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WEARABLES AND MACHINE LEARNING IN HEALTH MONITORING

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Contents

1. Introduction

The Internet of Things (IoT) technology is gaining increasing popularity and is widely applied across various industrial sectors such as smart cities, manufacturing, transportation, agriculture, smart homes, wearable technology, and smart devices [1]. Among these sectors, smart healthcare technology stands out, utilized for remote patient monitoring, commonly known as eHealth. Furthermore, wearable technology has long been recognized as a means of monitoring patients' health outside of hospital environments [2], providing a high quality of life and prompt response to health challenges. Traditional visits to healthcare providers are infrequent and may not offer the necessary continuous care required for early disease detection. The utilization of IoT technology offers a promising solution through wearable devices enabling continuous monitoring of health parameters.

To effectively address the challenges associated with health monitoring, it is crucial to properly store, integrate, and understand the collected data. During specialist visits, patients undergo measurements of vital parameters, which are then used to assess overall health status, leading to diagnostic conclusions. In tackling this challenge, an architecture is proposed, drawing inspiration from the formal description of human perception, previously successfully applied in environmental monitoring [3]. The proposed architecture consists of three key layers: Sensing, Integration and Association, and Application and Diagnostic, as illustrated on the Figure 1.1. The Sensing layer encompasses sensors for measuring patients' vital parameters, communicating with data transmission equipment in the cloud. The Integration and Association layer integrates and links sensor values into a common ontology, while the Application and Diagnostic layer contains algorithms and tools for disease detection.

In the Sensing chapter, an overview of radio communications capable of transmitting data over both long and short distances is provided, along with a review of sensors used in non-invasive measurement of human physiological parameters. Wearable technology, whether medically certified or uncertified, can track vital signs, potentially using data collected via smart technologies as input for various machine learning algorithms [4]. Additionally, a distinction can be made between invasive and non-invasive technologies used for monitoring key medical data [5]. One technology considered in this study is a wearable device capable of assessing physiological parameters. The issue of sensor connection, continuous data transmission, and processing providing real-time feedback to the user is still a subject of debate despite the increasing popularity of these devices. Smartwatches, fitness trackers, or other wearable devices are currently used for monitoring vital signs. These devices in-

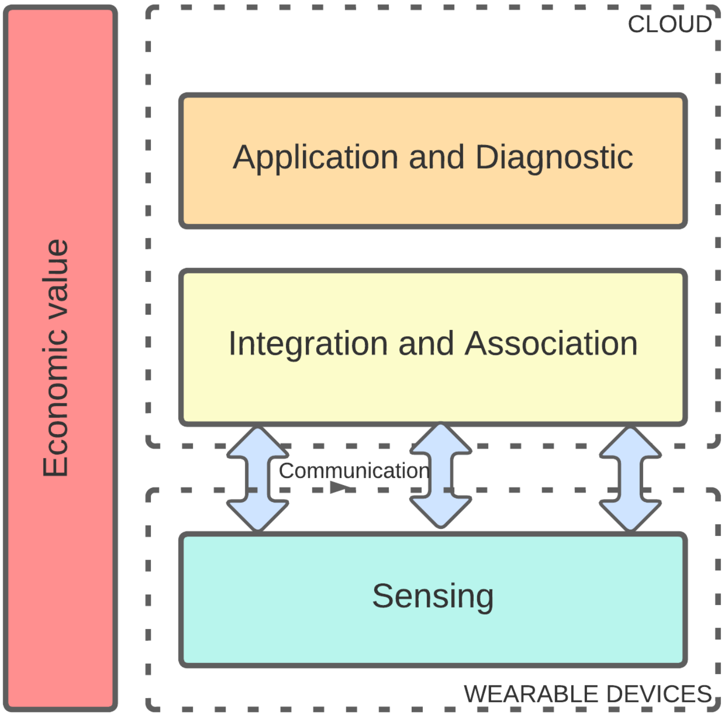

Figure 1.1. Observer network for health monitoring.

clude sensors for photoplethysmography (PPG), electromyography (EMG), accelerometry, electroencephalography (EEG), electrocardiography (ECG), electrodermal activity (EDA), skin temperature, blood oxygen saturation, etc. [6]. Moreover, battery charging and low-power wearable electronics pose two complex problems. Depending on the data sampling frequency and telemetry, it is usually necessary to refresh monitoring of important parameters while the system is awake and in daily use. Although providing users with instant responses sounds appealing, it would drain the battery. Another issue that may arise for wearable devices used to track important metrics is the limited data transmission to a cloud platform via a smartphone connected to the internet, either via WiFi or mobile 4G network [6].

Integrating and Associating technologies in healthcare, particularly through the application of Internet of Things (IoT) ontologies, represents a significant advancement in the management and monitoring of patient health. The Integration and Association layer, a critical component of healthcare IoT frameworks, enables the comprehensive gathering, storage, and analysis of health-related data from wearable devices. This data is meticulously organized within databases, either stored locally or on cloud platforms, facilitating immediate and secure access to health metrics [7]. Ontologies such as SAREF (Smart Applications REFerence) and its healthcare-focused extension, SAREF4EHAW, are instrumental in overcoming the challenges presented by the diverse array of sensors and platforms in the IoT ecosystem. These structured frameworks not only ensure the effective collation and interpretation of data from multiple sources but also support personalized patient monitoring [8] and early symptom detection [9], thereby enhancing the overall quality of healthcare services. The role of ontologies like SAREF4EHAW extends to the promotion of healthy lifestyles and the provision of early warning systems for potential health issues, such as cardiovascular incidents, by enabling continuous health monitoring and offering insights into the patient's condition [10]. Moreover, the adaptability of the SAREF ontology to the specific needs of different healthcare sectors underscores its importance in the digital transformation of healthcare, making it a cornerstone for interoperability and data integration across various IoT applications and solutions [11]. As the IoT continues to evolve within the healthcare domain, the expansion and rigorous validation of these ontologies are paramount. Ensuring their validity and reliability through comprehensive evaluation techniques is essential for their effective implementation and the realization of their full potential in improving patient care. The SAREF ontology, in particular, facilitates seamless communication between disparate IoT solutions and applications, adjusting to the unique requirements of different sectors within the healthcare industry. This adaptability makes it a key tool for advancing digital healthcare, enabling the creation of a more connected and efficient patient care ecosystem. While the direct application of ontologies in healthcare ventures beyond the scope of this discourse, their integral role in the technological integration and enhancement of healthcare systems is undeniable. By fostering a more collaborative and data-driven approach to patient care, these ontologies pave the way for a future where healthcare is not only more responsive but also more attuned to the individual needs of each patient.

The acquired data can be analyzed using machine learning algorithms to predict and diagnose various health problems and diseases, which is part of the Application and Diagnostic layer. Smart technologies utilizing various machine learning (ML) algorithms can be used for disease prediction and identification [12]. One technique for disease detection and prediction using wearable technology is machine learning (ML) [13]. ML algorithms are used to find patterns in data that a human observer could not identify. Wearable devices can serve as an alternative for monitoring vital parameters in hospitals where monitoring patients can be difficult and time-consuming. For example, the random forest method [14] can be used to determine the relationship between pain self-assessment scale and measurements made using wearable technology. Furthermore, specific patient data such as gender, age, blood pressure, smoking status, and cholesterol levels must be monitored to establish a diagnosis [15]. To achieve the highest level of prediction accuracy, several ML approaches are applied to data obtained, in some cases, from both healthy and diseased patients. This research analyzes the contribution of the ML algorithms used in assessing disease risk. To utilize appropriate ML techniques, collected data are stored and separated into test and training data sets before the processing phase [15]. Furthermore, during the development lifecycle of ML solutions, many issues and gaps have been identified, particularly regarding the availability of data sets, versioning ML models, and overall system performance [16], but they are not covered in this work.

This paper presents a network of observers for health monitoring, inspired by the architecture of the Forest Fire Watch Network and adapted to a case study of patient health monitoring using IoT and wearable devices. Sections 2 and 3 provide a review of related works in wearable device research and radio communications available for data transmission, as well as machine learning algorithms for disease detection, respectively.

2. IoT Implementation

The integration of wearable devices into healthcare represents a significant step towards facilitating continuous and targeted patient care. These devices, increasingly employed for medical data collection, play a crucial role in ensuring timely and accurate information acquisition. Data are collected from users continuously over a defined period. The devices consist of one or a combination of multiple sensors that enable precise and accurate measurements. Following data collection, this information must be securely stored in a suitable database to enable seamless processing and transmission to end-users. Subsequently, the data is relayed to its destination utilizing chosen radio technology, a decision contingent upon factors like energy consumption, data size, and distance from the receiver, as illustrated in Figure 2.1 [17]. Data can be continuously sent to the database or stored in the wearable device's internal memory and transmitted to the database after a certain period. It is necessary to consider the reduced use of device battery resources and enable their longer lifespan on a single charge. This comprehensive technological infrastructure not only facilitates precise data collection but also ensures its secure distribution, thereby advancing the quality and efficiency of healthcare provision. In this section, a brief overview of the technologies depicted in Figure 2.1, used for data transmission, is provided. Technologies vary depending on the distance at which they can transmit data, power, and the amount of data they can send. A brief overview of radio technologies used in wearable devices will provide better insights into choosing the ideal radio technology for data transmission.

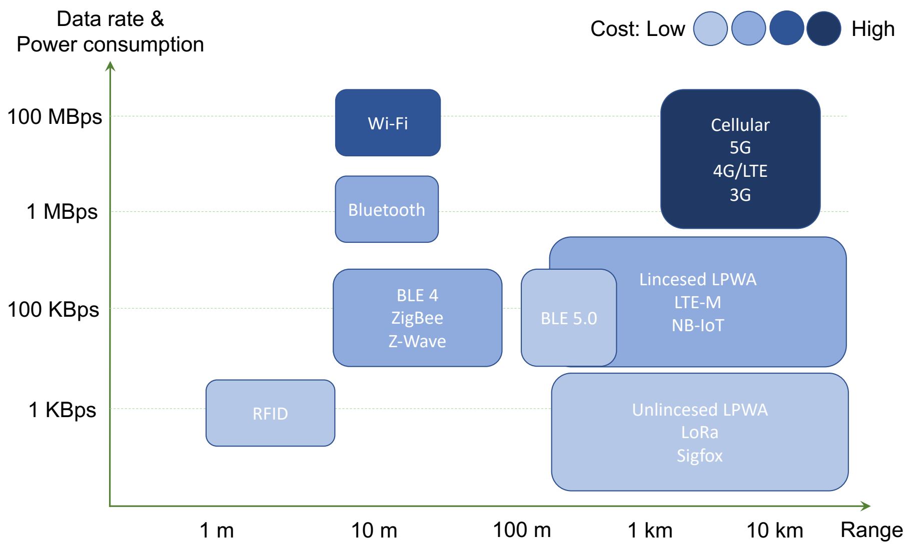

Figure 2.1. Range of communication protocols [17].

Radio Frequency Identification (RFID) technology facilitates data transmission through devices known as tags and readers, capable of communicating over distances up to 100 meters, especially with active tags. Although originally intended mainly for identification, contemporary RFID devices have expanded their functionality to include sensing and transmitting sensed data through the same protocols [18]. Data are transmitted via electromagnetic waves, allowing tags to send information back to the reader without direct contact or line of sight. RFID is categorized based on frequency ranges into low-frequency (LF) tags operating up to 135 kHz, high-frequency (HF) tags including Near Field Communication (NFC) at 13.56 MHz, and ultra-high-frequency (UHF) tags ranging from 865 MHz to 928 MHz, with active UHF tags reaching the furthest distances. Each frequency band has distinct characteristics and applications, from access control and animal identification in LF and HF bands to logistics and vehicle tracking with UHF tags. This classification by frequency supports various use cases, balancing range, speed, and cost to meet specific needs across different sectors [19].

ZigBee offers an alternative to Bluetooth, the technology can cover distances up to 150 meters outdoors.Data through ZigBee technology are transmitted across three main frequency bands: 868 MHz in Europe, 915 MHz in North America and Australia, and a worldwide available 2.4 GHz band. These frequencies allow for data rates of 20kbps, 40kbps, and up to 250kbps, respectively. This spectrum of operation ensures that ZigBee networks do not interfere with other common wireless networks such as Wi-Fi or Bluetooth, due to their different operational bands [20]. Designed for low power consumption, ZigBee devices can operate on batteries for extended periods, often measured in years, making them ideal for applications where long battery life is crucial.

LPWAN (Low Power Wide Area Networks) technologies facilitate data transmission across a wide variety of devices, including sensors and actuators, designed for IoT applications. These networks are distinguished by their long-range communication capabilities, often exceeding distances of up to 10-40 km in rural or less dense environments and 1-5 km in urban settings, thereby providing extensive coverage even in challenging indoor and underground locations [21]. Data within LPWANs are transmitted at low data rates, typically ranging from a few hundred bits per second to tens of kilobits per second, which aligns with the technologies' emphasis on energy efficiency and minimal power operation. This efficiency ensures that devices can operate on battery power for extended periods, often exceeding ten years, without the need for frequent recharging or battery replacement. LPWANs primarily utilize sub-GHz frequency bands (e.g., 868 MHz in Europe and 915 MHz in the US) for communication, leveraging the favorable propagation characteristics of these lower frequencies to achieve robust and reliable long-range connectivity. A notable aspect of LPWANs is their capacity to support a vast number of devices connected to a single receiver or network gateway. This capability is crucial for IoT applications, which may involve the deployment of thousands, or even millions, of connected devices within a single network. The scalability of LPWAN technologies ensures they can accommodate the burgeoning demand for IoT connectivity, providing a reliable communication framework for a wide array of applications, from agricultural monitoring and smart city infrastructure to utility management and asset tracking.

Bluetooth is used for RF-based short-range communication between mobile and stationary devices. To counteract interference and fading, this system employs frequency hopping methods (FHSS) in the ISM band over 79 channels. The best case data rate option for Bluetooth, which runs on 2.4 GHz frequency, allows up to 3 Mb/s, and the usable range is between 10 and 100 meters [22]. The Piconet communication architecture, which consists of one master device and up to seven slave devices, is the most fundamental type of Bluetooth communication. When the radio is activated and Bluetooth is transmitting or receiving data, the power consumption ranges from 2.5 to 100 mW [22]. Other Bluetooth protocols exist, including Bluetooth Low Energy (BLE), Bluetooth v3.0, Bluetooth v4.0, and Bluetooth v5.0. BLE protocol is used in devices with short battery live, such as smartwatches and fitness trackers. It consumes less power than the original Bluetooth technology, thus increasing the battery life [2].

