearable devices through the android app and transfers the data to the cloud. The second layer populates a customized knowledge base through trained parameters to help users make decisions. The third layer extracts facts from the custom knowledge base to provide the user with recommendations.

Raw data collected from the wearable sensors often has noise and may contain sensor errors. Hence, pre-processing of data should be done before further processing of data. The pre-processing of data includes (1) filtering irregular artifact removal data, (2) missing value imputation, (3) removing high-frequency noise, and (4) normalizing sensor data.
8.5.3 Data Analysis Mechanisms for Wearable Devices

Precise outbreak prediction models are necessary to obtain insight into the possible spread and consequences of communicable diseases. The prediction models help the Governments and other administrative bodies to propose new plans and assess already executed plans. It has been reported that COVID-19 has infected more than 2.5 million people with more than 170,000 confirmed deaths worldwide. The complexity of population-wide behavior in different geopolitical areas and differences in containment strategies has dramatically increased model uncertainty in addition to the many known and unknown variables involved in the spread.

Since no vaccine has been invented so far, the main focus in the management of the spread of the pandemic is to flatten the epidemic curve. The technologist and researchers are trying to assimilate information and technology in order to understand the behaviors and characteristics of this virus. In [71], the authors propose a mathematical Susceptible, Exposed, Infectious, Recovered (SEIR) and regression model to evaluate the spread of COVID-19 in India. They have performed an empirical study on the dataset provided by John Hopkins University, USA [72].

The four components of SEIR are: Susceptible (S) denotes the fraction of susceptible persons (those capable of contracting the disease), Exposed (E) is the fraction of exposed persons (those that have been infected but have no symptoms), Infected (I) is the fraction of infectious persons (those capable of transmitting the disease), and Recovered (R) is the fraction of the individuals recovered (those who have recovered from the disease). To study the infectious disease spread, this model assumes that no birth or death or new individual are introduced in the population. Everyone in this population of study is assigned one of the states as Susceptible (St), Exposed (Et), Infectious (It), or Recovered (Rt) over a period of time t. The total population at time t is denoted by $N_t = S_t + E_t + I_t + R_t$.

This model computes a basic reproductive number $R_0$ as given in Eq. (8.1), which denotes how many people will be affected from a single infected person over a period. $R_0$ presents a threshold for the stability of the disease-free equilibrium. The $R_0$ value greater than 1, equal to 1, and less than 1 indicates the spread is increasing in the absence of intervention, the spread is stable or endemic, and the spread is expected to stop, respectively. Thus, the growth of the virus outbreak can be estimated using $R_0$.

$$R_0 = \alpha \cdot \beta \cdot \frac{1}{\gamma + \mu} \cdot \frac{\varepsilon}{\mu + \varepsilon}$$

(8.1)

where

$\alpha$ : denotes the number of contacts per unit time
$\beta$ : probability of disease spread per contact
$\gamma$ : recovery rate
$\mu$ : death rate
\( \varepsilon \): rate of progression to infectious state
\[ \frac{1}{\gamma + \mu} \]: duration of infection
\[ \frac{\varepsilon}{\mu + \varepsilon} \]: probability of recovering from exposed stage

In [60], the authors propose a model based on machine learning to predict the sustainability of patients with severe COVID-19. They performed this study on the blood samples of 404 infected patients from Wuhan, China, to identify crucial predictive parameters of disease severity. This study is formulated as a classification problem with input parameters such as basic information, symptoms, blood samples, laboratory tests, including kidney, liver coagulation function, electrolyte and inflammatory factors, which severely increase the risk of associated patients, and outputs the survival rates or death at the end of the inspection period. They developed a prognostic model based on XGBoost machine learning that predicts the success rates of critical patients with more than 90% accuracy using the last sample and 90% from any other blood sample. This enables COVID-19 patients to detect, intervene early, and potentially reduce mortality.

In [73], the authors propose a machine learning and soft computing model to predict the outbreak of COVID-19. They have considered two scenarios to predict the outbreak. In the first scenario, data of 3 weeks is taken to predict the outbreak on day \( n \) and, in the second scenario, 5 days are used to predict the outbreak for day \( n \). The machine learning methods multilayer perceptron (MLP) and adaptive network-based fuzzy inference system (ANFIS) are used to predict the outbreak of five countries: Italy, Germany, Iran, the USA, and China. They have evaluated the performance using root mean square error (RMSE) and correlation coefficient \( R \) as shown in Eqs. (8.2) and (8.3), respectively.

