



# Smart Healthcare for ECG Telemonitoring System

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**Abstract:** Cardiovascular disorders are one of the major causes of sad death among older and middle-aged people. Over the past two decades, health monitoring services have evolved quickly and had the ability to change the way health care is currently provided. However, the most challenging aspect of the mobile and wearable sensor-based human activity recognition pipeline is the extraction of the related features. Feature extraction decreases both computational complexity and time. Deep learning techniques are used for automatic feature learning in a variety of fields, including health, image classification, and, most recently, for the extraction and classification of complex and straightforward human activity recognition in smart health care. This paper reviews the recent state of the art in electrocardiogram (ECG) smart health monitoring systems based on the Internet of things with the machine and deep learning techniques. Moreover, the paper provided possible research and challenges that can help researchers advance state of art in future work.

**Keywords:** Smart healthcare, ECG telemonitoring, IoT cloud, wearable sensor, machine learning, deep learning

## 1. Introduction

With a rapid increase in population, the number of patients and the need for health monitoring are increasing. Currently, health care system efficiency and affordability are becoming a big concern. Vast numbers of people are facing an increased healthcare systems expense. Thus, the emphasis must be on the health monitoring systems. Recently, the health monitoring system has played a crucial role in reducing hospital costs, the burden on the medical staff, and consultation time and waiting lists [1], [2]. Early detection and diagnosis of diseases are essential. It helps to slow the progress of disease effectively, and then it significantly reduces the cost of healthcare systems. However, the most recent technological advances can be used to tackle these issues [3].

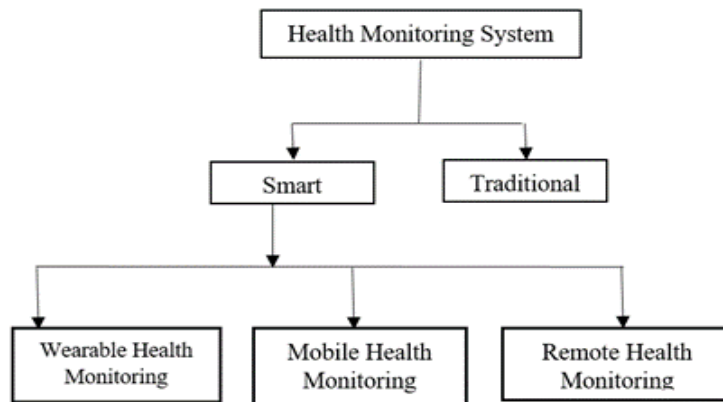
Wireless Body Area Network (WBAN) is a wireless sensor network with a particular purpose that incorporates various networks and wireless devices to enable remote monitoring for different environments. One of WBAN's targeted applications is in medical settings where conditions are constantly tracked in real-time for a large number of patients [4], [5], [6]. WBANs have been described as a vital component of a healthcare system based on Internet of Things technology, and the development of precise low form factor sensors is therefore crucial for the successful implementation of such a system [7]. Smart health care management systems play a vital role in the medical health industry. One of the leading revolutionary innovations in the medical sector is the wireless healthcare monitoring system. Smart wireless health monitoring devices allow the user to measure neural signals, heart rate, body temperature, and any suspicious movement in the patient's body [8]. The main contributors to the realization of a continuous remote health monitoring system are progressive developments in biosensors and wireless technology. Therefore, monitoring vital human signs such as the electrocardiograph (ECG) monitoring system is critical for minimizing and preventing the inability of people to manage proper assistance from healthcare doctors [9].

This paper provides a review of the current state of the art in smart health surveillance systems for electrocardiograms (ECG), based on the IoT with the machine and deep learning techniques. In addition, researchers will help advance state of the art in future work by providing potential lines of research and challenges in this analysis. The rest of the paper is organized as follows: a review background about health monitoring system and ECG waves are stated in section 2. Section 3 includes the IoT-based ECG monitoring system with both machine and deep learning and their performance evaluation. Some challenges of smart healthcare systems are presented in section 4. Finally, section 5 presented the conclusion and some suggestions.