Bluetooth Low Energy (BLE) technology was introduced as a solution to replace cables for connecting devices, particularly those operating with lower data rates (maximum 1Mbps) over short distances (theoretically up to 100 meters), all while consuming minimal power. With subsequent advancements, Bluetooth 4.0 emerged, also known as Bluetooth/LE, offering simplified pairing features and higher data rates (up to 24Mbps, Wi-Fi-based), all while maintaining lower power consumption. Its primary objective is to facilitate the connection of sensors and actuators within IoT environments [23].

LoRa employs a "star of stars" network architecture for long-range radio communication, operating at frequencies of 433MHz, 868MHz, or 915MHz. It utilizes Chirp Spread Spectrum modulation, achieving data rates from 290bps to 50kbps with high power efficiency [24]. The achievable range varies based on radio power, spanning from 2-5 km in urban areas to 45 km in rural regions. This technology addresses IoT needs by providing low latency, wide coverage, and efficient data transmission over shared channels. It balances transmission speed and range through spreading factor (SF), bandwidth (BW), and code rate (CR). Ideal for applications requiring long-range connectivity, LoRa finds use in environmental monitoring, agricultural measurements, and parking lot occupancy tracking.

Wi-Fi technology, as described in [25], facilitates data transmission across a variety of devices, including computers, smartphones, and other Wi-Fi-enabled devices. It operates effectively up to a maximum distance of approximately 100 meters under optimal conditions. Data through Wi-Fi is transmitted over radio waves, enabling high-speed internet access without the need for physical connections. The technology operates within the 2.4 GHz and 5 GHz frequency bands, allowing for diverse and flexible usage scenarios from simple web browsing to streaming high-definition videos. Wi-Fi's design focuses on user convenience and supports a range of data transmission speeds, depending on the specific Wi-Fi standard being used, such as 802.11b, 802.11g, 802.11n, or more advanced protocols like 802.11ac, which can offer speeds from as low as 11 Mbps to more than 1 Gbps. Designed with energy efficiency in mind, Wi-Fi includes features like power-saving modes to minimize energy consumption for devices, particularly useful for battery-powered devices. It supports a wide array of devices per network, limited more by the bandwidth availability and network setup than by the technology itself. The exact number of devices that can connect to a single access point varies but can range from a handful to several hundred, making Wi-Fi suitable for environments ranging from home networks to businesses and public hotspots.

The **NB-IoT** technology primarily targets Machine Type Communication (MTC) devices located in remote areas, necessitating a coverage threshold of at least 23 dB. Unlike LoRa, NB-IoT deployment is confined to areas serviced by 4G/LTE base stations, rendering it unsuitable for rural or suburban regions lacking 4G coverage. The cost efficiency of the NB-IoT network enables the deployment of a multitude of devices with battery longevity exceeding 10 years. It is anticipated that NB-IoT network expansion will offer cost-effective services in remote regions in the future [26].

Considering the range offered by various technologies, Bluetooth Low Energy (BLE) and Long Range (LoRa) stand out as technologies with potential applications in the field of eHealth, owing to their potential in terms of low energy consumption and optimal range. BLE functions as a short-range technology, transmitting data over shorter distances with reduced energy consumption while maintaining speed and data quantity at an optimal level. On the other hand, LoRa technology facilitates the transmission of data over long distances, similarly preserving speed and data quantity per transmission. The following sections will provide detailed explanations of BLE and LoRa technologies through case study examples, emphasizing their capabilities and benefits within the eHealth sector and their application in everyday life.

Furthermore, the technologies were presented through case studies involving two wristbands. The BLE wristband underwent testing to determine the range distance in an enclosed space, thereby indicating the optimal receiver position for data collection. In contrast, the LoRa wristband underwent tests for both the range distance and the accuracy of measured parameters such as heart rate and temperature. This practical experimentation provided valuable insights into the performance of both technologies in real-world scenarios, offering significant implications for their application in eHealth.

2.1. Bluetooth Low Energy (BLE)

The Bluetooth Low Energy (BLE) protocol operates on frequency 2.4GHz band, divided into 40 channels width 2MHz, Figure 2.2. Three channels 37, 38, and 39, on frequency 2402, 2426, and 2480 MHz, are used for advertising and discovery services, and they are called advertising channels. The other 37 channels, on frequency between 2400 to 2480MHz, are used for transferring data between devices [27].

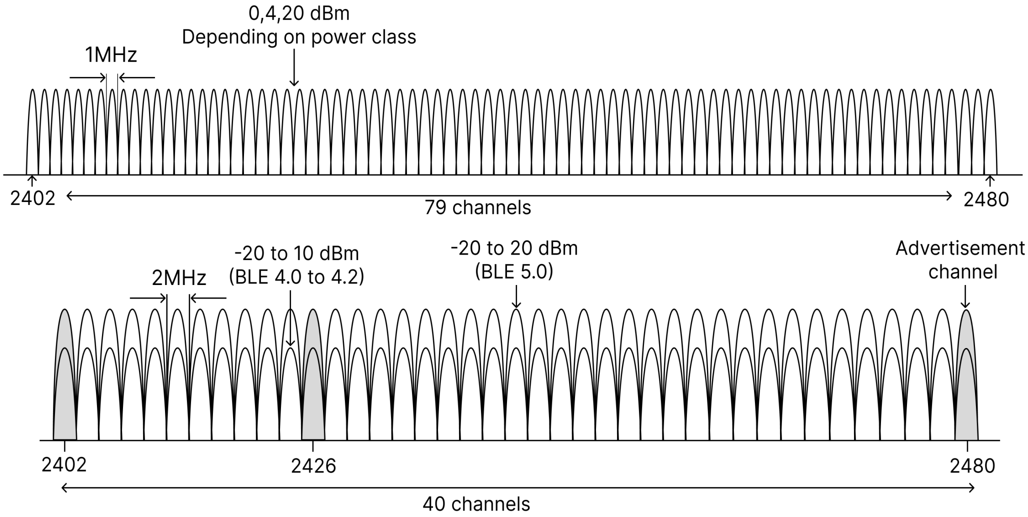

Figure 2.2. BLE sharing 2.4GHz frequency band.

The BLE transceivers use advertising events for broadcasting small blocks of data or to agree on the parameters of the connection established in the data channels. The advertiser, the device which has some data to transmit, sends an advertising frame. The advertiser can send 31-bit data directly to the advertising frame or can establish a connection in the data channel, and after that the advertiser, starts receiving and waits for possible connection establishes request. Once a sent connection request has been received by a single device running as a device that wants to connect, the two devices can proceed with the pear-to-per connection in the data channels. If the connection between the two devices is made in the data channel, the device that initiated the connection is *master* and the advertiser becomes *slave*. Communication between *master* and *slave* devices starts after the *master* device sends frame to *slave*. Until one of these two devices has a job to send or until the current connection event ends, the *master* and *slave* devices send a frame on the same channel. The communication channel closes if two are received for the second frame with a CRC error by *master* or *slave* or either the each of devices misses a radio packet [28]. The described process is shown in the Figure 2.3.

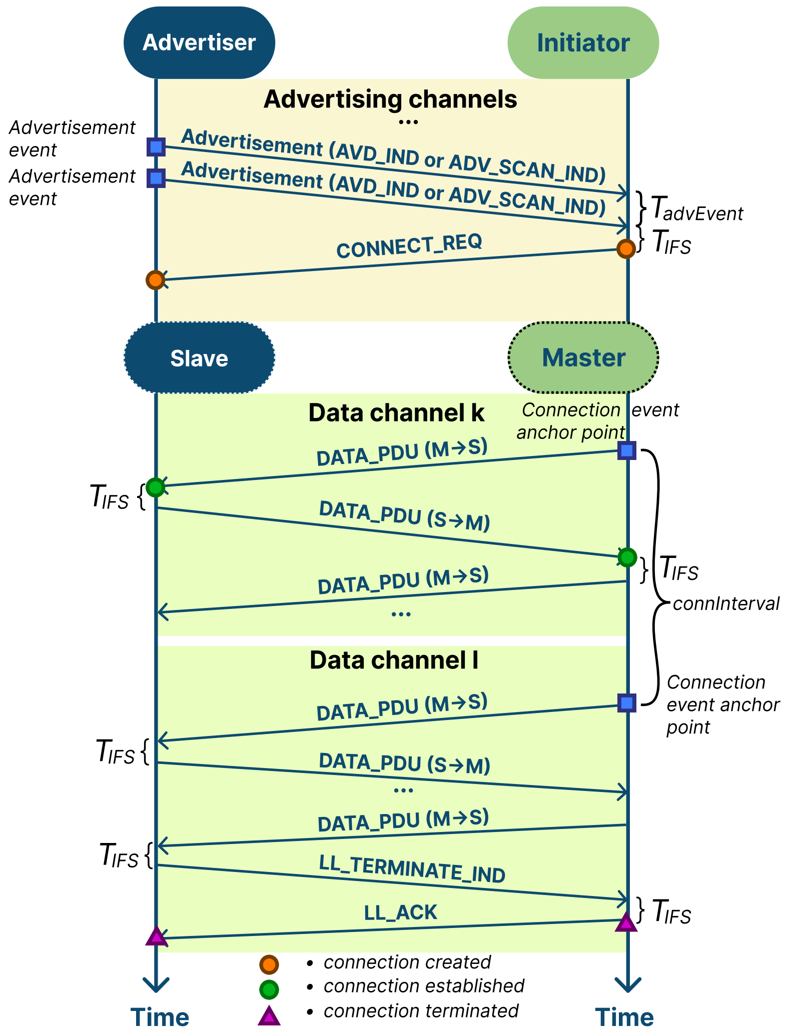

Figure 2.3. Display device rounding, connection establishment, data transfer, and connection established ending in BLE.

2.1.1. Connecting BLE to Android device

Low-cost BLE bracelets are becoming more popular and are increasingly used to monitor the vital parameters of patients. The data collected from the bracelet of each patient needs to be downloaded and stored in a database. To enable their download, an Android application was implemented in a way that scans available devices in range, connects to them, downloads their data and saves data in a database. The following sections shows the parts of the Android application code responsible for scanning and connecting devices.

After launch, the Android application initiates a search for available devices in range, scans available devices and saves them in an internal database with their MAC address, name and Received signal strength indication (RSSI). Vital parameters data starts downloading after connecting to an individual bracelet.

```
YCBTClient.startScanBle(new BleScanResponse() {
    @Override
    public void onScanResponse(int i, ScanDeviceBean scanDeviceBean) {
```

```
            if (scanDeviceBean != null) {
                if (!listVal.contains(scanDeviceBean.getDeviceMac())) {
                    listVal.add(scanDeviceBean.getDeviceMac());
                    deviceAdapter.addModel(scanDeviceBean);
                    list_of_devices.add(scanDeviceBean);
                }
                rssi_values = String.valueOf(scanDeviceBean.getDeviceRssi());

                Log.e("device", "mac=" + scanDeviceBean.getDeviceMac() + ";name=" + scanDeviceBean.getDeviceName() + "rssi=" + scanDeviceBean.getDeviceRssi());
            }
        }
            }, 6);
            break;
```

Listing 2.1. Scan devices within range and save them to the list.

Once the device scanning process is complete, the Android application connects to the individual scanned device. The Android app connects to each device on the list starting with the first device on the scanned list. After the bracelet is connected, the Application initiates the download of the measured data.

```
ScanDeviceBean scanDev = list_of_devices.get(k);
SPHelper.setParam(MainActivity.this, "key", scanDev.getDeviceMac());
connectedMAC = scanDev.getDeviceMac();
try {
    YCBTClient.connectBle(connectedMAC, new BleConnectResponse() {
        @Override
        public void onConnectResponse(final int i) {
            connected.setText("Connected to " + connectedMAC);
        }
    });
} catch (Exception e) {
    Log.e("Error", String.valueOf(e));
}
break;
```

Listing 2.2. Connecting to the devices sorted in a list.

Once the device scanning process is complete, the Android application connects to the individual scanned device. The Android app connects to each device on the list starting with the first device on the scanned list. After the bracelet is connected, the Application initiates the download of the measured data.

2.1.2. Collecting data

The process of data collection of BLE bracelets using the Android applications was developed so that measurement data from patients could be collected and transferred to a database. Once the desired bracelet is connected to the app, it starts downloading data according to the data exchange protocol between the two BLE devices. At the application level, data is retrieved from visible bracelets within range, after which the device on which the Android application is running sends data via an Internet connection to the database. It saves the downloaded data to the database for each device depending on its MAC address, and the data is ready for further processing after saving to the database. Figure 2.4 illustrates the process of Android applications up to the time the data is saved to the database.

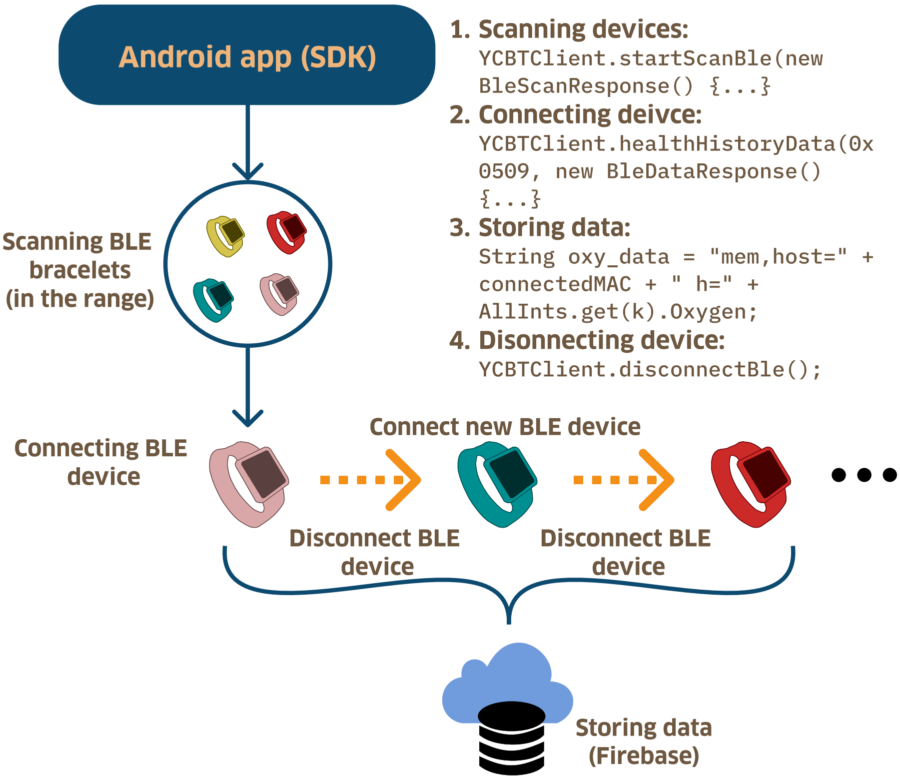

Figure 2.4. Process of Android application to store measured data from patients.