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum (D - P)^2} \quad (8.2)
\]

\[
R = \frac{N \sum (PD) - \sum (D) \sum (P)}{\sqrt{\left[ N \sum D^2 \left( \sum D \right)^2 \right] \left[ N \sum P^2 \left( \sum PD \right)^2 \right]}} \quad (8.3)
\]

where \( N \) represents the number of samples, \( P \) and \( D \) represent the predicted output and expected output values, respectively.

### 8.6 Challenges Associated with Wearable Devices in the COVID-19 Scenario

This section elaborates on various challenges involved with wearable devices regarding COVID-19. Five main challenging factors include quick identification of infection and providing clinical guidelines, accurate predication of infections,
efficient algorithms based on recent techniques such as machine learning and deep learning, user centric software applications, security and privacy, and underlying protocol standards.

**Quick Identification of the Virus and Clinical Guidelines** The COVID-19 pandemic caused an alert on public health surveillance. The popularity of wearable devices allows for a new perspective on infectious disease precautions. The wearable biosensors are recording many signals of physiology. And when paired with advanced analytics, they provide a “huge potential” to identify changes in physiology that signify clinical deterioration requiring medical intervention. The challenges in wearable devices include quick identification of the virus and to get the clinical guidelines from the physicians to track the contact patterns of the infected person.

**Accurate Prediction** In the current COVID-19 situation, rapid wearable diagnostics are urgently needed to identify and isolate COVID-19 cases and to track and prevent the spread of the virus. The physiological data collected from the wearables should be capable of predicting symptoms of disease; it could open the door to research into tracking and managing other diseases and conditions. The wearables should allow direct implementation of automated vital signs such as temperature, blood, and oxygen/heart rate tracking for the individuals who are in quarantine or the people in isolation at home with alerts sent out.

**Efficient Algorithms** Wearables should be able to measure the core temperature, which is one of the possible symptoms of Covid-19. Detection of characteristic changes in body temperature and other critical data enables COVID-19 symptoms to be identified early on. Combined use of the detection algorithm and the wearables should help immensely to isolate and avoid further spread of COVID-19. Tracing the origin of an outbreak, quarantining patients who are potentially contaminated, treating critically ill patients, and preventing cross-infection between medical personnel and patients all take enormous human resources; and an intensified epidemic would further strain the systems.

**User Centric Applications** The WIoT device supporting application software that are developed need to be user-friendly and have user centric interfaces. User experiences play vital roles in the software, hardware components, and physical interfaces. Users include the common public, including the elderly, differently abled persons, young children, adults, community dependent, professionals, and care givers. Therefore, the software development should be simple, efficient, affordable, and long-term applicable.

**Security and Privacy** In the current COVID-19 pandemic situation, the difficulties of using such wearable devices include the protection and privacy of the data obtained, which is special and crucial from the point of view of patient safety.
Protocol Standards  Caution is to be taken when the data network is incorporated into the systems and the protocols involved. Real time processing and offloading into remote cloud servers must be optimized and efficient for underlying network capabilities. Additionally, the wearable devices are resource constrained due to being battery operated. Hence, the protocol standards and networking capability must be energy efficient.

8.7 Conclusion and Discussion

This chapter addressed the important role of wearable devices as part of the healthcare system toward handling the COVID-19 pandemic. The wearable devices are a specialized IoT. Apart from typical sensing and internet connectivity, wearable devices have added features such as being lightweight, worn by users, user friendly, and connected to networks with health professionals. First, the comprehensive overview of existing wearable devices for combating COVID-19 was presented. Next, a generalized framework for wearable devices that includes layers such as sensing, networking, processing, and application layers was demonstrated. Then, the detailed processes of data gathering, data processing, and data analysis were presented. Finally, the challenges associated with wearable devices were presented.