## 2. Health Monitoring Systems (HMS)

Health monitoring systems are classified into two types; smart systems and conventional or wired systems. Smart systems include wearable health monitoring systems (WHMS). It deals with wearable devices or biosensors that can be used to assess critical human body parameters consisting of WHM such as Remote health monitoring system (RHMS) and/or Mobile health monitoring system (MHM) as in [10], [11], [12]. MHMS deals with smartphones, PDA, etc. Many mobile devices based on smartphones are becoming common day by day, and one can take care of their health at any time without more effort. And this system is easy to use RHMS. Fig. 1 shows the classification of the HMS [13]. RHMs are necessary to monitor the patient, and treatment is done by sending/receiving data remotely. This type of system can measure a variety of symptoms and can be implemented at homes and hospitals [14]. For remote health monitoring, the Internet of Things platform is important (IoT).

Since HMS applications are not limited, it can be used in hospital, residential and outdoor environments with either global positioning system (GPS) or radio frequency identification (RFID) technologies [15]. The idea of smart health is adapted from the advances in medical sector information technology and communication that activates the notion of electronic health (e-Health). However, smart health is a health service provision through context-aware networking and smart city sensing infrastructure. Smart health is part of e-health, but it focuses on smart cities' information and communication technologies. The notion of smart health, e-health, and m-health cannot be segregated in its implementation [16], [17].



**Fig. 1 - The classification of health monitoring systems [14]**

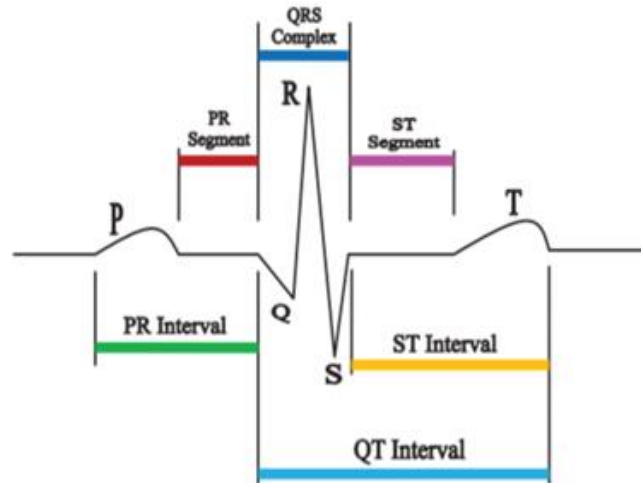
Electrocardiogram (ECG) offers crucial information regarding heart irregularities as the most important critical. It is a recording of the electrical activity produced by the heart on the surface of the body. Skin electrodes are put on specified positions on the body and collect ECG measurement information. ECG signals are needed for cardiac patients with multiple arrhythmias to be monitored over a prolonged period. Early detection and therapy of these cardiac arrhythmias can prolong life [18]. Three main steps are involved in ECG analysis: receiving the signals from the sensor, filtering the raw signals, and signal analysis. Moreover, the sensing stage requires an analog to digital converter [19]. The wireless ECG heart monitoring system requires a computationally effective and reliable QRS detection technique [20]. The ECG signal includes five peaks and valleys known as P, Q, R, S, and T [21].

- P-wave: Prior to depolarisation in the atrium.
- Q-wave: The anteroseptal area is triggered by the ventricular myocardium.
- R-wave: It depolarises the ventricular myocardium.
- S-wave: activation of the posterobasal component of the ventricles.
- T-wave: rapid-ventricular repolarisation

The ECG signal intervals are shown in Fig. 2. The QRS complex wave is the most important part of the cardiac system to determine. The ECG parameters normal values are shown in Table 1 [22], [23], [24].

