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SMART PARKING SOLUTIONS FOR OCCUPANCY SENSING

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Contents

1. Introduction

Intense technological development nowadays is reshaping many areas of everyday life and impacting human behaviour. The Internet of Things (IoT) vision of ubiquitous and pervasive connection of smart things gives rise to a future environment composed out of physical and digital world. In this environment it is possible to receive information about or from the psychical world that was previously not available to us, and moreover, interconnect it to exchange and use this information with the digital world [1]. The IoT applications are being employed in diverse areas of industry, communication, wireless sensor networks, data mining, assisted living, etc. giving rise to the concept of Smart City. The Smart City is constituted out of gathered and processed information, covering a wide range of entities such as transportation, health, food and education for the overall improvement of life quality [2]. One of the most important topics addressed by the European Commission, and most nations in the world, is the development of an urban city model aimed at increasing the quality of life of people working and living in them. Smart and Sustainable Mobility is one of the central concepts in the vision of the Smart City, where IoT plays an important role [3, 4]. In urban city areas, due to the rise of cars, existing parking systems are inadequate or unable to handle parking loads [5]. Moreover, parking facilities are not accessible in a adequate manner, since it is estimated that drivers spend around 7.8 minutes in finding free parking lots [6]. Studies have shown that in traffic dens environments in urban areas 30- 50% of drivers are in search for free parking [7]. In addition, the IBM survey [1] reported that due to traffic in metropolitan cities such as Beijing or Madrid drivers spend on average 30 to 40 minutes searching a free parking space. One of the major issue that arise from this is the increase of fuel consumption and air pollution [8]. Furthermore, consequences of traffic jams are the frustration of drivers and higher probability of accidents [7]. Finally, traffic congestion leads to cost-effective losses since in a city of 50,000 inhabitants, having on average 250 parking lots, generates an annual cost of 216,000 US dollars [9].

Existing Smart Parking solutions for detecting occupancy include usage of adequate sensing technologies and transmission to a centralized system for further processing using appropriate radio technology (short- range and long-range) such as Wi-Fi, ZigBee LoRa, NB-IoT, Sigfox, BLE. These devices use detection techniques based on sensors such

[1] IBM Survey. Available online: https://www-03.ibm.com/press/us/en/pressrelease/35515.wss (accessed on 20 September 2021)

as light, magnetometer, infrared detector, distance sensors or a combination of sensing technologies [10, 11, 12, 13]. In order to detect the vehicle presence in parking slots, different approaches have been utilized, which range from image recognition to sensing via detection nodes. The last one is usually based on getting the presence data from one or more sensors (depending on the deployment scenario and parking lot environment), controlled and processed by a micro-controller that sends the data through radio interface. Consequently, given nodes have multiple components, adequate software is required for its control and state-machine to communicate its status to the receiver.

In the last decade the development of dynamic and complex IoT system and number of connected devices keeps increasing exponentially as well as the data collected by these devices which need to be properly analyzed. [14]. Effective analysis of big data can extract meaningful information and correlation amongst a vast quantities of data generated by sensor devices which are a key factor for the success in many domains and especially in the Smart City applications [15]. Therefore, IoT devices need to be able to manage data collection, Machine-to-Machine (M2M) communication, pre-processing of the data if needed whilst compensating among cost, processing power and energy consumption [16].

Along with great advancements in technology, including availability of cheap and massive computing, hardware and storage arose Machine Learning (ML) holding a vast potential for data analysis and precise predictions made from the past observations for given new measurements [17]. Machine learning is the most prominent artificial intelligence (AI) algorithm, which is been utilized in various fields from computer vision, computer graphics, natural language processing (NLP) to speech recognition, decision-making, and intelligent control [18], as well as in intrusion detection systems [19]. Within IoT devices application of ML can enable users to gain deeper insight into data correlations and mine the information and features that are hidden within this data [20]. With that regard, IoT applications that use sensor technology, network communication, data mining and machine learning could prove to be quite efficient in solving the previously presented problem of free parking space [21]. In recent years Deep Learning (DL) has been actively employed in IoT applications as one of Machine Learning approaches [22]. In recent years the field of Deep Learning has become rather prominent and the concept of artificial neural networks (NN), inspired by brain nervous system, has gain large interest amongst researches [23]. Neural networks have the capacity to learn hierarchical representations and are well suited for machine perception tasks, where the crude underlying features cannot be individually interpreted [24]. This makes them a powerful ML tool that achieves state-of-the-art results in a wide range of supervised and unsupervised machine learning tasks. Neural Networks have been efficiently implemented in a variety of fields like patter recognition, signal processing and control of complex nonlinear systems [23]. Moreover, NNs have also been applied in prediction of future occupancy status such as in [25, 26]. DL reliably mines real-world IoT data from noisy and complex environment in contrast to conventional

ML techniques and is a strong analytical tool for huge data giving better performance for such tasks [27]. Recent review of literature presented in [28] pointed out to several open issues and challenges with regards to design of Smart Parking spaces, emphasizing the utilization of car parking with emerging technologies such as Deep Learning.