References

1. Ayatollahitafti, V., et al.: Requirements and challenges in body sensor networks: a survey. J. Theor. Appl. Info. Tech. 72(2) (2015)
2. Johnson, M., et al.: A comparative review of wireless sensor network mote technologies. In: 8th IEEE Conference on Sensors (IEEE SENSORS 2009), Christchurch, New Zealand (2009)
3. Flammini, A., Sisinni, E.: Wireless sensor networking in the internet of things and cloud computing era. Procedia Eng. 87, 672–679 (2014)
4. Kern, N., Schiele, B., Junker, H., Lukowicz, P., Troster, G.: Wearable sensing to annotate meeting recordings. Pers. Ubiquit. Comput. 7, 263–274 (2003)
5. Lukowicz, P., Ward, J., Junker, H., Starner, T.: Recognizing workshop activity using body worn microphones and accelerometers. In: Proceedings of Pervasive Computing, pp. 18–23 (2004)
6. Lee, S., Mase, K.: Activity and location recognition using wearable sensors. IEEE Pervasive Comput. 1, 24–32 (2002)
7. Rodgers, M.M., Pai, V.M., Conroy, R.S.: Recent advances in wearable sensors for health monitoring. IEEE Sensors J. 15(6), 3119–3126 (2015). https://doi.org/10.1109/JSEN.2014.2357257
8. Uddin, M., Salem, A., Nam, I., Nadeem, T.: Wearable sensing framework for human activity monitoring. In: Proceedings of the 2015 Workshop on Wearable Systems and Applications, pp. 21–26 (2015)
9. Yang, C.-C., Hsu, Y.-L.: A review of accelerometry-based wearable motion detectors for physical activity monitoring. Sensors. 10(8), 7772–7788 (2010)
10. Mathie, M.J., Coster, A.C.F., Lovell, N.H., Celler, B.G.: Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement. Physiol. Meas. 25, R1–R20 (2004)
8 Wearable Devices and COVID-19: State of the Art, Framework, and Challenges

11. Zhu, X., Liu, W., Shuang, S., Nair, M., Li, C.-Z.: Intelligent tattoos, patches, and other wearable biosensors. In: Narayan, R.J. (ed.) Medical Biosensors for Point of Care (poc) Applications, pp. 133–150. Woodhead Publishing, Duxford (2017)

12. Khan, Y., Ostfeld, A.E., Lochner, C.M., Pierre, A., Arias, A.C.: Monitoring of vital signs with flexible and wearable medical devices. Adv. Mater. 28, 4373–4395 (2016)

13. Bandodkar, A.J., Wang, J.: Non-invasive wearable electrochemical sensors: a review. Trends Biotechnol. 32, 363–371 (2014)

14. Dubey, H., et al.: Fog computing in medical Internet-of-Things: architecture, implementation, and applications. In: Khan, S.U., Zomaya, A.Y., Abbas, A. (eds.) Handbook of Large-Scale Distributed Computing in Smart Healthcare. SCC, pp. 281–321. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-58280-1_11

15. Mukhopadhyay, S.C.: Wearable sensors for human activity monitoring: a review. IEEE Sensors. 15, 1321–1330 (2015)

16. Rodgers Mary, M., Vinay, P., Conroy Richard, S.: Recent advances in wearable sensors for health monitoring. IEEE Sensors. 15, 3119–3126 (2015)

17. Fang, Y., Jiang, Z., Wang, H.: A novel sleep respiratory rate detection method for obstructive sleep apnea based on characteristic moment waveform. J. Healthc. Eng. 2018, 1–10 (2018) https://www.hindawi.com/journals/jhe/2018/1902176/

18. Pang, Y., Jian, J., Tu, T., Yang, Z., Ling, J., Li, Y., et al.: Wearable humidity sensor based on porous graphene network for respiration monitoring. Biosens. Bioelectron. 116, 123–129 (2018). https://doi.org/10.1016/j.bios.2018.05.038

19. Molinaro, N., Massaroni, C., Lo Presti, D., Saccomandi, P., Di Tomaso, G., Zollo, L., et al.: Wearable textile based on silver plated knitted sensor for respiratory rate monitoring. In: 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 2865–2868. IEEE (2018). http://ieeexplore.ieee.org/document/8512958/

20. Dieffenderfer, J., Goodell, H., Mills, S., McKnight, M., Yao, S., Lin, F., et al.: Low-power wearable systems for continuous monitoring of environment and health for chronic respiratory disease. IEEE J. Biomed. Health Inform. 20(5), 1251–1264 (2016) http://ieeexplore.ieee.org/document/7479442/