Utilization of BLE bracelets in real environments nursing homes and hospitals for monitoring vital parameters of patients heavy depend on the straight of their range. The range of a bracelet is testing as signal strength data, which has been shown in this section. In this scenario the BLE bracelet serves as a signal transmitter, the Android application running on the device as a receiver. One receiver, an Android application, in that case, retrieves data from all transmitters in range. To measure the signal strength, the Fitness Tracker BLE bracelet was used as a transmitter and a receiver of the Huawei MediaPad T3 10 tablet on which the implemented Android application was implemented and running. The measurement were performed by connecting the bracelet to the Android application and downloading the data, and among the downloaded data was the RSSI signal strength of the transmitter. RSSI data is stored in a database along with the read time for each BLE bracelet depending on their MAC address.

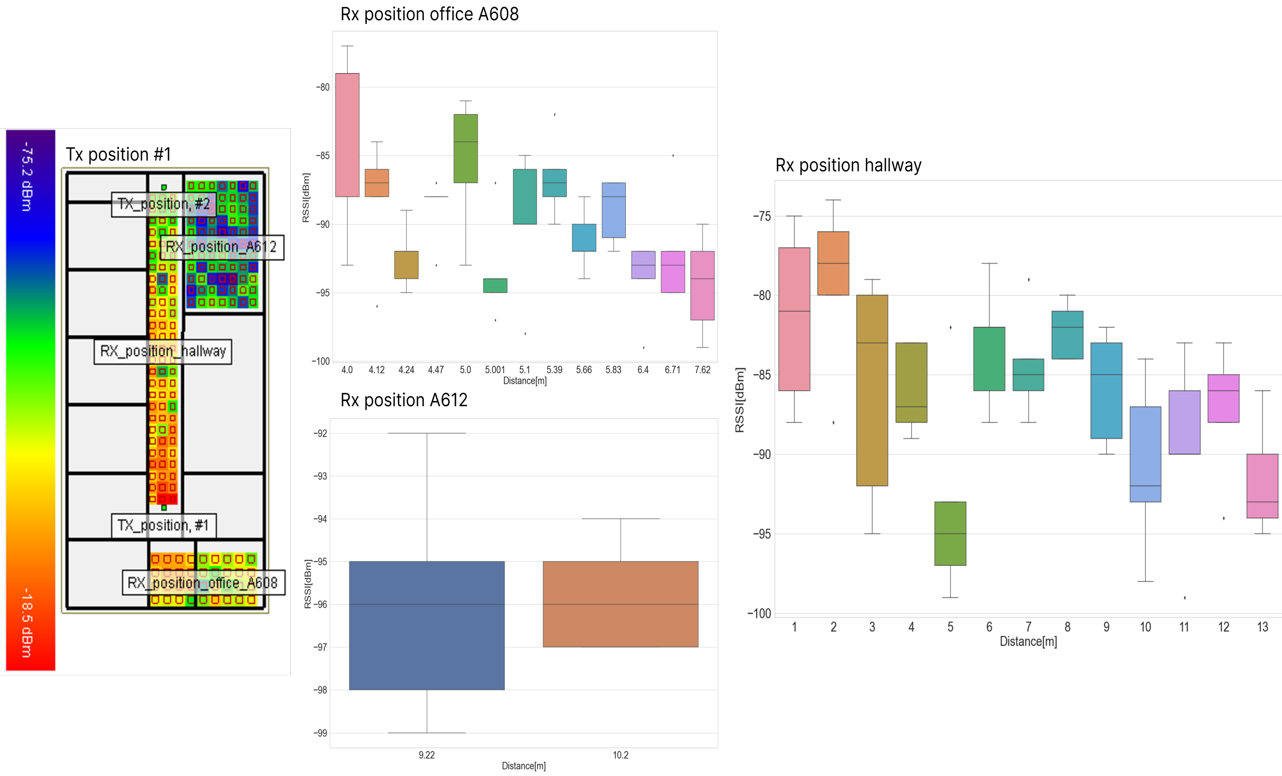

Figure 2.5. Heat map of the sixth floor of the faculty building with graphs of RSSI signal distribution graphs for transmitter position #1.

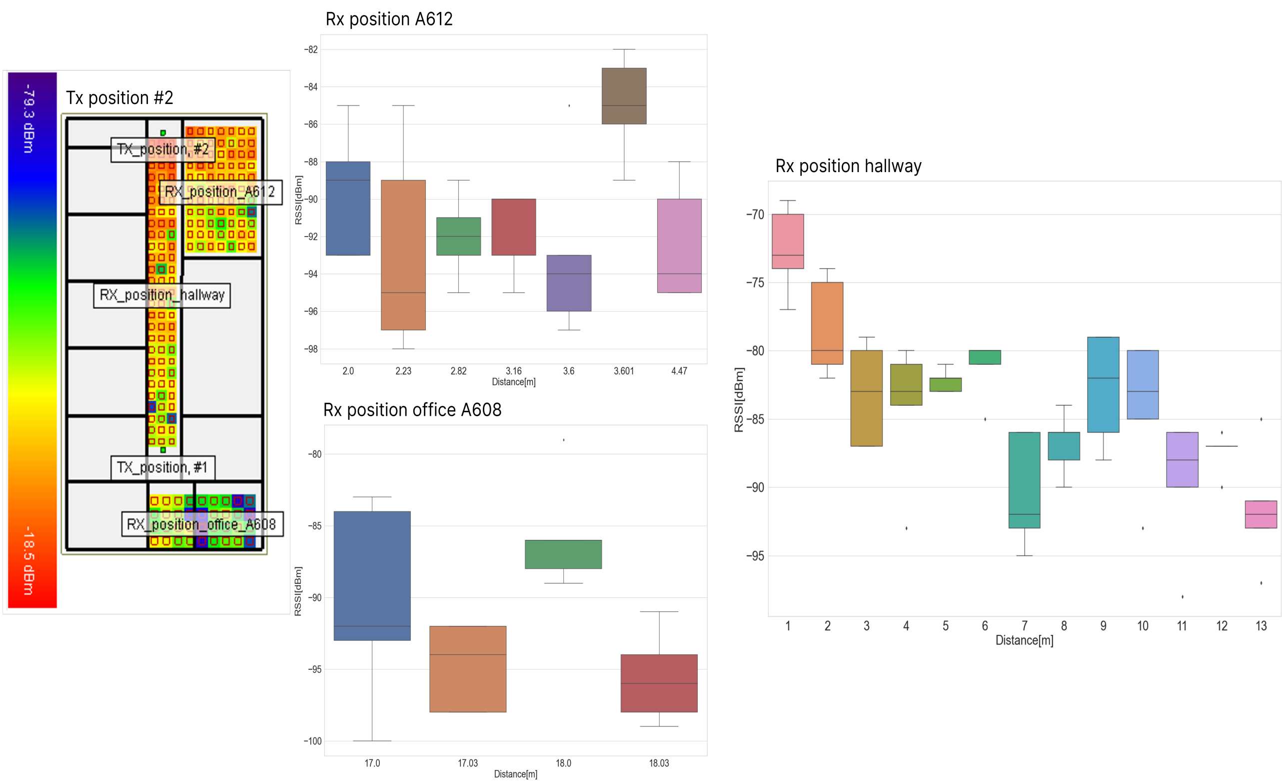

Figure 2.6. Heat map of the sixth floor of the faculty building with graphs of RSSI signal distribution graphs for transmitter position #2.

Indoor measurements were performed on VI. floor of the Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture in Split (FESB). The BLE bracelet, and transmitter, are placed in two positions inside the hallway as shown in Figure 2.5, position *#1* and position *#2*, while the reader, Android tablet application, moved by marked positions.

Figure 2.5 and Figure 2.6 shows the simulation, a heat map for the 2.4GHz frequency, where it shows the signal strength distribution for the transmitter power of -30dBm. The graphs show the measurement results for the three scenarios, the first measurement was performed in the hallway on a direct line between the bracelets and tablets. The second measurement was performed in the *A608* office and the last in the *A612* laboratory. After processing the obtained results, the obtained graph shows the range of values of the RSSI signal for each distance and scenario.

For position #1 of the receiver, the obtained data shows for the measurements in office *A608* which were performed behind one and two non-bearing walls. The sharp signal drop shown on the Box plot graph is the signal strength readings behind two non-load bearing walls, while the weaker signal strength drop shown on the graph is the value for the readings behind one non-load bearing wall. When the receiver is located in the *A612* laboratory, the signal strength is recorded at two positions located behind a non-bearing wall. The signal strength in the hallway was recorded at thirteen positions, where the signal strength of the BLE wristband decreased with distance with sudden signal drops at certain distances.

By placing the transmitter in position #2, the obtained ddata shown for the receiver position in laboratory *A612* and office *A608* show the signal strength values from one non-bearing wall. By increasing the distance for those two scenarios, the signal strength decreases with increasing distance, with a sudden increase in signal strength at certain distances. The signal strength for readings in the hallway on the direct line of the transmitter and receiver was recorded for thirteen positions where the distance between the transmitter and the receiver decreased as the distance increased. For position #2 of the transmitter in this scenario, the signal strength was read at a distance of 18.03m, and the receiver was located behind a non-bearing wall.

The range of signal strength values for each distance varies depending on the way the signal propagates through space, i.e. due to fading, interference, rejection, reflection and so on. The signal strength, between the transmitter and the receiver, decreases with increasing distance. In the hallway, the signal strength decreases more slowly, as long as the transmitter and receiver are on the same line, while when moving the receiver in space, the signal strength decreases sharply and the signal is weaker. Insight into the obtained results shows that the coverage of the BLE device is up to 18.03 m, which allows a minimum coverage of three rooms of 20m^2, one with one receiver.

In order to collect all data from wearable BLE devices, it is necessary to position the receiver in the optimal place in the space. Depending on the environment in which it is located, the position of the receiver is unique for each location due to the influence of Multipath on signal propagation in space. Multipath affects signal propagation in space and signal reception in the same area for another

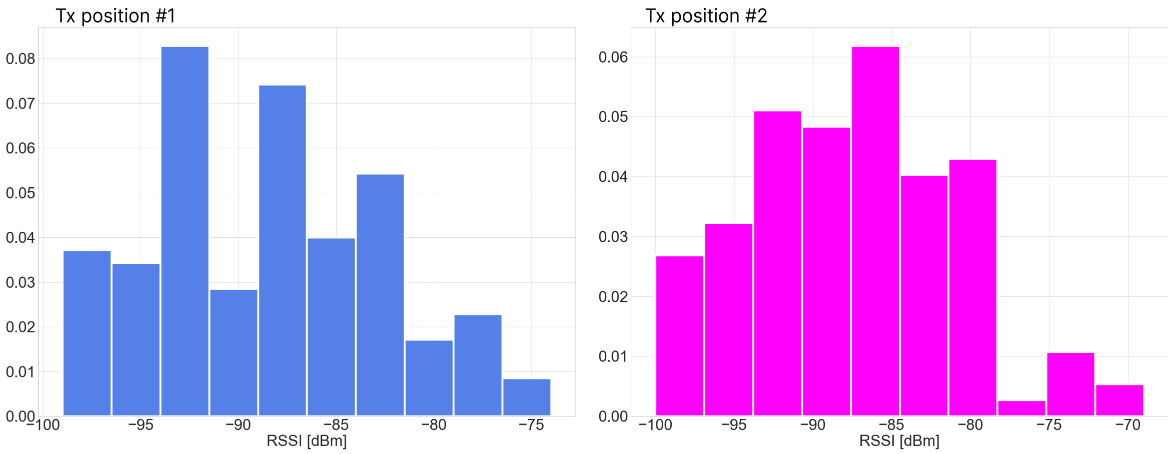

Figure 2.7. Normalized histogram showing the obtained RSSI values.

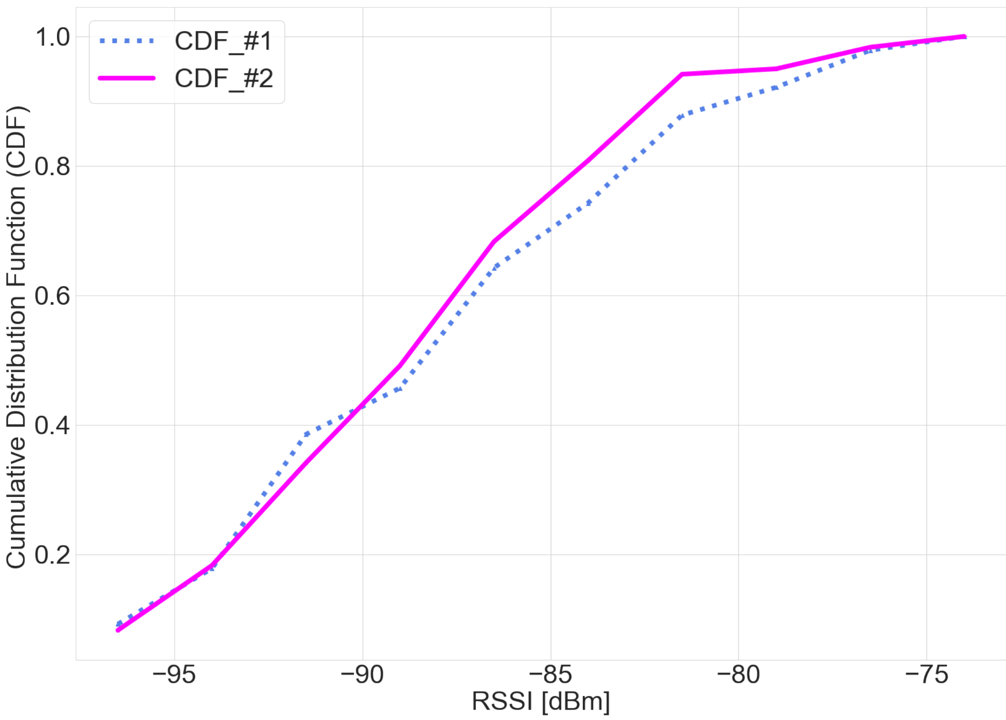

Figure 2.8. The Cumulative Distribution Function of wearable BLE device.

measurement will have small but different values for the same area. Depending on the measured signal strength of wearable BLE devices, it is possible to statistically explain the optimal position of the receiver in the environment. The optimal position of the receiver on a support can be the value that deviates the least from the mean value of the signal, i.e. the place where the difference between the minimum and maximum value is the smallest, it can be the place where the strongest signal strength from the bracelet is received. The measured values of the RSSI signal for positions #1 and #2 are shown via a normalized histogram in Figure 2.7. The left graph shows the signal strength distribution for position #1, while the left graph shows for position #2. Histograms show the measurement results, where on the abscissa are the measurement results within the range of the measured size, and on the ordinate is the strength of the received signal from the wearable bracelet. The displayed results include all measurement points at positions in the hallway, office and laboratory for both displayed histograms. For transmitter position #1, the measured values in the office include the values measured behind two non-load-bearing walls, while for position #2 the values for the queue position include only the values behind one non-load-bearing wall. The distribution of values for position #1 has a maximum at two places in the value range of -85dBm to -95dBm. While at the signal distribution for position #2 the maximum is in the interval between -85dBm to -90dBm. If the results of the normalized histogram are presented via the cumulative distribution function, Figure 2.8, it is possible to determine the optimal position of the receiver. From the preliminary results, it is evident that 70% ($\pm$ 5%) of the values are below the range of -85dBm. Therefore, the optimal position of the receiver would be in the area below -85dBm and would enable maximum reception of the signal to the receiver.