Smart Parking solutions vary with regards to sensing technologies and methods that are used for parking space occupancy prediction and classification. When regarding the architecture of these solutions it can be noticed that they are generally constituted out of three distinguishing components: type of sensors, communication protocols, and software applications [29]. Therefore, this paper presents an overview of scientific literature about the concepts of Smart Parking solutions within the IoT paradigm, categorizing them based on their architecture. Chapter 2 provides the general description and discussion about sensor technologies, communication protocols and parking occupancy classification or prediction techniques. Insight into different sensor types employed for different parking status observations is provided, followed by description of commonly used network protocols. Moreover, description of Machine Learning techniques used for prediction or classification of free parking based on the various data collected form the sensing devices, with presentation of most frequently utilized algorithms within Smart Parking solutions are given. In Chapter 3 relevant scientific literature is presented and discussed in terms of previously elaborated technological architecture. Finally, in Chapter 5, concluding remarks are given with guidelines for future work.

2. Technological architecture

This Chapter brings a comprehensive theoretical introduction into the technological architecture of Smart Parking solutions, providing the general definitions, descriptions and discussion about the each part of the architecture. Firstly, different sensor types are presented that have been identified in the scientific literature, with clarification of their functionalities. Secondly, communication/network protocols are introduced with appropriate categorization. Finally, motivation for Machine Learning deployment in general is given, with elaborated explanations of some of the most frequently used algorithms within Smart Parking solutions.

2.1. Sensor technologies overview

Architecture of Smart Parking solutions is based on sensors that sense the environment change and collected data about parking availability. As the most significant element of above mentioned solutions, they are selected based of the particular requirements of a specific parking lot [6]. With that regard, several crucial factors must be taken into account when choosing the best option for the designated employment. For one, they are required to be autonomous from human interaction to provide information about the changes in the environment and at the same time, they must be energy efficient by keeping the energy consumption as low as possible [29]. What is more, the accuracy of the collected sensor data must be kept high while keeping the device cost at minimum level as possible [13], by reducing their size and extending their performance and lifetime [6]. Finally, the sensor type determines the appropriate network/ communication technology for sending the data for further processing in the backhand [29], which therefore must also be taken into account when employing sensors in a specified parking space. Within the research community, there are two types of sensor categorization:

- intrusive and non-intrusive sensors [30],
- active and passive sensors [13].

If the procedure of sensor installation is invasive, like tunneling under the road or placing them in the holes on the road surface, sensors are characterized as intrusive [31]. The non- intrusive sensor are ones that are non-pavement invasive, i. e. they do not affect the road surface [30]. If a sensor needs an external power source for performance and operation it is classified as an active sensor, in contrast to passive sensors that do not require an additional power supply [6]. In the following, some of most frequently employed sensors within scientific researches are presented.

Infrared (IR) sensor

An Infrared sensor is a device that recognizes and quantifies the amount of IR radiation emitted from an object [32]. Infrared sensors can be active and passive ones. Active ones are considered to be intrusive, whereas the passive ones are characterized as non-intrusive [31]. Active IR have two major components: a Light Emitting Diode (LED) that emits radiation and a receiver that measures the IR radiation reflected back to it from any nearby object [32]. The major drawback of these sensors is their high investment and maintenance costs as well as their sensitivity to change in the weather conditions like rain, snow or fog [7]. In accordance with the stated reasoning they are considered not to be suitable for open parking lots. However, they can accurately detect free space in indoor parking facilities as well as the correct position and speed of a vehicle on a multilevel parking area [13]. In contrast to active IR sensors, passive infrared sensors do not emit IR radiation but detected the difference in temperature among the surroundings and an object [32]. They determine the occupancy of a parking space by measuring the thermal energy emitted by the vehicle and/or the road [13]. It is recommended that they are situated under the ground or on the parking lot ceiling, which is therefore costly and hard to maintain [7]. Like the with active ones, they main disadvantage is their sensitivity to change in weather conditions and thus are not preferable to be used in open parking areas [32], [7].