21. Benreguia, B., Moumen, H., Merzoug, M.A.: Tracking COVID-19 by tracking infectious trajectories. arXiv preprint arXiv:2005.05523 (2020)

22. Ionescu, C.M., Copot, D.: Monitoring respiratory impedance by wearable sensor device: protocol and methodology. Biomed. Signal Process. Control. 36, 57–62 (2017). https://doi.org/10.1016/j.bspc.2017.03.018

23. Reinvuo, T., Hannula, M., Sorvoja, H., Alasaarela, E., Myllyla, R.: Measurement of respiratory rate with high resolution accelerometer and EMFit pressure sensor. In: Proceedings 2006 IEEE Sensors Applications Symposium, 2006, pp. 192–195. IEEE (2006) [cited 6 Jan 2015]. http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1634270

24. Yuasa, Y., Takahashi, K., Suzuki, K.: Wearable flexible device for respiratory phase measurement based on sound and chest movement. In: 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 2378–2383 (2017)

25. Ejupi, A., Menon, C.: Detection of talking in respiratory signals: a feasibility study using machine learning and wearable textile-based sensors. Sensors. 18(8), 2474 (2018) www.mdpi.com/1424-8220/18/8/2474

26. Shkel, A.A., Kim, E.S.: Wearable low-power wireless lung sound detection enhanced by resonant transducer array for pre-filtered signal acquisition. In: 2017 19th International Conference on Solid-State Sensors, Actuators and Microsystems (TRANSDUCERS), pp. 842–845. IEEE (2017). http://ieeexplore.ieee.org/document/7994180/

27. McCaughey, E.J., McLachlan, A.J., Gollee, H.: Non-intrusive realtime breathing pattern detection and classification for automatic abdominal functional electrical stimulation. Med. Eng. Phys. 36(8), 1057–1061 (2014). https://doi.org/10.1016/j.medengphy.2014.04.005