2.2. LoRaWAN

LoRaWAN is a Media Access Control (MAC) protocol designed for low-power devices, primarily those powered by batteries, within wide area network systems. The initial specification for this protocol was introduced in 2015, followed by a subsequent specification in 2017. LoRaWAN operates on an unlicensed ISM frequency spectrum, offering a low data rate, with specific frequency bands varying by region. Each region has a designated portion of the ISM frequency spectrum exclusively allocated for LoRa traffic. For instance, in Europe, LoRa transmission is intended within the frequency range of 863 to 870 MHz, with a fixed frequency of 433 MHz. Different frequency plans are established for each region, defining parameters crucial for both uplink and downlink communication between the LoRa module and the gateway, including spreading factor (SF) and bandwidth (BW).

According to the LoRaWAN specifications applicable to the EU region, end-devices are required to have access to a minimum of 16 frequency channels within the frequency range of 863 to 870 MHz. Specifically, the first three channels, operating at 868.1, 868.3, and 868.5 MHz frequencies, are mandated to be implemented for communication between end-devices and gateways. Furthermore, the ETSI (European Telecommunications Standards Institute) standard [29] stipulates that each LoRa module utilizing the EU863-870 frequency plan must include three predefined channels, namely:

- 868.10 MHz, bandwidth = 125 kHz,
- 868.30 MHz, bandwidth = 125 kHz,
- 868.50 MHz, bandwidth = 125 kHz.

Uplink channels facilitate data transmission from LoRa end-devices to gateways, while downlink channels are exclusively designated for transmitting data from gateways to LoRa end-devices. Additionally, the EU region permits operation at frequency channels ranging from 433.05 to 434.79 MHz. During downlink communication, the LoRa module initiates two time frames within which the gateway is expected to respond. In the first time frame, the downlink channel frequency aligns with the uplink frequency. Conversely, for the second time frame, a fixed predefined data rate and frequency are determined. By default, a frequency of 869.525 MHz, a Spreading Factor (SF) of 12, and a bandwidth of 125 kHz are utilized (The Things Network - TTN employs a nonstandard SF9 and 125 kHz bandwidth data rate on frequency 869.525 MHz).Under the ETSI standard, the 863-870 MHz band is further divided into five additional frequency bands, labeled G, G1, G2, G3, and G4. Each of these bands comes with precisely defined limitations, including the frequency range and duty cycle (Table 2.1).

The duty cycle determines the maximum proportion of a specific time period during which an individual device (such as a LoRa module or gateway) can utilize a particular channel to transmit its packets. Following data transmission, the device must await the expiration of this period before

Table 2.1. G frequency ranges

	Frequency area (MHz)	Duty cycle
G	863-870	$\leq$0.1 %
G1	868-868.6	$\leq$1 %
G2	868.7-869.2	$\leq$0.1 %
G3	869.4-869.65	$\leq$10 %
G4	869.7-870	$\leq$1 %

it can resume transmitting. By employing a duty cycle, the likelihood of collisions during packet transmission between two or more legitimate devices is reduced.

LoRaWAN operates within three bandwidth ranges: 125 kHz, 250 kHz, and 500 kHz. The selection of one of these three bands depends solely on the frequency band specified for the particular regional area (for instance, 125 kHz and 250 kHz bandwidths are utilized in Europe). Depending on the bandwidth and operating frequency, the lower and upper cutoff frequencies can be calculated. The lower cutoff frequency is determined by subtracting half of the bandwidth from the operating frequency, while the upper cutoff frequency is calculated by adding these two values. For instance, with an operating frequency of 867.1 MHz and a 125 kHz bandwidth, the lower cutoff frequency would be 867.0375 MHz and the upper cutoff frequency would be 867.1625 MHz. Regarding the transmission power of end devices and gateways, there are six predefined options: 2, 5, 8, 11, 14, and 20 dBm. For the EU863-870 frequency region, a default transmission power of 14 dBm is specified, although the G3 band can utilize transmission power up to 27 dBm, typically employed for downlink communications.

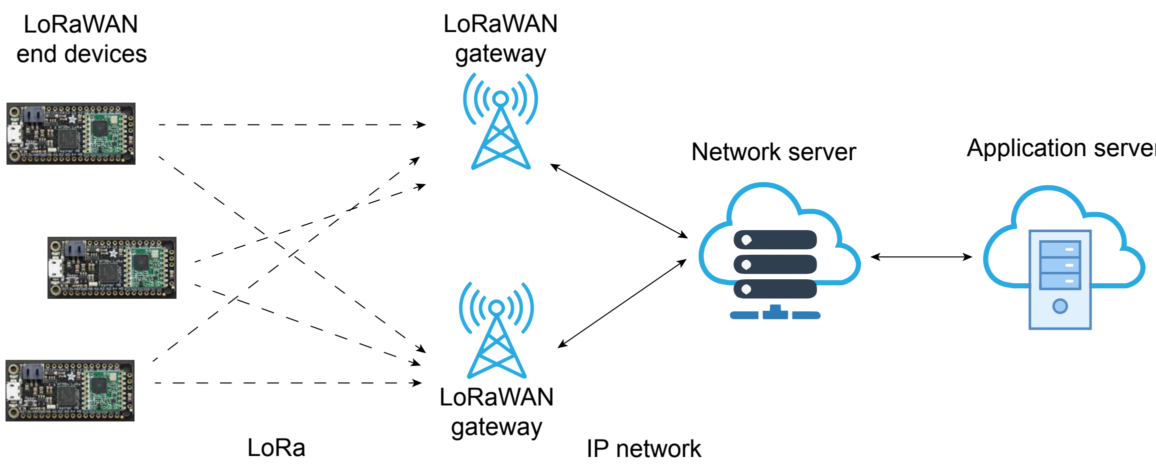

Figure 2.9. LoRaWAN architecture.

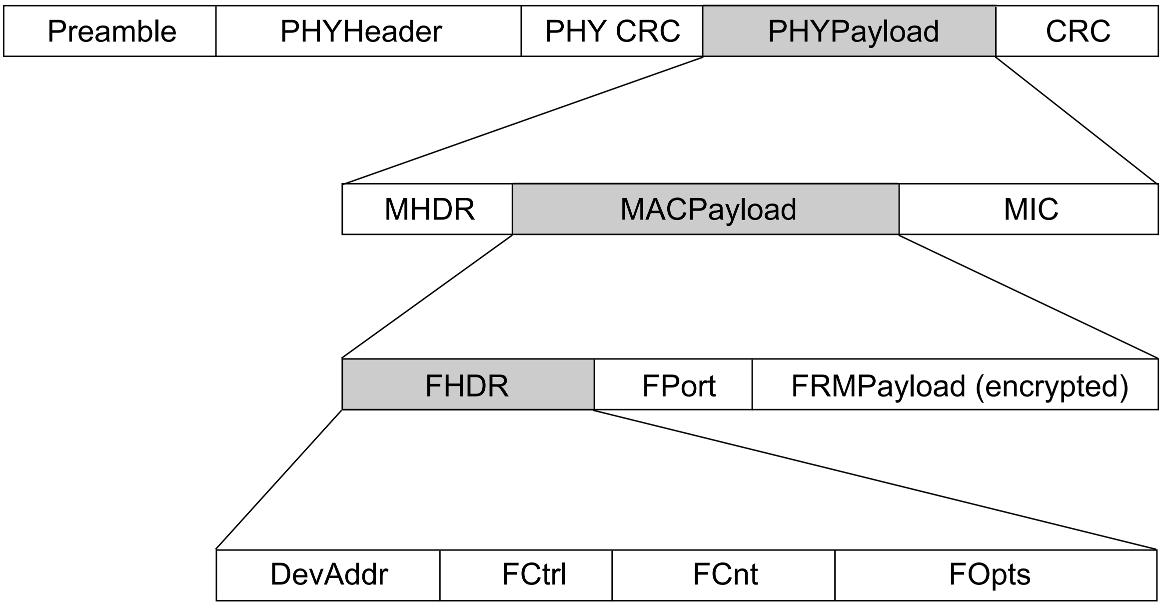

Figure 2.10. Structure of LoRaWAN packet.

2.2.1. LoRaWAN Architecture

LoRaWAN adopts a star network architecture (depicted in Figure 2.9), comprising three key participants: LoRa modules (End Nodes), which can be tailored for various applications, one or more LoRa gateways, and a central network server. The gateway facilitates the transmission of packets between the LoRa module and the central network server. Packet transmission within the LoRaWAN network occurs between modules and gateways using the LoRaWAN protocol, while communication between the gateway and the central server utilizes high-speed network technologies like WiFi, Ethernet, 4G, and 5G. The central server then relays the received packets to the application server for further processing and application usage.

2.2.2. End Devices

LoRaWAN end nodes are categorized into three classes: Class A, Class B, and Class C [30]. In essence, Class A devices are designed to transmit information to the gateway device at any time, typically triggered by events, with a focus on minimizing battery consumption, particularly for battery-operated devices. Class B devices are synchronized with time and have specific time slots allocated for communication. Conversely, Class C devices remain consistently active, enabling immediate message reception from gateways. Furthermore, as demonstrated in this study, the cost-effectiveness of LPWA (Low Power Wide Area) devices enables malicious attackers to launch jamming attacks using readily available components like a radio module (such as LoRa) and Arduino.

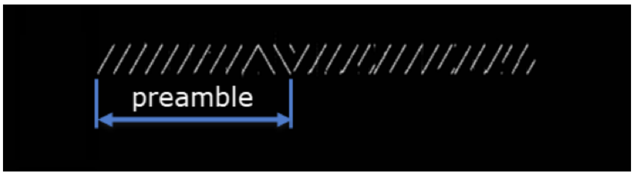

Figure 2.11. An example of LoRa packet containing preamble.

2.2.3. Structure of the LoRaWAN packet

The structure of the LoRaWAN packet is defined according to the LoRaWAN specification, as depicted in Figure 2.10. The transmission of LoRa packets begins with a preamble, followed by the radio and MAC layers of the packet. The preamble header is crucial as it allows the receiver to filter incoming traffic based on the received preamble, thereby determining whether the packet is intended for it. The preamble header comprises several up-chirps followed by an additional two up-chirps and two and one-quarter down-chirps (as illustrated in Figure 2.11). The conclusion of the preamble header is marked by the last four and one-quarter chirps. Upon receiving the preamble, the receiver can only ascertain the presence of a transmitting LoRa module; however, it cannot identify the specific module to which the packets belong. The importance of the preamble lies in its role in accurately filtering modulated signals, especially given the utilization of ISM radio frequencies and the multitude of unlicensed devices transmitting LoRa signals. Therefore, precise detection of the LoRa signal is imperative. The MAC layer resides above the physical layer and is responsible for encrypting application data. It comprises the MAC header, which specifies the message type, and the MAC payload, containing encrypted information. Following the MAC payload header is the Message Integrity Code (MIC) header [31], which ensures packet integrity using the AES-128 CMAC protocol and the Network Session Key (NwkSKey). LoRaWAN generates both the network NwkSKey and the Application Session Key (AppSKey) from the 128-bit AES AppKey. The AppSKey is utilized to encrypt the application payload (FRMPayload) with AES-128 in Counter mode (CTR). Additionally, the MAC payload includes a frame header (FHDR), wherein the first four bytes represent the address of the end device to which the packet belongs. The FHDR also contains the Frame Counter, which increments with each subsequent packet. The Frame Counter (FCnt) in LoRaWAN serves to prevent potential replay attacks.

GlobalSat LW-360HR is a wearable device with BLE/ GPS/ LoRa functions. The technology covers a wide range of active areas based on GPS satellite positioning and LoRa® 's long-distance transmission technology (Up to 10+ KM) to integrate the mobile app and cloud application. The device implements step/calories/distance monitor, heart rate information and skin temperature.

2.2.4. Heart rate measurements

Heart rate measuring properties of the GlobalSat were examined through the experiment (Figure 2.12), following the previously described methodology, on 5 subjects, comparing the heart rate readings form the bracelet and the pulse oxymeter. The experiment resulted with 157 heart rate data from all subjects. The distribution of the readings from the GlobalSat and the pulse oxymeter is presented on the Figures 2.13 and 2.14, where small deviations in reading can be noticed. Figure 2.15 illustrates the error of the GlobalSat readings when compared with the pulse oxymeter as a reference. It can be noticed that the reading errors are within the range of -26 beats per minute (bpm) and 26 bpm. However, 80% of the readings are in the error range from -4 bpm to 4 bpm. With normal heart rate for sitting (office work) activities being 60 bpm - 100 bpm, the error represents 4 % - 6 % of the overall device reading.