**Table 1 - Values of normal ECG parameters**

Features	Normal Range/Second
RR Interval	0.6-1
PR Interval	0.12-0.20
QT Interval	0.32-0.44
QRS Complex	< 0.12

**Fig. 2 - The standard of ECG signal**

### 3. IoT-based ECG Monitoring System

The Internet of Things (IoT) is a new reality that is improving our life. The popularity of Internet-based healthcare computing has increased the number of interconnected objects and items [25], [26]. IoT has found numerous applications in several fields, including smart health care, remote health tracking, power management, smart cities, smart homes, and environmental surveillance [27]. The IoT works with various devices that interact using different protocols in a heterogeneous environment [28]. Wearable and Internet of Things (IoT) technologies have recently been developed to enable real-time and continuous individual electrocardiogram (ECG) monitoring [29].

The IoT-cloud related to personal healthcare monitoring using personal body area networks (BAN) is an extensively researched subject in healthcare. One of the most sought applications in the healthcare domain is remote monitoring of heart rate variability (HRV), and it is useful for clinicians to treat various physiological diseases. HRV is required to specify the physical fitness and sporting activity in sports medicine, and it may be needed for patients recovering at home post surgeries [30]. The structure of the IoT-based ECG monitoring system is demonstrated in Fig. 3. which includes the IoT-based ECG monitoring system main parts:

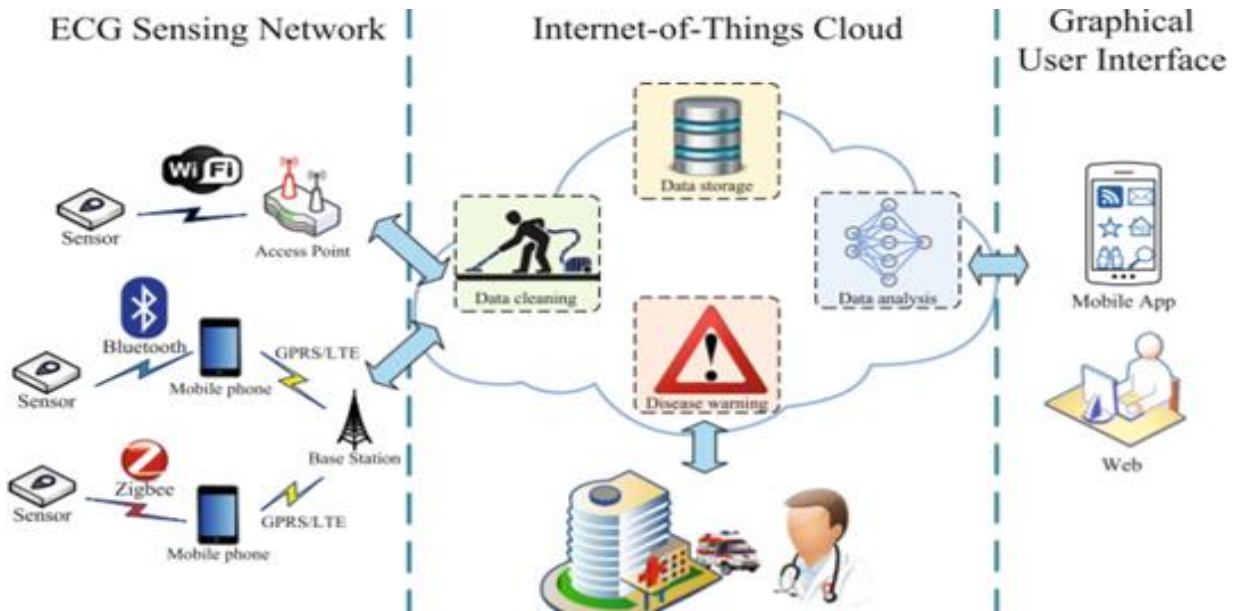


Fig. 3 - The IoT-based ECG monitoring systems framework

### 3.1 Data Acquisition

The ECG sensing network is the base of the entire system that gathers physiological data from the body's surface using electrodes placed on the skin. The data is then transmitted through a wireless channel to the IoT cloud. The essential component of ECG is the Instrumentation Amplifier, which is responsible for taking the voltage difference between leads and amplifying the signals [31], [32]. Electrodes help ECG to register cardiac events. The ECG electrodes can be categorized as wet and dry electrodes. (Ag/AgCl) was used in [33], [34] as a wet electrode. Therefore, dry electrodes have been found with merits that overcome the limitation of the wet electrodes like no skin irritation and skin preparation and long-time monitoring continuously. Medical experts and researchers tend to use Carbon Nanotubes CNT-based ECG electrodes or wearables [35], [36], [37]. Fig. 4 displays the AD8232 ECG sensor together with Electrodes [38]. A novel smart clothing-based wearable ECG measurement was proposed that helps better in continuous and effective data acquisition [39].



Fig. 4 - AD8232 ECG Sensor and ECG Electrodes [40]

### 3.2 Data Transmission

ECG data collected from sensors is transmitted via a particular wireless protocol to the IoT cloud, such as Wi-Fi, Bluetooth, ZigBee, etc. [23]. These three protocols provide adequate data rates while consuming energy at an acceptable level. Table 2 illustrates a comparison among these protocols [41]. Because of the limited Bluetooth and ZigBee communication range, a smart device is usually needed if the ECG data are to communicate with the IoT cloud through the General Packet Radio Service (GPRS) or Long-Term Evolution (LTE) wireless protocols [42]. Other communication protocols used for the sending layer include RFIDs Near Field Communication (NFC) and Ultrawide Bandwidth (UWB). The RFID offers two-way connectivity between the RFID tag and the RFID reader. The collected data in the concentrator is transferred further to the cloud or HCO via Wi-Fi or the mobile data network for global communication to retain patient data for archival storage [43]. Mobile communication standards such as 3G, 4G,5G,

and LTE are used in diverse health monitoring systems. As part of the data acquisition layer, low-power sensors used in an IoT architecture can be acquired over the Internet via a concentrator. [44]. This layer supports Raspberry Pi and Arduino hardware platforms since they provide the atmosphere for application development [45], [46].

**Table 2 - A comparison among wireless-based ECG sending networks**

Standards	Wi-Fi	Bluetooth	ZigBee
Protocol	IEEE 802.11	IEEE 802.15.1	IEEE 802.15.4
Coverage	20-200 m	20-30 m	2-20 m
Data rates	11.54 Mbps	3-24 Mbps	10-250 kbps
Power consumption	Medium	Low	Low
Terminal dependency	The collecting of data is independent of the smart terminal.	For receiving and transmitting sensed data, smart terminals are required.	For receiving and transmitting sensed data, smart terminals are required.

### 3.3 Cloud Processing and Storage

IoT has provided vital services with cloud computing to support massive storage and ample processing space, such as intelligent healthcare [47]. A diversity of objects is interconnected to the IoT cloud systems that generate large volumes of data which require an intelligent storage mechanism [48]. The sensing network gathers healthcare information, and the IoT cloud deals with data operations such as analysis, processing, and storage [49]. In addition to helping to get good prediction and diagnosis, the IoT cloud offers an efficient platform for the long storage of medical data [50].

### 3.4 Graphical User Interface (GUI)

Data imagination management is achieved using a graphical user interface (GUI) such as mobile applications and websites to respond immediately. In addition, GUI provides easy entry to the acquired visualized ECG data in the IoT cloud in real-time [45]. A summary of the state of arts-based IoT in smart healthcare monitoring systems has been conducted and presented, as shown in Table 3.