28. Jubran, A.: Pulse oximetry. Crit. Care. 19(1), 272 (2015) [cited 2 Feb 2019]. http://ccforum. content/3/2/R11
29. Nilashi, M., Asadi, S., Abumalloh, R.A., Samad, S., Ibrahim, O.: Intelligent recommender systems in the COVID-19 outbreak: the case of wearable healthcare devices. J. Soft Comput. Decis. Support. Syst. 7(4), 8–12 (2020)
30. Tripathy, A.K., Mohapatra, A.G., Mohanty, S.P., Kougianos, E., Joshi, A.M., Das, G.: EasyBand: a wearable for safety-aware mobility during pandemic outbreak. IEEE Consum. Electron. Mag. 47, 777–780 (2020)
31. Mohammed, M.N., Syamsudin, H., Al-Zubaidi, S., Saiaf, A.K., Ramli, R., Yusuf, E.: Novel COVID-19 detection and diagnosis system using IOT based smart helmet. Int. J. Psychosoc. Rehabil. 24(7) (2020)
32. Mujawar, M.A., Gohel, H., Bhardwaj, S.K., Srinivasan, S., Hickman, N., Kaushik, A.: Aspects of nano-enabling biosensing systems for intelligent healthcare; towards COVID-19 management. Mater. Today Chem. 17, 100306 (2020)
33. Kanis, M., Winters, N., Agamanolis, S., Cullinan, C., Gavin, A.: iBand: a wearable device for handshake augmented interpersonal information exchange. Extended Abstracts Ubicomp 2004 (2004)
34. Chamberlain, S.D., Singh, I., Ariza, C.A., Daitch, A.L., Philips, P.B., Dalziel, B.D.: Real-time detection of COVID-19 epicenters within the United States using a network of smart thermometers. medRxiv (2020)
35. Nittas, V., von Wyl, V.: COVID-19 and telehealth: a window of opportunity and its challenges. Swiss Med. Wkly. 150(1920), w20284 (2020)
36. Tayal, M., Mukherjee, A., Chauhan, U., Uniyal, M., Garg, S., Singh, A., Bhadoria, A.S., Kant, R.: Evaluation of remote monitoring device for monitoring vital parameters against reference standard: a diagnostic validation study for COVID-19 preparedness. Indian J. Community Med. 45(2), 235 (2020)
37. Swatch, Synchrobeat. http://www.swatch.com/synchro/index2.html
38. SpotMe. http://www.spotme.ch
39. nTag. http://www.ntag.com
40. Charm Tech Badge. http://www.charmed.com
41. Khan, S., Shakil, K.A., Alam, M.: Cloud-Based Big Data Analytics—A Survey of Current Research and Future Directions. In: Big Data Analytics, pp. 595–604. Springer, Singapore (2018)
42. Qi, J., Yang, P., Min, G., Amft, O., Dong, F., Xu, L.: Advanced internet of things for personalised healthcare systems: a survey. Pervasive Mobile Comput. 41, 132–149 (2017)
43. Huang, Y., Zheng, H., Nugent, C., McCullagh, P., Black, N., Hawley, M., Mountain, G.: Knowledge discovery from lifestyle profiles to support self-management of chronic heart failure. In: 2011 Computing in Cardiology, pp. 397–400. IEEE (2011)
44. Rafferty, J., Nugent, C., Chen, L., Qi, J., Dutton, R., Zirk, A., et al.: NFC based provisioning of instructional videos to assist with instrumental activities of daily living. In: 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 4131–4134. IEEE (2014)
45. Alwashmi, M.F.: The use of digital health in the detection and management of COVID-19. Int. J. Environ. Res. Public Health. 17(8), 2906 (2020)
46. Marinsek, N., Shapiro, A., Clay, I., Bradshaw, B., Ramirez, E., Min, J., Trister, A., Wang, Y., Althoff, T., Foschini, L.: Measuring COVID-19 and influenza in the real world via person-generated health data. medRxiv (2020)
47. Behar, J.A., Liu, C., Tsutsui, K., Corino, V.D.A, Singh, J., Pimentel, M.A.F., Karlen, W., et al.: Remote health monitoring in the time of COVID-19. arXiv preprint arXiv:2005.08537 (2020)
48. Capodilupo, E.R., Miller, D.J.: Changes in health promoting behavior during COVID-19 physical distancing: utilizing WHOOP data to examine trends in sleep, activity, and cardiovascular health. medRxiv (2020)
49. Zhu, G., Li, J., Meng, Z., Yu, Y., Li, Y., Tang, X., Dong, Y., et al.: Learning from large-scale wearable device data for predicting epidemics trend of COVID-19. Discret. Dyn. Nat. Soc. Article ID 6152041, 8 pp (2020)
50. Zhang, F., Wang, H., Chen, R., Hu, W., Zhong, Y., Wang, X.: Remote monitoring contributes to preventing overwork-related events in health workers on the COVID-19 frontlines. Precis. Clin. Med. 3(2), 97–99 (2020)

51. Chung, Y.-T., Yeh, C.-Y., Shu, Y.-C., Chuang, K.-T., Chen, C.-C., Kao, H.-Y., Ko, W.-C., Chen, P.-L., Ko, N.-Y.: Continuous temperature monitoring by a wearable device for early detection of febrile events in the SARS-CoV-2 outbreak in Taiwan, 2020. J. Microbiol. Immunol. Infect. 53(3), 503 (2020)

52. Vaishya, R., Javaid, M., Khan, I.H., Haleem, A.: Artificial intelligence (AI) Applications for COVID-19 Pandemic. Diabetes Metab Syndr Clin Res Rev. 14(4), 337–339 (2020). https://doi.org/10.1016/j.dsx.2020.04.012

53. Hussain, S., Kang, B.H., Lee, S.: A wearable device-based personalized big data analysis model. In: International Conference on Ubiquitous Computing and Ambient Intelligence, pp. 236–242. Springer, Cham (2014)

54. Smieszek, T., Salathe, M.: A low-cost method to assess the epidemiological importance of individuals in controlling infectious disease outbreaks. BMC Med. 11, 35 (2013)

55. Salathe, M., Kazandjieva, M., Lee, J.W., Levis, P., Feldman, M.W., Jones, J.H.: A high-resolution human contact network for infectious disease transmission. Proc. Natl. Acad. Sci. U. S. A. 107, 22020–22025 (2010)

56. Cauchemez, S., Bhattarai, A., Marchbanks, T.L., et al.: Role of social networks in shaping disease transmission during a community outbreak of 2009 H1N1 pandemic influenza. Proc. Natl. Acad. Sci. U. S. A. 108, 2825–2830 (2011)