Figure 2.12. GlobalSat and HR pulse oxymeter comparison

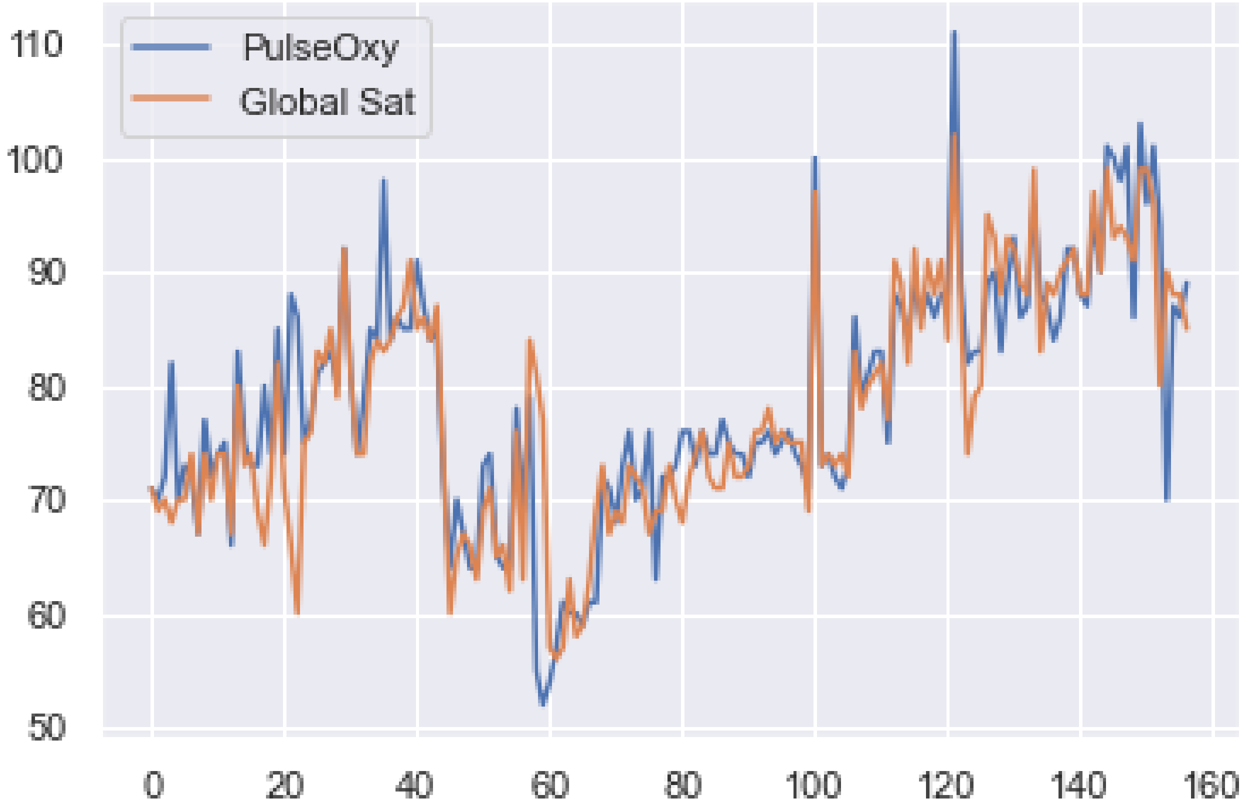

Figure 2.13. Comparison of the GlobalSat HR readings with pulse oxymeter

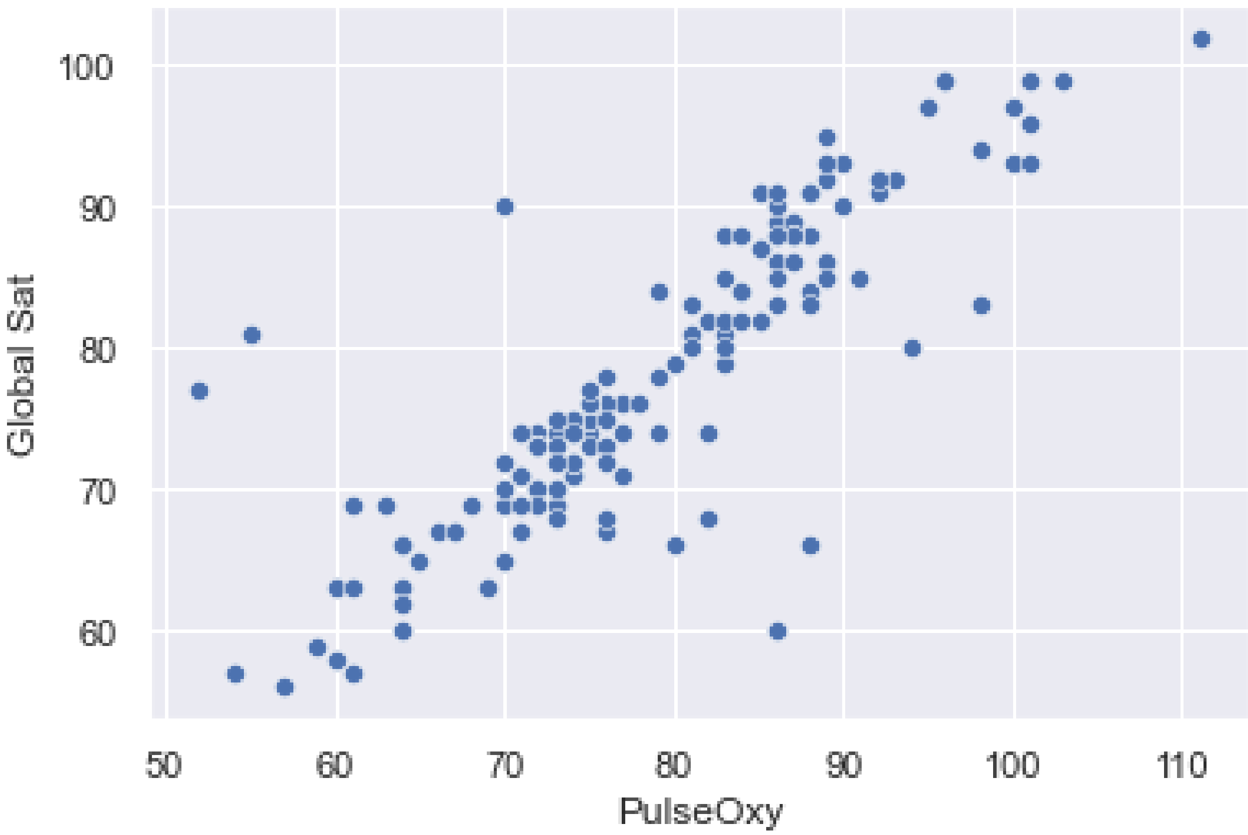

Figure 2.14. Scatterplot of the GlobalSat HR readings with pulse oxymeter readings

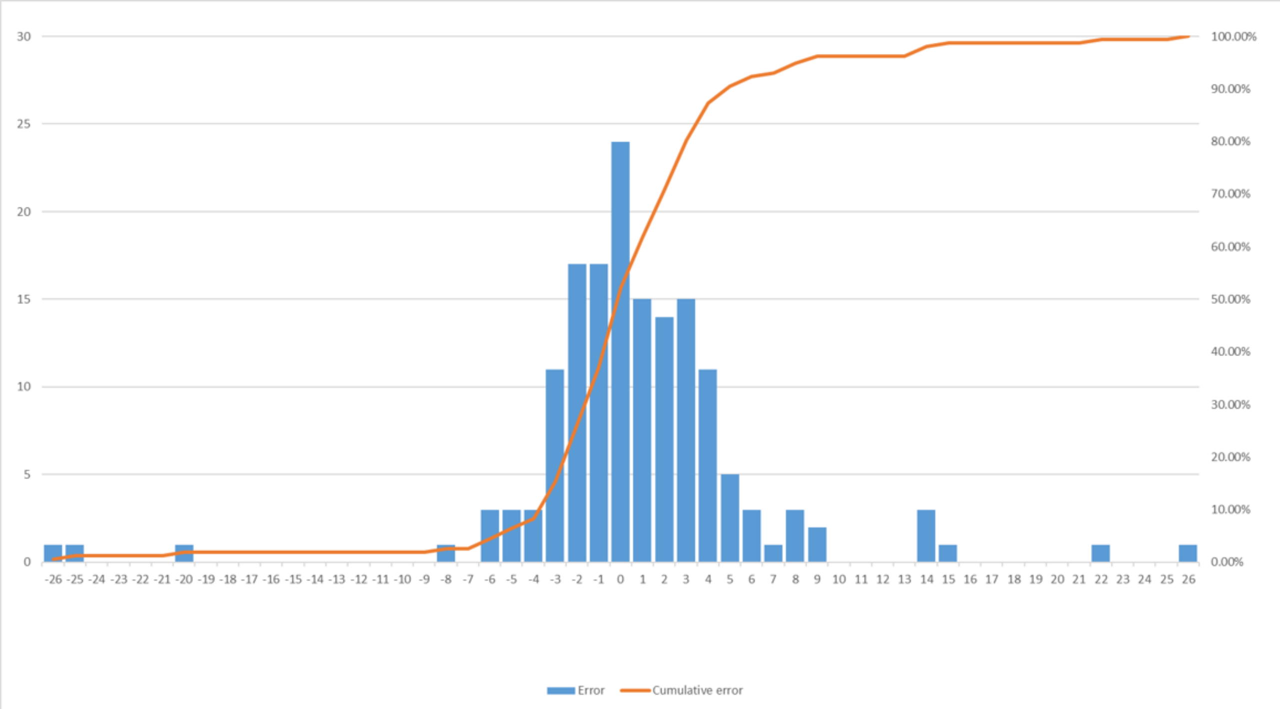

Figure 2.15. The error from the GlobalSat bracelet readings compared with the pulse oxymeter

2.2.5. Temperature measurements

Temperature measurement feature was also conducted for the GlobalSat bracelets as previously described, comparing the measurements with the T-type thermocouples on the bottles with the heating water (Figure 2.16). The results are graphically presented on the Figure 2.17 with the average error GlobalSat bracelet of 2.6°C. The error has its peak (7.26°C / 8.27 °C) with the sudden changes in temperature, while in the steady conditions, the error between GlobalSat and the thermocouples is at its minimum (0.93°C / 1.08 °C) due to slower response of the bracelet to changes in temperature, which is not the case for the human skin at the wrist.

Figure 2.16. Setup for GlobalSat bracelet temperature features testing

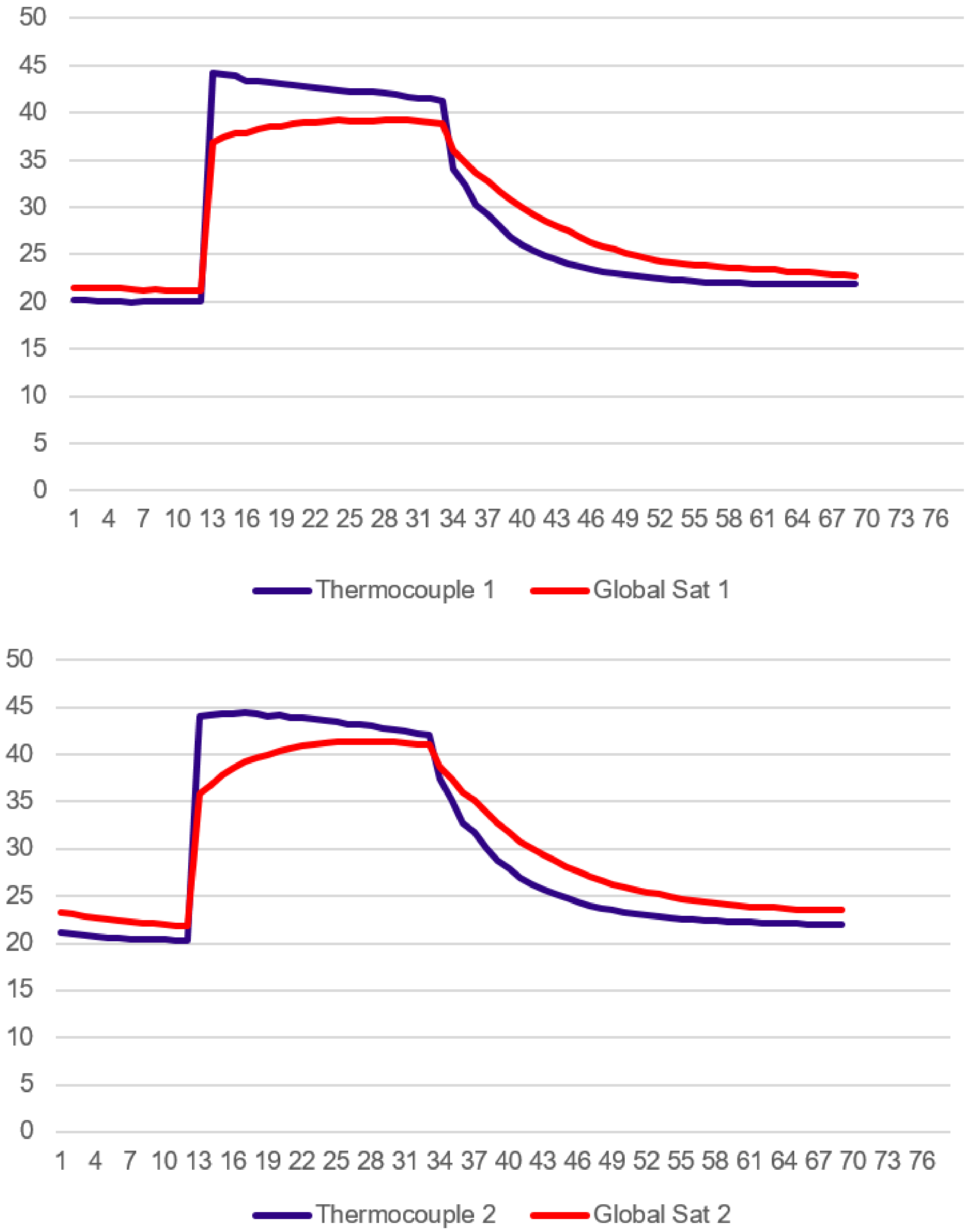

Figure 2.17. Comparison of the GlobalSat temperature readings with thermocouple readings

2.2.6. LoRa range

From the manufacturers info, the device supports BLE function (Link distance - 10 m) and the LoRa transmit distance from 1 km to 3 km (Open space - 3 km / City - 1 km). Figure 2.18 shows locations of packets captured by public LoRaWAN gateways that were sent by GlobalSat bracelets during the period of three months. Red dots present location of public LoRaWAN The Things Network gateways, while blue circles show GPS location sent by GlobalSat bracelet via LoRaWAN radio that was forwarded to our dedicated server for further processing and visualization. As can be seen, GlobalSat bracelets equipped with GPS and LoRaWAN radio modules can serve as a real-time tracking device in urban (and rural) areas.