**Table 3 - The summary of the state of arts-based on IoT in the smart healthcare monitoring system**

Ref.	Year	Model	Microcontroller	Platform	Connectivity	Limitation(s)
[12]	2018	Wearable	CY8C4248-BLE, Cypress	Smartphone, tablet, PC.	Bluetooth, RF	-It does not include analog parts due to its simple hardware structure.
[33]	2018	IoT/ Wearable	TI MSP430 and CC3100	Laptop, PC with Energia IDE	Wi-Fi	-Multiple filtering process causes a delay due to the usage of complex moving average algorithm. -Wet electrodes
[11]	2019	Portable	MSP430F5529	Android, PC	Wi-Fi	-Insufficient memory implemented
[45]	2019	IoT/ Wearable	ATmega328 embedded in the Arduino Uno	Mobile App. and web pages	Wi-Fi	Due to the fail of some trials, it still needs improvement to raise the efficiency by more than 80%.
[10]	2020	Portable/ Wearable	MCP73831	Smartphone, PC	LAN, Bluetooth, Sixfox	-Batteries with a higher capacity of 2400 mAh are not recommended due to the weight. -SD cards
[46]	2020	IoT/ Wearable	ATmega328 embedded in the Arduino Lilypad	Mobile App.	Wi-Fi	-Limited source of power energy due to Its small size.

[39]	2020	IoT/ Wearable	nRF52840	Smartphone, PC	Bluetooth Wi-Fi	-Existence of some jitters
[34]	2021	IoT/ Wearable	MSP430f449	Android	BLE Wi-Fi	-Ag-AgCl wet electrodes

BLE: Bluetooth Low Energy, LAN: Local Area Network, PC: personal computer, RF: radiofrequency

#### 4. Smart Healthcare ECG Monitoring

The interaction between mobile networks, wireless communications, and artificial intelligence is transforming the way people live and survive in the age of the IoT through a number of technological developments, specifically improved computing power, high-performance processing, and enormous memory space. The term smart city design was coined with the introduction of cyber-physical systems, which involve the seamless integration of physical systems with computing and communication services, as a paradigm shift from the conventional city model to a smart city design. A smart city is fundamentally designed to be ICT-driven and capable of delivering a range of services, including smart driving, smart homes, smart living, smart governance, and smart health. [51].

#### 4.1 ECG Monitoring and Machine Learning

During the growth of artificial intelligence and its integration with sensors, machine learning (ML) techniques have experienced significant changes in wearable health monitoring systems based on IoT [52], [53], [54], [55], [56]. To track basic health parameters, IoT-based sensors are used to classify many diseases such as chronic illnesses, diabetes, and many more. The primary health parameters such as temperature, pulse rate, ECG, blood pressure and breathing airflow, fall detection of the individual are extracted using different sensors related to health. The values obtained from these sensors are sent to the cloud through a platform based on IoT. Data obtained from the sensor can be used with artificial intelligence such as machine learning to diagnose the symptoms and recognize diseases. The health industry uses machine learning algorithms to identify diseases, perform medical diagnoses, and predict and classify diseases based on symptoms. Fig. 5 shows the IoT model for the healthcare system based on ML. Current ML recognition relies on hand-crafted features that are unable to handle complex operations, particularly with the current influx of multimodal and high-dimensional sensor data, while deep learning methods require a process of learned features [57]. The research path is the deep learning technology of artificial intelligence technologies [58], [59], [60].