57. Temime, L., Opatowski, L., Pannet, Y., Brun-Buisson, C., Boelle, P.Y., Guillemot, D.: Peripatetic health-care workers as potential superspreaders. Proc. Natl. Acad. Sci. U. S. A. 106, 18420–18425 (2009)

58. Barrat, A., Cattuto, C., Tozzi, A.E., Vanhemets, P., Voirin, N.: Measuring contact patterns with wearable sensors: methods, data characteristics and applications to data-driven simulations of infectious diseases. Clin. Microbiol. Infect. 20(1), 10–16 (2014)

59. Cattuto, C., Van den Broeck, W., Barrat, A., Colizza, V., Pinton, J.F., Vespignani, A.: Dynamics of person-to-person interactions from distributed RFID sensor networks. PLoS One. 5, e11596 (2010)

60. Yan, L., Zhang, H.T., Goncalves, J., Xiao, Y., Wang, M., Guo, Y., et al.: A machine learning-based model for survival prediction in patients with severe COVID-19 infection. MedRxiv (2020)

61. Haleem, A., Javaid, M., Vaishya, R.: Effects of COVID 19 pandemic in daily life. Curr. Med. Res. Pract. 10(2), 78–79 (2020). https://doi.org/10.1016/j.cmpr.2020.03.011

62. Bai, H.X., Hsieh, B., Xiong, Z., Halsey, K., Choi, J.W., Tran, T.M., Pan, I., Shi, L.B., Wang, D.C., Mei, J., Jiang, X.L.: Performance of radiologists in differentiating COVID-19 from viral pneumonia on chest CT. Radiology. 296(2), E46–E54 (2020). https://doi.org/10.1148/radiol.2020200823

63. Hu, Z., Ge, Q., Jin, L., Xiong, M.: Artificial intelligence forecasting of COVID-19 in China. arXiv preprint arXiv:2002.07112 (2020)

64. Gozes, O., Frid-Adar, M., Greenspan, H., Browning, P.D., Zhang, H., Ji, W., Bernheim, A., Siegel, E.: Rapid AI development cycle for the coronavirus (COVID-19) pandemic: initial results for automated detection & patient monitoring using deep learning CT image analysis. arXiv preprint arXiv:2003.05037 (2020)

65. Pirouz, B., ShaffieeHaghshenas, S., ShaffieeHaghshenas, S., Piro, P.: Investigating a serious challenge in the sustainable development process: analysis of confirmed cases of COVID-19 (new type of coronavirus) through a binary classification using artificial intelligence and regression analysis. Sustainability. 12(6), 2427 (2020)

66. Ting, D.S., Carin, L., Dzau, V., Wong, T.Y.: Digital technology and COVID-19. Nat. Med. 26(4), 459–461 (2020)

67. Wan, K.H., Huang, S.S., Young, A., Lam, D.S.: Precautionary measures needed for ophthalmologists during pandemic of the coronavirus disease 2019 (COVID-19). Acta Ophthalmol. 98(3), 221–222 (2020)
68. Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., Bai, J., Lu, Y., Fang, Z., Song, Q., Cao, K.: Artificial intelligence distinguishes COVID-19 from community-acquired pneumonia on chest CT. Radiology. 19, 200905 (2020)
69. Smeulders, A.W., Van Ginneken, A.M.: An analysis of pathology knowledge and decision making for the development of artificial intelligence-based consulting systems. Anal. Quant. Cytol. Histol. 11(3), 154–165 (1989)
70. Chowel, G., Viboud, C.: A practical method to target individuals for outbreak detection and control. BMC Med. 11, 36 (2013)
71. Pandey, G., Chaudhary, P., Gupta, R., Pal, S.: SEIR and regression model based COVID-19 outbreak predictions in India. arXiv preprint arXiv:2004.00958 (2020)
72. Dong, E., Du, H., Gardner, L.: An interactive web-based dashboard to track COVID-19 in real time. Lancet Infect. Dis. 20(5), 533–534 (2020). https://doi.org/10.1016/S1473-3099(20)30120-1. Published online Feb 19
73. Ardabili, S.F., Mosavi, A., Ghamisi, P., Ferdinand, F., Varkonyi-Koczy, A.R., Reuter, U., et al.: Covid-19 outbreak prediction with machine learning. Available at SSRN 3580188 (2020)