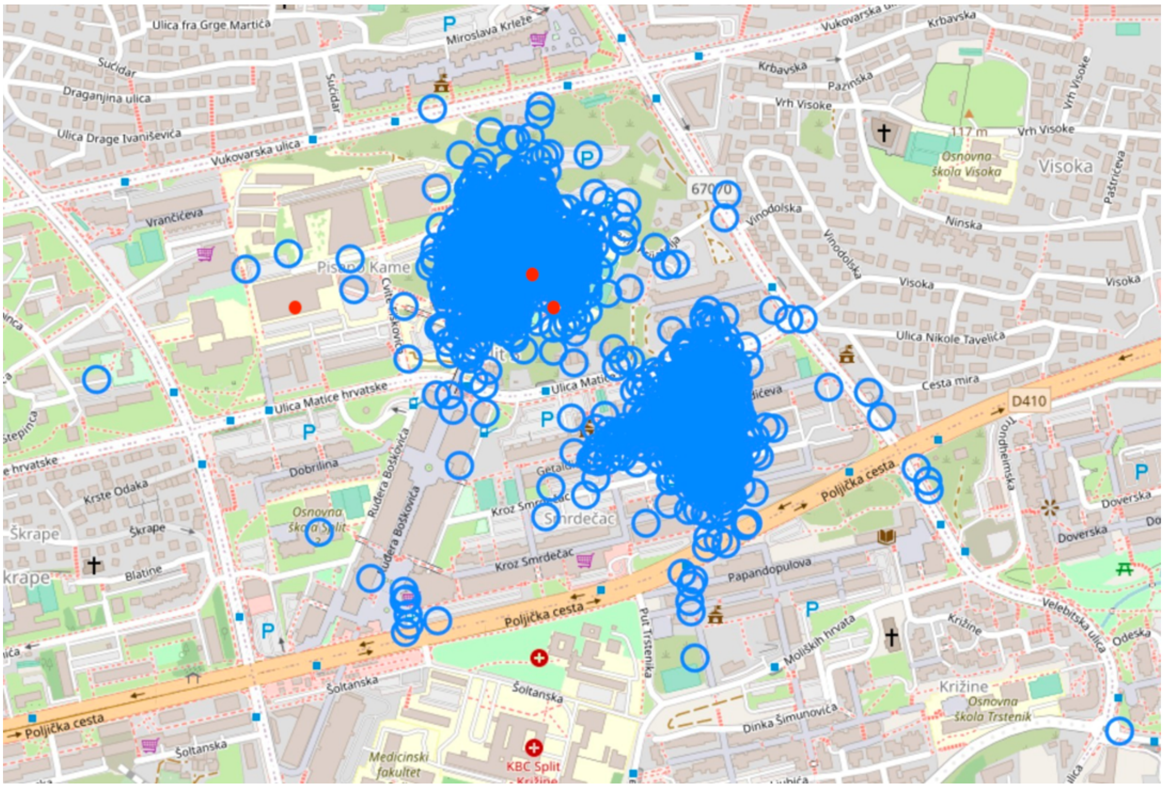

Figure 2.18. Captured GSP location of LoRaWAN GlobalSat bracelets sent as a part of a LoRaWAN packet during a period of three months.

2.3. Wearable Devices - Sensors

In today's era of advancing technology, wearable devices have emerged as indispensable tools for monitoring and managing various aspects of health and wellness. These devices have revolutionized the way we track and understand our bodies, offering insights into vital parameters and potential health issues in real-time. As wearable technology continues to evolve, the need for efficient data transmission from these devices to central databases or other connected platforms becomes increasingly crucial. Among the plethora of radio technologies available, Bluetooth and Bluetooth Low Energy (BLE) stand out as the most widely utilized for this purpose. BLE, particularly, has become the head for transmitting data from wearable devices to central repositories, thanks to its low power consumption, reliability, and widespread compatibility. This technology has facilitated seamless communication between wearables and other devices, enabling the integration of health data into broader healthcare systems and applications.

The presented radio technologies are used for transmitting data measured by wearable devices for non-invasive vital parameter measurement. In this part, sensors used in wearable devices to detect various diseases will be presented. Table 2.3 presents the performance of these devices, including their sensor capabilities, energy consumption, battery life, and communication protocols. To ensure wearable technology is comfortable to wear, the size, shape, and warmth of the product must fall within an acceptable range. Consequently, different types of batteries, such as lithium polymer, lithium-ion, and cell batteries, are used in wearable technology. Continuous power supply is crucial for healthcare solutions to ensure the proper functioning of the devices. Power sources for these devices can be rechargeable or non-rechargeable USB-compatible batteries, as mentioned in [32]. The overall energy consumption depends on factors such as the amount of collected data, sensor design complexity, and the number of transmission and reception states. Each gadget is unique, and wearable technology manufacturers have conducted studies on energy consumption, as shown in Figure 2.1. Wearable technology utilizes different sensors depending on their purpose, such as smartwatches and fitness tracking devices [6]. Each sensor in a wearable device measures a specific quantity, and the combination of these quantities yields the desired result. Commonly used sensors in wearable technology include PPG, EMG, accelerometers, EEG, EKG, EDA, gyroscopes, magnetometers, barometers, skin temperature sensors, blood oxygenation sensors, and others.

Table 2.2. Unique characteristics of wearable technology.

Ref.	Wearable device	Sensors	Power (current) consumption	Battery	Communication protocol
[14]	BIOPAC	PPG100C, RSP100C	5 mA	/	USB
[6]	Empatica E4	PPG, EDA, Infrared Thermopile, 3-axis accelerometer	250mA	Lithium-ion (rechargeable)	BLE
[6]	SPEAC	EEG, ECG, EMG	600mA	Lithium-polymer (rechargeable)	Wi-Fi
[6]	ByteFlies Sensor Dots	3-axial acceleration (ACC), 3-axial gyroscope (GYR)	65mA	Lithium-polymer (rechargeable)	Wi-Fi
[6]	Epi-Care Free	3-dimensional accelerometer	700mA control unit, 900mA sensors	Lithium-polymer (rechargeable)	Bluetooth
[32]	MindWave Mobile II (Neurosky)	EEG/ECG	80mA	AAA battery	Bluetooth V2.1
[33]	Wearable Biometric Patches (WBP)	ADT7420 digital temperature sensors	0.21mA sensor	/	Bluetooth
[34]	Galvanic skin response (GSR) (BITalino Kit)	EMG, ECG, EDA, EEG, ACC, LUX, BTN	65mA	Lithium-polymer (rechargeable)	BLE, Bluetooth
[35]	V07 Smart Wristband [36]	Heart rate monitor Pedometer, Sedentary reminder, Sleep monitor	40mAh	Lithium-polymer (rechargeable)	Bluetooth V4.0

Table 2.3. Unique characteristics of wearable technology.

Ref.	Wearable device	Sensors	Power (current) consumption	Battery	Communication protocol
[37]	Fitbit	ECG, EDA	Charging dock /USB charging	Lithium-polymer (rechargeable)	Bluetooth V4.0
[38]	MetaMotionR	Accelerometer, Gyroscope, Magnetometer	100mA	Lithium-polymer (rechargeable)	BLE
[39]	MVN Link - Xsens	3D Accelerometer, 3D Gyroscope, 3D Magnetometer, barometer	150mAh	Lithium-Ion (rechargeable)	WiFi
[40]	Intelligent mask (Cusstom made)	Triboelectric Respiratory sensors			Bluetooth
[41]	ISFET Sensor Patch	Na+, K+, and PE/PP microfluidics	15 mA	USB charge	USB
[42]	Shimmer device	Accelerometer, Gyroscope, Pressure/Temperature Sensor (EEG)	1.23mA	Lithium-Ion (rechargeable)	Bluetooth
[42]	Samsung Gear Sport	Accelerometer, Barometer, Gyro sensor, Optical HR sensor, Light sensor (EEG, PPG)	300mAh	Lithium-Ion (rechargeable)	Bluetooth, Wi-Fi
[43]	BITalino Kit	EMG, ECG, EDA, EEG, ACC, LUX, BTN	65mA	Lithium-polymer (rechargeable)	BLE, Bluetooth
[44]	ADXL - 335 (connected to Arduino MEGA-2560)	3-axis ACC	350μA	Battery	/

3. Application and Diagnostic - ML algorithms

The machine learning techniques used to process the data obtained from non-invasive wearable technologies are summarized in the current section. One technique for detecting and predicting disease is machine learning, which uses computer learning from data processed, trained, and tested using data from wearable devices [45]. To learn more about the connections between the data aspects, several ML approaches are applied, as noted in [46]. There are three types of learning algorithms: Supervised, Unsupervised, and Reinforcement Learning.

- The objective of a supervised learning algorithm, which requires the assistance of a supervisor, is to learn how to translate input data to output data using input data, with the supervisor providing the precise values.
- The finding of symmetries between input data is the goal of an unsupervised learning method, which only has input data.
- A hybrid of the first two types using both labeled and unlabeled data. Unsupervised learning combined with Supervised generated from a portion of the labelled data.
- Algorithms that use reinforcement learning make choices depending on what must be done to achieve the greatest results.

Regression and classification problems are solved using supervised learning algorithms. When categorizing unique data, the classification task is utilised, and when analyzing continuous data, the regression job is employed, [46]. The approaches discussed in this part make use of wearable data in conjunction with patient personal data, self-reported pain scales, and other data. Data used by a wearable device is kept in databases, cloud platforms, etc. Table 3.3. shows machine learning methods along with their contributions for each article that is being discussed.

3.1. Decision tree (DC)

Decision Tree algorithms are indispensable in machine learning, offering a structured approach to modeling decisions and their outcomes. Figure 3.1 illustrates the structure of a Decision Tree, showing how by segmenting a dataset into smaller, more uniform subsets and forming a corresponding decision tree, these algorithms provide a clear, interpretable framework for decision-making. Each node in this tree, as depicted in Figure 3.1, represents a data attribute test, guiding the categorization process through branches that denote potential attribute values, from the root node down [45]. The decision nodes within the tree are crucial points where data is divided based on specific criteria, leading to various branches, while the leaf nodes are the endpoints providing the final classification or decision without further subdivision [47]. This method is particularly effective in areas like medical diagnostics, where inductive inference plays a crucial role in identifying issues. While Decision Trees are lauded for their simplicity, ability to handle both numerical and categorical data, and their applicability to both regression and classification problems within a supervised learning framework, they are not without challenges, such as susceptibility to overfitting in complex scenarios. However, by leveraging metrics like entropy and information gain for optimal data splitting at each node, these algorithms ensure the model's efficacy in predicting new outcomes. Their versatility in handling different types of data and the structured approach to predictive modeling highlights their value in applications ranging from medical diagnostics to customer segmentation, situating Decision Trees firmly within the domain of supervised learning due to their reliance on labeled datasets for training. The blend of theoretical robustness and practical utility, as demonstrated by Figure 3.1, makes Decision Trees a cornerstone of the machine learning domain, widely recognized for their ease of understanding and implementation [47].

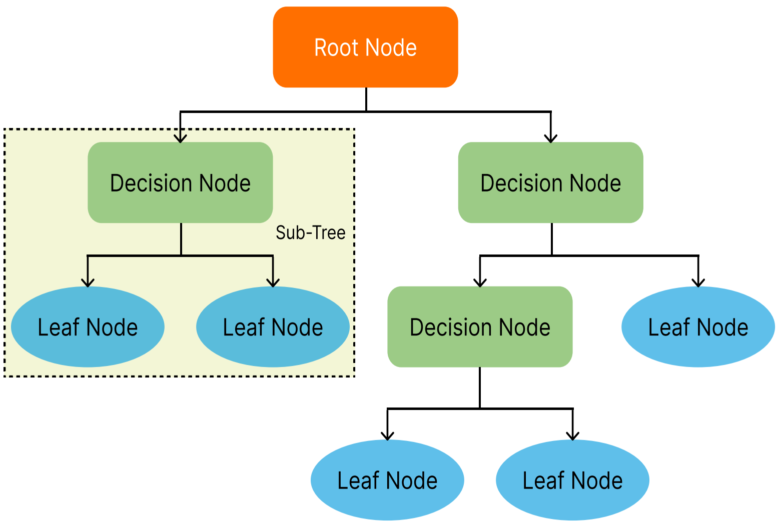

Figure 3.1. Decision Tree.

Regression modeling instead of classification is used in the decision tree approach for the detection of dyspnea disease because the prediction dyspnea score can be continually quantified [14]. To overcome the limitations of the available data, k-fold cross-validation is employed [45]. This technique allows for the assessment of the generalization ability of the model on unseen data and the evaluation of the model's stability on unseen participants using the leave-one-participant-out cross-validation and test on the remaining folds. The complete training set is partitioned into a training and test dataset for k-fold cross-validation, with each fold serving once as the test set. The process is repeated k times. This methodology facilitates the identification of crucial features in various respiratory metrics [14].

The disease is diagnosed by supervised learning and the classifier is trained using information from the patient's temperature profile. Parallel programming was utilized in the past to process the data and promptly provide them to the user. Each patient under monitoring had clinical information on his family history, device trials, biopsy results, and temperature profile collected. To select the best machine learning (ML) approach, several techniques such as Decision Trees (DT), Support Vector Machines (SVM), Random Forests (RF), and Back Propagation Neural Networks are used, and the one that achieves the highest accuracy is chosen based on the data obtained. If the data collected is limited in size, k-fold cross-validation is used to ensure the reliability of the results [33].

Several ML models were used to obtain the highest accuracy while collecting data for the walking activity recognition model (WARM) using wearable motion sensors in [38]. In common machine learning classification methods, the moving average and moving standard deviation versions of these gathered data were employed. While keeping the detection prevalence at the same level as the prevalence of walking activities in the data, Decision Tree was able to achieve a precision of 88% on the training set and 77% on the test set. The periods of walking and non-walking exercise were previously divided by the authors. They took advantage of information on hip rotation and wearable sensors with limited memory and processing capability that stored real-time activity.

In [40] is details the utilization of triboelectric respiratory sensors integrated into a commercial mask for the measurement of respiratory events. Data were collected for five typical respiratory behaviours: normal breathing, deep breathing, coughing, sneezing, and laughing. A thorough analysis and feature extraction were performed for each of these behaviours from the collected signals. Twelve features were extracted, including average values, variance, standard deviation, root mean square, and kurtosis from the original signal in the time domain; as well as pulse factor, waveform factor, peak factor, and skewness from the time-frequency domain, along with the unbiased estimated coefficient of variation and edge factor from the frequency domain. Based on these extracted features, a Decision Tree (DT) was employed to develop a classification model that enhances the accuracy of recognizing respiratory behaviours. The algorithm can successfully classify different types of respiratory signals with an average accuracy of 97.2%.

3.2. Random forest (RF)

The Random Forest algorithm, stands as a paradigm-shifting approach in machine learning for tackling both classification and regression challenges for supervised learning [48]. It operates by constructing an ensemble of decision trees, each depending on values drawn from a random vector, ensuring diversity and robustness across the model. This methodology not only converges the generalization error to a limit as the forest grows but also balances the strength and correlation of individual trees to enhance prediction accuracy. Random Forests' adaptability to a wide array of data types, their competency in managing both numerical and categorical variables, and their interpretability contribute significantly to their widespread application [49]. Notably, Random Forests excels by having each tree vote for a class in classification tasks or average predictions for regression, effectively handling high-dimensional data with minimal tuning. The internal mechanisms, such as variable importance metrics and feature selection for node splitting, provide deep insights into the data's structure, affirming the algorithm's capacity to mitigate overfitting despite dataset complexity. The blend of theoretical robustness and practical utility cements Random Forests as an indispensable tool in predictive modeling, particularly valuable in scenarios with noisy or incomplete data. In essence, Random Forests have revolutionized machine learning by integrating multiple decision trees to address classification and regression problems, offering a versatile and powerful toolkit that adapts to diverse learning tasks. Their method of leveraging randomized decision trees and aggregating predictions showcases an unparalleled ability to navigate through high-dimensional spaces and predict outcomes accurately, underscoring their critical role in advancing the field of machine learning [50].