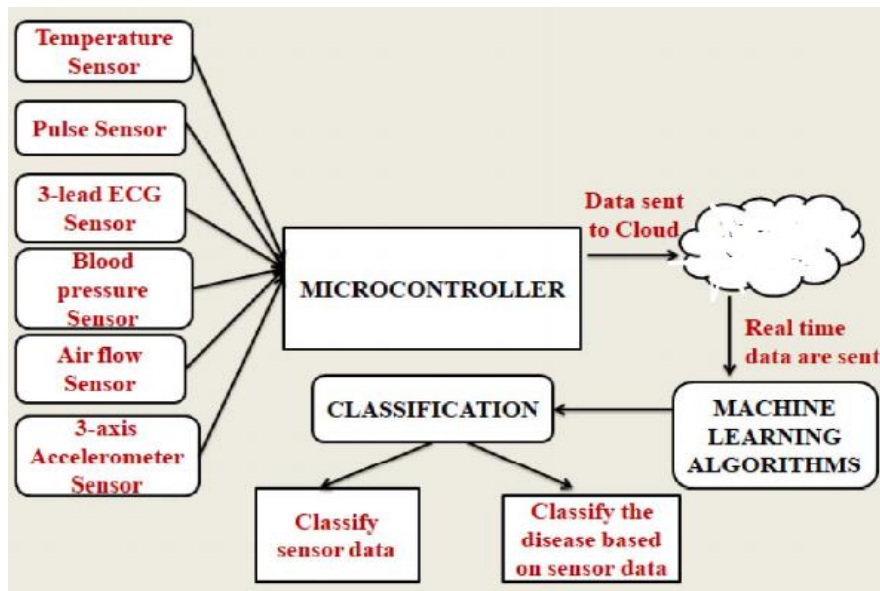


Fig. 5 - The IoT model for the healthcare system based on ML

#### 4.2 ECG Monitoring and Deep Learning

In recent years, deep neural networks have been commonly used in ECG automated diagnosis to satisfy high-speed and high-precision ECG analysis [61]. The system can obtain users' ECG signals through light wearable devices. Next, the systems analyze data in the cloud with an ensemble deep learning algorithm and predict users' health status to enhance the accuracy of heart disease prediction as in [62]. Furthermore, the avoidance of false positives is a significant safety element because medication, such as anticoagulation, is a death risk. Therefore, preventing false positive factors



plays an important role in the protection of a diagnostic support system. For Atrial Fibrillation (AF) detection, long-term memory (LSTM) deep learning algorithm is used to increase machine decision safety and reliability [63]. The convolutional neural network (CNN) techniques showed high accuracy in the heart abnormality. Unlike classical machine learning, which requires a hand-crafted feature to work optimally, feature extraction can be learned within deep learning. It can provide cognitive behavior and enhance the potential for decision-making. Currently, deep learning is the most common detection [64], [65], [67], [69], [70]. Table 4 summarizes the state of arts that use ML and DL in smart healthcare monitoring systems.

**Table 4 - summarizes the state of arts that uses ML and DL in the smart healthcare monitoring system**

Ref.	Year	Model	Classifier	Connectivity	Platform	Dataset	Performance
[52]	2019	IOT/ML/ wearable/	Ensemble Random forest	WIFI	Android IOS	UCI respiratory	Accuracy 96%
[53]	2019	IOT/ML/ wearable	E-NN	Bluetooth WIFI	Mobile application	Firestore Real- Time Database	Accuracy 95%
[63]	2019	IOT/DI/	LSTM	Bluetooth WIFI	PDA, Mobile, PC	Physionet's fantasia	Accuracy 97.57 %
[54]	2020	IOT/ML/ wearable	Random Forest	A/N	A/N	MIT-BIH	Accuracy 94.07%
[55]	2020	IOT/ML/	TSVM	Wi-Fi	PDA	Physionet data	Accuracy 95.58%
[62]	2020	IOT/DI/ wearable	Ensemble deep learning	Bluetooth Wi- Fi	Gateway devices.	Cleveland and Hungarian	Accuracy 98.5%
[64]	2020	IOT/DI/ wearable/	1DCNN(1D ResNet)	4G or 5G.	PDA, Mobile, PC	160,948 signal lead ECG signals	F1 84.91%
[65]	2020	IOT/DI/ wearable	CNN Pretrind MobileNetV2	Wi-Fi	A/N	MIT-BIH	AP 75%
[66]	2020	IOT/DI	CNN	Wi-Fi	A/N	CUDB VFDB	Accuracy 97.592%
[68]	2020	IOT/DI/ wearable	DCNN	Bluetooth Wi- Fi	PDA, Mobile, PC	CEBS	Sensitivity 0.98

### 4.3 Performance Evaluation

Performance assessment has several measures, including precision, sensitivity, accuracy, and specificity, as given by Equations 1-4 [71], [72], [73]. Referring to Equation (1) - (4), true positives (TP) are correctly predicted positive instances, and false negatives (FN) are incorrectly predicted negative instances. On the other hand, True negatives (TN) are, meanwhile, negative instances that are accurately predicted. Finally, false positives (FP) are positive examples that are wrongly predicted. Sensitivity refers to a skin lesion correctly classified [74], [75].