Random Forest (RF) outperformed the Decision Tree (DT) in detecting dyspnea disorders, as observed from the data obtained through wearable sensors from patients and patient self-reports (as shown in Table 3.3). Heart rate and respiration data from wearable BIOPAC devices were collected and analyzed for this purpose [14]. RF algorithms were used on the acquired data in order to identify a link between measurement findings and the patient's self-reported pain experience. The RF classifier in [33] is one of the strategies used to diagnose breast cancer using Wearable Biometric Patches. A random forest method was used to estimate the level of hydration (HL) using Galvanic skin response (GSR) data obtained with EDA sensors.

The study by [34] used k-fold cross-validation with the collected data being used for both training and testing. They used the random forest classification algorithm to predict patients' cardiovascular risk, which incorporated input from patient lifestyle interviews and data from wearable sensors. Similarly, in [15], k-fold cross-validation was employed, and the results were validated with one participant left out. In another study [37], RF regression was applied to analyse data from a wearable Empatica E4 device to predict blood sugar levels. A non-invasive wearable device facilitates real-time monitoring of sweat electrolytes during physical activity, enabling the analysis of their relationship with the core body temperature. The designed device has been tested and compared with the commercially available HORIBA-LAQUAtwin device. The RF (Random Forest) regression algorithm has proven to be an effective indicator in predicting body temperature based on the measurements of sodium and potassium in sweat, with a Root Mean Square Error (RMSE) of 0.02 °C [41].

3.3. k-Nearest Neighbor (kNN)

The k-Nearest Neighbor (kNN) algorithm is a straightforward and widely used machine learning method for classification and regression, especially useful when the data distribution is unknown [51]. This "instance-based" and "lazy learning" approach relies on storing training examples and calculating distances between samples to categorize new instances based on the majority vote of their nearest neighbors. The simplicity of kNN, a non-parametric model, lies in its reliance on the Euclidean distance for determining closeness without making assumptions about the underlying data distribution [45]. Choosing the right 'k' value is critical for kNN's effectiveness, influencing accuracy and requiring experimentation for optimization. Despite its benefits, including ease of implementation and adaptability, kNN faces challenges such as high computational demands and substantial storage needs, as it retains the entire dataset for making predictions. Several variants of kNN have been developed to improve its performance and efficiency, addressing its inherent weaknesses. These include locally adaptive kNN, which optimizes 'k' based on the local neighborhood, and weighted kNN, where attributes are assigned different weights to influence classification. Integration's with other algorithms, like k-means, have also been explored to reduce computational load and improve accuracy. kNN's application extends across various fields, including healthcare for predicting medical outcomes like cardiac risks and financial modeling for stock market analysis. Its ability to handle nonlinear data makes it particularly useful in these domains. However, compared to other algorithms like SVM or logistic regression, kNN can be computationally slower and less efficient with very large datasets. Despite these limitations, kNN's flexibility and the development of improved variants continue to make it a valuable tool in the machine learning toolkit, driving ongoing research to enhance its performance further [52]. The Figure 3.2 represents a simple example of the kNN algorithm described.

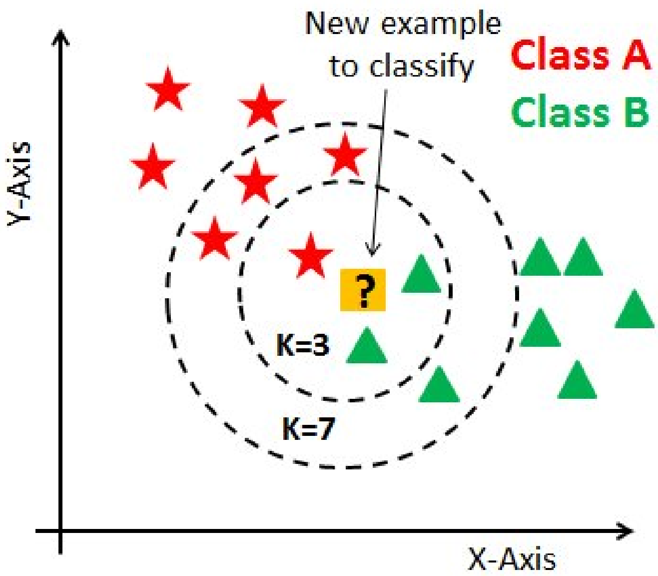

Figure 3.2. k-Nearest Neighbor algorithm [53].

The work posture stability is one of the crucial parameters during some activities. MVN Link - Xsens wearable devices try to detect stable and unstable postures in six different positions. After collecting raw data from the wearable device, processing data using different feature selections and extraction: mean, range, variance, standard deviation, root mean squared, skewness, kurtosis, and the first five fast Fourier Transformation (FFT). For classification selection, models training is used besides k-Nearest Neighbor (kNN) also Gaussian Naive Bayes (GNB), Kernel Naive Bayes (KNB), Logistic Regression (LR), Discriminant Analysis (DA), Support Vector Machine (SVM), Decision Tree (DT), Bagged Trees (BT) and Optimizable Ensemble (OE) classification. To assess the classification performance of machine learning models, k-fold cross-validation with a value of *k* equal to *5* was employed. By processing data derived from the centre of pressure in the anterior-posterior direction, an accuracy of 91.6% was achieved using the Optimizable Ensemble approach with SC1 and FS1 data sets. For PPS - perception of postural studies 87.4% accuracy was achieved with KNN based on data SC1 + FS1. And only on Pelvis ACC data 90.5% accuracy using FS1 + OE. In [39] the authors try to investigate the abilities of ACC-based measurement to assess the stability of working posture, to detect the effects of work-related factors, and the ability to classify stable and unstable working postures.

3.4. Support vector machine (SVM)

Support Vector Machine (SVM) is a significant algorithm in machine learning, heralded for its robustness in classification, pattern detection, and prediction tasks [46]. Central to SVM's efficacy is its foundation in statistical learning theory, particularly the concept of Structural Risk Minimization (SRM) which contrasts with the Empirical Risk Minimization (ERM) principle utilized by conventional neural networks. SRM's focus on minimizing an upper bound on expected risk equips SVM with superior generalization capabilities. Initially designed for classification, SVM's application has been adeptly extended to regression.

Consider an example of data clusters in Figure 3.3, where a hyperplane is meticulously drawn to segregate the two clusters effectively, thus maximizing the margin width between them. This task of finding the optimum location for the hyperplane, which is central to achieving the maximal margin width, is recognized as a complex optimization challenge. Crucially, the points that lie in close proximity to the margin, known as support vectors, are instrumental in determining the precise orientation of the hyperplane. These support vectors underscore the delicate balance required in the spatial arrangement that dictates the separation between differing data clusters.

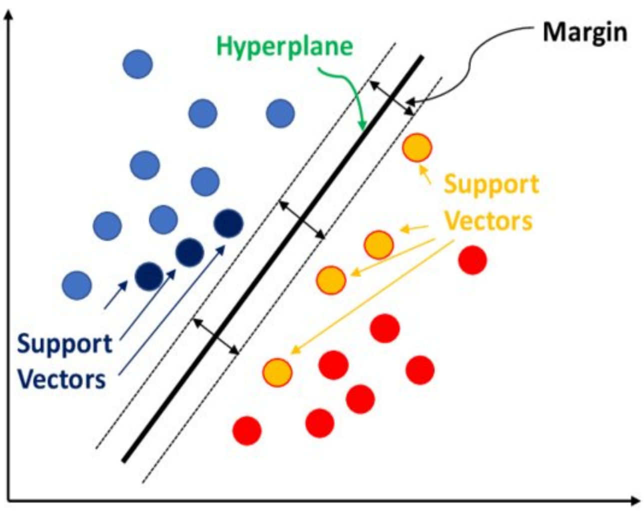

Figure 3.3. Support Vector Machine [54].

Building upon this foundational concept, the algorithm forges ahead by constructing a model through the identification of an optimal separating hyperplane. This hyperplane not only maximizes the margin between diverse classes for classification endeavors but is also adept at fitting a function within a predetermined threshold for regression challenges. The intrinsic strength of the SVM algorithm is illuminated by its proficiency in managing linearly inseparable data. This is achieved through the utilization of kernel functions, which empower the algorithm to navigate a high-dimensional feature space where linear separability becomes attainable. Such a technique not only broadens SVM's applicability across a vast array of problems but also enhances computational efficiency. This is because it enables operations to be conducted within the input space, rather than necessitating navigation through the more complex high-dimensional feature space as described [55].

Despite the algorithm's reliance on the comprehensive training dataset a factor that introduces challenges related to computational demands and data storage SVM's utility as a tool in the machine learning arsenal is undisputed. Its versatility, anchored in the Structural Risk Minimization (SRM) principle and the strategic implementation of kernel functions, highlights its critical role across multiple domains. These range from healthcare to financial modeling, among others. As the field of machine learning continues to evolve, the significance of SVM is further cemented, fueled by relentless research endeavors aimed at optimizing its functionality and broadening its spectrum of application.

Using the SVM classifier, it is possible to predict hip discomfort in patients who use the wearable MindWave Mobile II (Neurosky) device. The obtained statistics were combined with data from a patient's self-reported numerical rating scale (NRS), [32]. The kernel is used by SVM to do nonlinear mapping, which allows for the correlation of data. In this instance, the SVM technique is utilised to estimate the severity of patients' hip pain using the Gaussian Radial basis function (RBF) kernel [46].

The wearable device was placed on the heads of the patients for 7-10 minutes and data was gathered from EEG/ECG sensors with a frequency range of 0 to 40 Hz. Using the SVM method, the accuracy of all pain levels identified using wearable devices mounted on a head and combined with NRS was 79.6%. According to the author, this approach may be used to identify disorders in people of both sexes and is a suitable way to objectively and non-invasively monitor patients suffering [32]. According to a study [35], it is suggested to use a SVM as a machine learning technique to analyze data collected from wearable technology. The study recommends using SVM classification or regression to evaluate vital sign data collected from wearable devices that monitor pregnant women's heart rate, temperature, blood glucose, and uterine contraction, to predict the risk of stillbirth, preterm birth, or miscarriage [36].

3.5. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) stand as a crucial technology in deep learning, excelling in fields like visual and speech recognition, and language processing. Born from insights into biological vision, CNNs use multi-layer architectures to intricately process data, evolving from early concepts like recognition to sophisticated models capable of complex pattern recognition with minimal pre-processing [6]. The architecture of CNNs comprises of input layer like raw datasets, convolutional layers for feature extraction, pooling layers for reducing data size while maintaining essential information, and fully-connected layers for high-level analysis, leading to an output layer, often employing softmax for classification 3.4.

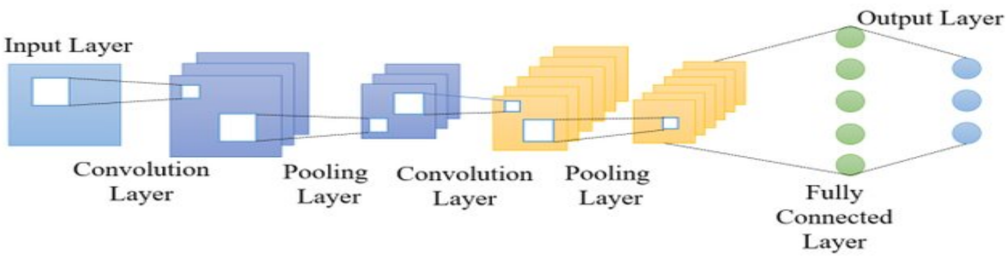

Figure 3.4. Convolutional Neural Network architecture [56].

Innovations such as inception modules have allowed CNNs to analyze data at various scales, with methods like batch normalization and improved optimization techniques enabling deeper, more precise networks. Additionally, CNNs have seen advancements in computational efficiency and model simplification, allowing for broader deployment across diverse hardware. Their automatic feature extraction capabilities have made them invaluable across numerous applications, transforming industries by enhancing the accuracy and efficiency of data analysis. Related to that, wearable sensors for health monitoring employ CNNs alongside other machine learning strategies to predict medical conditions such as epilepsy seizures and diagnose diseases like breast cancer. These devices measure vital parameters through sensors, with CNNs processing this data to achieve high diagnostic accuracy, demonstrating the significant impact of machine learning in enhancing health diagnostics [57].

Furthermore, this approach utilizes wearable sensors that can detect EDA, PPG, blood volume pulse, accelerometry, and skin temperature to predict epilepsy seizures. The Back Propagation Neural Network (BPNN) is a type of neural network that propagates information from the gradient to the inputs of the previous model in reverse, as described in [58]. This technique is combined with a decision tree, a support vector machine, and a random forest for the diagnosis of breast cancer [33]. Utilizing photoplethysmographic sensors (PPG), continuous and non-invasive monitoring of cardiorespiratory parameters can be performed by capturing blood volume variations in body organs, as described in [42]. The data were processed using deep learning, namely through Convolutional Neural Networks (CNN), employing both one-dimensional (1D) and two-dimensional (2D) CNN architectures. In this context, the 1D CNN model achieved a maximum accuracy of 96.71%. Data processing through Machine Learning techniques enhances the accuracy of diagnostic information obtained from wearable devices.

3.6. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, excel at learning from sequences of data, making them ideal for predicting future events. Their design addresses the vanishing and exploding gradient problems typical in traditional recurrent neural networks, allowing them to capture long-term dependencies in data sequences effectively. By integrating memory cells that regulate the flow of information, LSTMs can remember inputs over long intervals, enabling precise predictions in diverse applications such as stock market trends, weather forecasting, and natural language processing, as described in [59]. At the heart of LSTM's architecture are structures known as memory cells, which contain gates that control the flow of information. These gates - the input, output, and forget gates - decide what information is stored, outputted, or discarded, ensuring that the network maintains relevant information over long periods. This selective memory capability allows LSTMs to learn patterns and sequences, making them highly adept at tasks that require the prediction of future events based on historical data.

LSTMs are particularly useful in scenarios where the sequence and timing of data points are critical. For example, in financial modeling, LSTMs can analyze historical stock prices to forecast future trends. In weather prediction, they can process sequences of atmospheric data to predict future weather conditions. Their ability to process and remember long sequences of data also makes them effective in natural language processing tasks, such as predicting the next word in a sentence or translating text from one language to another. The effectiveness of LSTMs in predicting future events lies in their deep learning capabilities, allowing them to identify and learn patterns in vast amounts of data. By processing data sequences with LSTMs, organizations and researchers can uncover insights and make informed predictions, driving advancements across various fields. As deep learning technology continues to evolve, LSTMs will remain a crucial tool in the arsenal of methods for analyzing sequential data and forecasting future events.