$$\text{Accuracy} = \frac{TP + TN}{(TP + TN + FP + FN)} \quad (1)$$

$$F1 = \frac{TP + TN}{(TP + \frac{1}{2}(FP + FN))} \quad (2)$$

$$\text{Sensitivity} = \frac{TP}{(TP + FN)} \quad (3)$$

$$\text{Specificity} = \frac{TN}{(TN + FP)} \quad (4)$$

## 5. Smart Healthcare Monitor Challenges

Smart health monitoring systems based on IoT offer various advantages, such as remote diagnosis, early alarms, continuous monitoring of home care, etc. These innovations would eventually affect the quality of life of individuals while reducing healthcare service providers' costs. However, there are several challenges to developing these

technologies, particularly in the area of bio-signal monitoring. These include the design of electronic sensors, the transfer of data, and learning, as illustrated next.

### 5.1 Design of Electronic Sensor

Conventional electrodes used to detect ECG signals are based on wet transducing electrodes utilizing silver-silver chloride (Ag-AgCl) that transform ionic current on the skin surface to electronic amplification and signal conditioning currents. These sensors depend on conducting gel that presents many challenges, such as drying out, skin discomfort, dis-conditioning if not carefully placed. These concerns consider wet electrode systems unsuitable for use outside the clinical environment and especially unsuitable for remote wearable clinical ECG monitoring [76]. The development of alternative techniques, such as capacitive sensing-based dry electrodes. The critical drawbacks of these sensors are artifacts of movement, generation of triboelectric charge due to the friction within the garment, and poor subject-sensor coupling. On the other hand, Electric Potential Sensing Technology (EPS)-based dry electrodes have proven to be adequate for ECG monitoring with the potential to be integrated into wearable sensor sensors [77]. The concept of smart ECG wearables is motivating because of strict size, weight, and energy usage limits.

### 5.2 Transfer of Data and Throughput

Latency along with coverage is a necessity for real-time monitoring reliability. Implementation of deep learning in smart devices will reduce the amount of computation required on the data. However, this strategy is hindered by the need to convey data and restricted memory space since deep learning increases processing time. It is not ideal for mobile devices with low energy. Thus, leveraging mobile cloud-based training tools to reduce training time and memory consumption. The framework may become self-adaptive with this sort of implementation and require minimal user inputs for a new source of information. Moreover, it is worth using techniques such as optimal compression to minimize computing time and resource consumption.

### 5.3 Transfer Learning for Smart Healthcare

Transfer learning for activity recognition is an essential process. It helps the machine to use previously learned skills to progress in different domains. The main reasons why transfer learning is used include the reduction in training time, the robustness of activity data, and the ability to reuse knowledge in new domains. Moreover, transfer learning in smart healthcare will reduce target, source, and environment-specific applications implementation that has not received the required attention.

## 6. Conclusion

In today's world, cardiovascular disease is the most life-threatening disease. Conventional ECG monitoring becomes inconvenient to the subject. Therefore, wireless communication-driven healthcare systems support lightweight, intelligent sensing at low cost, suitable for mass-market consumer penetration. Smart healthcare has emerged as a growing sector due to customer awareness and rapid technological advances in medical sensors. Networking and physiological data processing have recently made new devices and services possible. The advancement of wearable technology, combined with advances in IoT and artificial intelligence such as deep learning, minimizes post-denoise feature extraction's complexity and execution time due to dimensionality reduction. Moreover, it increases the accuracy of detecting and diagnosing abnormalities in smart ECG monitoring and taking the appropriate action in real-time. We find that methods of deep learning can typically achieve better output than conventional ECG modeling methods. However, there are still some outstanding challenges and concerns associated with these deep learning methods that need to be considered.

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