The study developed a method for the continuous monitoring of arterial blood pressure (ABP) using non-invasive and cuffless techniques, specifically through the analysis of photoplethysmogram (PPG) and electrocardiogram (ECG) signals, as presented in [60]. By applying deep learning, particularly convolutional neural networks (CNN) such as ResNet and WaveNet, and recurrent neural networks (RNN) including Long Short-Term Memory (LSTM) models, the research aims at accurately predicting ABP. Optimal results were achieved using ResNet followed by three LSTM layers, achieving a mean absolute error (MAE) of 4.118 mmHg for systolic and 2.228 mmHg for diastolic blood pressure, indicating the method's high precision in accordance with American national standards. This research highlights the potential of deep learning in enhancing methodologies for non-invasive monitoring of key cardiovascular parameters.

The stress levels in video game players can be assessed by utilizing wearable sensors [43]. By processing such data through deep neural networks, the stress levels of players can be evaluated. The collected data include ECG (Electrocardiogram), EMG (Electromyogram), and EDA (Electrodermal Activity). The LSTM (Long Short-Term Memory) model has proven to be an effective tool for accurately predicting stress with a 92% accuracy rate, highlighting a promising platform for further research.

Through the analysis described in [44], it is possible to detect diabetes. Using non-invasive accelerometer sensors placed on the hip, ankles, and knee, data are collected and stored raw in a database. These are then processed using deep learning methods CNN-LSTM, combining the strengths of CNN for feature extraction and LSTM for classification based on temporal information. The classification of diabetes using acceleration data achieves an accuracy of 91.25%, representing an improvement over existing methods.

Table 3.1. Review of used machine learning algorithms.

Ref.	ML technique	Accuracy	Contribution
[14]	DT, RF	87%	A DT regressor model is developed and chosen for its ability to handle nonlinear relationships and dominant feature selection. The study shows the potential of using sensors and ML algorithms to assess dyspnea in patients and significantly for patients who cannot report themselves, by obtaining multiple factors with different importance weighting.
[6]	CNN	/	Use of machine learning and wearable technology to predict seizures in individuals with epilepsy, by using historical trends from self-reported seizure diaries and multiple sources of information.
[35]	SVM	91.4%	The RPRM system remotely monitors pregnant women to detect abnormalities and prevent potential health risks during pregnancy, and can be enhanced using more efficient ML algorithms and GPS sensors to monitor multiple patients in a specific area.
[32]	SVM	79.6%	The proposed system uses a wearable device with a single electrode and machine learning to objectively evaluate pain during ADL, and could be a useful tool for characterizing patients' pain, determining the need for operative therapy, and monitoring the effects of pain treatment.
[15]	RF	80%	The random forest algorithm achieved the best performance for classifying patients into cardiovascular risk classes. The study used patient interview data and biosignal data, processed to extract 35 features, to determine cardiovascular risk, and concluded that further investigations are needed for developing a soft sensor.
[33]	DT, SVM, RF, BPNN	78%	The Cyrcadia Breast Monitor (CBM) captures temperature data from both breasts and has demonstrated an accuracy of 78% in predicting breast lesions. The CBM uses temperature profiles collected from 16 sensors that may detect cancer earlier than mammography.
[34]	RF	91.3%	RF algorithm achieved the best performance among the eight supervised classifiers used in the study to predict skin hydration levels based on GSR data, which can be useful in medical and healthcare settings.
[37]	RF	91% - 100%	Using self-reported data and data from the non-invasive wearable device for seizure forecasting in people with epilepsy can contribute to accurate seizure forecasts incorporated with a Machine Learning algorithm.

Table 3.2. Review of used machine learning algorithms.

Ref.	ML technique	Accuracy	Contribution
[38]	DT	88%	Walking activity recognition model (WARM) has been recorded using wearable sensor in real life conditions. Data were collected using a motion sensor with low computing and memory resources that measures the rotation of the hip.
[39]	kNN	87.4%	Five measures are suggested to improve the assessment of postural stability at work. ACC offers the capacity to evaluate the stability of work postures. The feature set (FS) machine learning approach was used, and it produced greater accuracy.
[40]	DT	97.2%	Gathering data via a non-invasive, wearable sensor integrated into a mask enables the effective and dependable continuous real-time observation of respiratory functions, aiding in the early identification and prevention of respiratory illnesses.
[41]	RF	0,02°C (RMSE)	By employing machine learning for the analysis of this data, it is feasible to predict core body temperature, representing a significant advancement in the monitoring and management of hydration and the overall health status of individuals in real-time.
[42]	CNN	96.71%	Enhancement of diagnostic methods for information obtained via PPG sensors regarding the reliability of heart rate (HR) and heart rate variability (HRV) assessment.
[60]	LSTM	4.118 mmHg (systolic), 2.228 mmHg (diastolic) (MAE)	Continuous and non-invasive monitoring of arterial blood pressure is achievable through the application of deep learning, utilizing ResNet and LSTM models. The high precision of these predictions, aligned with national standards, demonstrates a significant potential for advancements in monitoring and managing cardiovascular health, emphasizing the effectiveness of these techniques.
[43]	LSTM	92%	A real-time automated stress monitoring system for young gamers could help prevent stress-related issues. Leveraging deep learning to analyze physiological signals enhances our ability to manage emotional states in contexts ranging from gaming to human-machine interactions, highlighting artificial intelligence's growing role in health and therapy.
[44]	CNN, LSTM	91.25%	Diabetes detection using gait analysis, by combining advanced machine learning techniques and data collected through wearable sensors, can enhance diabetes diagnostics, offering potential for early detection and reducing the need for invasive testing.

Table 3.3. Review of used machine learning algorithms.

Ref.	ML technique	Accuracy	Contribution
[38]	DT	88%	Walking activity recognition model (WARM) has been recorded using wearable sensor in real life conditions. Data were collected using a motion sensor with low computing and memory resources that measures the rotation of the hip.

4. Conclusion

This comprehensive analysis delves into the integration of wearable technology with machine learning, showcasing a notable transformation in health monitoring aimed at substantially enhancing patient care and the precision of medical diagnostics. The research examines radio technologies utilized for data transmission across various distances, which can be integrated within wearable devices. It also reviews the wearable non-invasive devices themselves, which have the potential for use in diagnosing patient conditions at home.

Data collected through wearable devices are stored using chosen radio technologies in a database, where the gathered data, combined with the deployment of sophisticated machine learning models such as Decision Trees, Random Forests, k-Nearest Neighbors, Support Vector Machines, Convolutional Neural Networks, and Long Short-Term Memory networks, can be used for detecting and early diagnosis of various illnesses.

The paper conducts a case study on Bluetooth Low Energy (BLE) and LoRaWAN (Long Range Wide Area Network) radio technologies, which have potential applications in wearable devices. Their range and performance for use in both urban and rural environments were tested. Additionally, these technologies pave the way for real-time, continuous health monitoring, marking the advent of a new era in medical care and patient management.

Moreover, the paper provides insights into machine learning techniques for analyzing and interpreting the medical data produced by wearable devices. These techniques stand as a foundational element in diagnosing diseases, forecasting health issues, and enabling timely medical interventions. The combination of state-of-the-art technology and advanced analysis aimed at enhancing diagnostic processes allows for early disease detection and encourages a preventative approach to healthcare management. Additionally, the intelligent use of these technologies greatly reduces the necessity for traditional diagnostic methods, alleviating pressure on healthcare resources and promoting a more streamlined, effective care delivery.

This comprehensive research lays the groundwork for an upcoming shift in health monitoring, where smart integration of wearable technology and machine learning not only improves patient outcomes but also transforms the healthcare landscape. This approach increases diagnostic precision, supports personalized treatment strategies, and leads to a new age of improved medical accuracy, patient-focused care, and the overall health of the global population.

With the rapid advancement of technology, not only are technology-driven healthcare solutions becoming predominant, but there is also an emphasized imperative for continuous research and innovation in this dynamic field. The path forward in integrations and innovations, and most importantly, commitment, is directed towards enhancing the lives of patients globally.

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Labels:

IoT	Internet of Things
ML	Machine Learning
PPG	Photoplethysmography
EMG	Electromyography
EEG	Electroencephalography
ECG	Electrocardiography
EDA	Electrodermal activity
SAREF	The Smart Applications REFerence
SAREF4EHAW	
RFID	Radio Frequency Identification
LF	Low-Frequency
HF	High-Frequency
UHF	Ultra-High-Frequency
LPWAN	Low PowerWide Area Networks
FHSS	Frequency-hopping spread spectrum
BLE	Bluetooth Low Energy
LoRaWAN	Long Range Wide Area Network
WPAN	Wireless Personal Area Network
Wi-Fi	Wireless Ethernet
RF	Radio Frequencies
NB-IoT	Narrowband Internet of Things
MTC	Machine Type Communication
LTE	Long-Term Evolution
LoRa	Long Range
CRC	Cyclic redundancy check
MAC	Media Access Control
RSSI	Received Signal Strength Indicator
CDF	Cumulative Distribution Function
SF	Spreading Factor
BW	Bandwidth
TTN	(The Things Network
ETSI	European Telecommunications Standards Institute
LPWA	Low Power Wide Area
ISM	Information Security Management
MIC	Message Integrity Code
NwkSKey	Network Session Key
AppSKey	Application Session Key
CTR	Counter mode
FHDR	Frame header
FCnt	Frame Counter
GPS	Global Positioning System
USB	Universal Serial Bus
ACC	Acceleration
GYR	Gyroscope
WBP	Wearable Biometric Patches
GSR	Galvanic Skin Response

LUX	Large Underground Xenon
BTN	Button
HR	Heart Rate
NA	Sodium
K	Potassium
PE/PP	Polyethylene/Polypropylene
SVM	Support Vector Machine
RF	Random Forest
WARM	Walking Activity Recognition Model
RMSE	Root Mean Square Error
FFT	Fast Fourier Transformation
GNB	Gaussian Naive Bayes
KNB	Kernel Naive Bayes
LR	Logistic Regression
DA	Discriminant Analysis
BT	Bagged Trees
OE	Optimizable Ensemble
ERM	Empirical Risk Minimization
NRS	Numerical Rating Scale
RBF	Gaussian Radial basis function
HL	Level of Hydration
k- NN	*k*- Nearest Neighbour
RNN	Recurrent Neural Networks
MAE	Mean Absolute Error
CNN	Convolutional Neural Networks
BPNN	Back Propagation Neural Network
CBM	Cyrcadia Breast Monitor
FS	Feature Set
SRM	Structural Risk Minimization

WEARABLES AND MACHINE LEARNING IN HEALTH MONITORING

Abstract:

The integration of wearable technology and machine learning into health monitoring systems represents a pivotal advancement in the improvement of patient care and diagnostic accuracy. This paper elaborates on the utilization of wearable devices that measure various vital parameters and distribute the data to a designated storage database using Bluetooth Low Energy (BLE) and Long Range (LoRaWAN) technologies. Coupled with a range of machine learning models, including Decision Trees, Random Forests, k-Nearest Neighbors, Support Vector Machines, Convolutional Neural Networks, and Long Short-Term Memory networks, this technology facilitates the prediction and early detection of various diseases. Through comprehensive case studies, this research assesses the precision of wearable devices in measuring and transmitting essential health parameters, emphasizing their applicability in healthcare environments. The study underscores the transformative potential of machine learning algorithms in processing data from wearable devices, showcasing their efficiency in disease diagnosis, health issue prediction, and enabling timely medical interventions. This research establishes a foundation for a promising future where the confluence of wearable technology and machine learning in healthcare could markedly improve patient monitoring, diagnosis, and treatment modalities, thereby contributing significantly to the advancement of the healthcare industry.

Keywords:
IoT, Wearable devices, non-invasive, health, monitoring, machine learning, sensors, BLE, Bluetooth, LoRaWAN.

NOSIVI UREĐAJI I STROJNO UČENJE U PRAĆENJU ZDRAVLJA

Sažetak:

Integracija nosive tehnologije i strojnog učenja u sustave za praćenje zdravlja predstavlja ključan napredak u poboljšanju skrbi za pacijente i točnosti dijagnostike. Kroz detaljnu analizu, ovaj rad istražuje kako nosivi uređaji, mjereći različite vitalne parametre i distribuirajući prikupljene podatke putem tehnologija poput Bluetooth Low Energy (BLE) i Long Range (LoRaWAN), omogućavaju predviđanje i rano otkrivanje raznih bolesti. Ova revolucionarna kombinacija tehnologija otvara vrata za kontinuirano i precizno praćenje zdravstvenog stanja pacijenata izvan tradicionalnih medicinskih ustanova, naglašavajući važnost stalnog pristupa zdravstvenim informacijama za rano otkrivanje i upravljanje zdravstvenim stanjima. Rastuća popularnost tehnologije Interneta stvari (IoT) dodatno potiče inovacije u zdravstvenoj skrbi, čineći pametne tehnologije ključnim elementom u razvoju rješenja za daljinsko praćenje pacijenata, poznato kao eHealth. Ova integracija ne samo da poboljšava kvalitetu života pacijenata pružajući brze odgovore na zdravstvene izazove, već također omogućuje medicinskim stručnjacima pristup važnim podacima u realnom vremenu, što je presudno za pravovremenu dijagnozu i intervenciju. S obzirom na izazove povezane s obradom i interpretacijom velikih količina podataka koje generiraju nosivi uređaji, primjena modela strojnog učenja, uključujući drveta odlučivanja, nasumične šume, k-najbliže susjede, strojeve potpornih vektora, konvolucijske neuronske mreže i mreže dugoročne kratkotrajne memorije, postaje neizostavna. Ovi algoritmi su se pokazali izuzetno učinkovitima u analizi podataka i otkrivanju uzoraka koji mogu ukazivati na početak bolesti, čime se omogućuje ranija intervencija i potencijalno spašavaju životi. Kroz sveobuhvatne studije slučaja, ovaj rad daje pregled preciznosti i učinkovitosti nosivih uređaja i algoritama strojnog učenja u kontekstu zdravstvene skrbi, naglašavajući njihovu sposobnost transformacije pristupa dijagnozi i liječenju. Integracija nosive tehnologije i strojnog učenja definira ključnu ulogu u napretku zdravstvene industrije, u vidu poboljšanja praćenja pacijenata, dijagnostičke sposobnosti i terapijskih metoda liječenja.

Ključne riječi:
internet stvari, nosivi uređaji, neinvazivni, zdravlje, praćenje, strojno učenje, senzori, BLE, Bluetooth, LoRaWAN