Ultrasonic sensors

Ultrasonic sensors, can be categorized as non-intrusive and active sensors [30]. Their principle of operation is based on the emission of acoustic waves on a determined frequency range of 25 kHz to 50kHz which is then reflected back if there is an object that stands in its wave's path [29]. As was the case with the IR sensors, they are also prone to environmental changes and as such far more suited to be used in indoor parking lots [32]. However, the ultrasonic sensors are very good at distinguish between a vehicle and a person that passes by the parking space based on the radius at which wave was reflected [7] having high detection accuracy and are therefore widely used as part of the architecture of Smart Parking solutions [29]. Another reason for their frequent usage is their low cost and simplicity in installation as well as low maintenance [13].

To get good performance and obtain information about parking occupancy these sensors should be placed above every parking space, usually mounted on the ceiling [7].

Camera sensors

A widely adopted approach by numerous researchers for Smart Parking solutions is a camera (or cameras) being a non-intrusive and active sensor [32]. However, camera requires image processing for information retrieval since it does not have the ability to process images alone, therefore needing an aid of external devices or diverse computational tools and algorithms for detection of free space [29]. For this problem, in indoor parking areas, cameras can be placed above the parking lot and an appropriate algorithms can be used to segment vehicles and detect occupancy of parking space, where as for a open parking lots it has an advantage over other solutions since it can cover large number of parking spaces [7]. Although cameras as sensors provide good quantity of information they tend to be costly for deployment as well as maintenance [32].

Radio-frequency identification (RFID) sensors

RFID sensors are non-intrusive and passive sensors comprised out of an transceiver, transponder, and antenna and are found today as commonly utilized technology for Smart Parking solutions [32]. The principle of operation is as follows: the RFID reader emits the electromagnetic waves thus activating the RFID tags which then backscatter the received signals containing the tags' unique ID to the reader. As a par of the Smart Parking solutions RFID tags can be put inside the vehicle where a transceiver and antenna can be set at the entrance of a parking lot to identify the tag as the vehicle to occupies a parking spot, thus changing the parking spot status to occupied [7]. For this reason they are very well suited for indoor parking areas in contrast to open parking lots since RFID systems have a range limitation in the distances between the reader and the tag [13]. Their greatest advantage in contrast to other Smart Parking sensing devices is their cost- effectiveness and ease in deployment [33].

Magnetometers

Magnetometers are categorized as intrusive and passive sensors that have been some of the most frequent stationary parking detection sensors, particularly utilized in urban city areas [10]. They sense the change in the earth electromagnetic field which is triggered by metallic objects in their presence [29]. Therefore, they are usually located under the parking lot to sense the presence of a vehicle also making them are resilient to changes in weather conditions and thus appropriate for outdoor and indoor parking areas [32]. Novel solutions offer the in-ground as well as surface-mounted sensors. Although they are rather accurate in detecting the real-time parking space occupancy, the in-ground types are not cost-effective to employ or maintain since they need to put below every parking space [7].

Inductive loop detector

Inductive loop detectors are classified as intrusive and passive sensors for vehicle detection placed below ground [30]. They consists out of an inductive loop of wire that utilizes the electromagnetic induction principle; i. e. flow of the electric current that is transmitted through the wire generates an electromagnetic field whose inductance can be measured [34]. The inductance of the loop initiates a signal whose frequencies range from 10 KHz to 50 KHz and above, but the passing of a vehicle interrupts the field reducing the inductance [30]. Finally, a pulse is sent the controller to indicate the passing or a presence a vehicle [13]. This sort of sensors are expensive to install and maintain (causing traffic disruption) and are generally used for indoor parking areas [7].

Microwave Radio Detection and Ranging (RADAR)

Microwave radars were devised for object detection before and during Word War II and are non-intrusive and passive sensors [30]. In general, they transmit microwave beams in the microwave spectrum (frequencies usually range between 1–50 GHz) and based on the reflected signal they measure the velocity of the moving object, as well as its distance and angle [32]. But, they cannot detect stationary objects. To overcome this issue, a dual microwave Doppler radar is employed to detect both moving as well as stationary vehicles [7]. Microwave radars are very resilient to harsh weather conditions making them suitable for both closed as well as closed parking lots [13]. The main disadvantage of these sensors is the high price of deployment and maintenance [32].

Light Detection and Ranging (LIDAR)

In the past decade a non- intrusive active sensor- LIDAR sensors, have emerged as novel robust approach in contrast to traditional vision sensors [35]. By emitting a set of LASER lights pulses that are aftewards reflecetd from the object in its environment, a LIDAR sensor calculates the distance from the time of reflection flight [36]. Using this technique, 3D depiction of the object can be obtained and as such LIDAR sensors a commonly used for vehicle detection in Smart Parking solutions [32].

Acoustic sensors

Acoustic sensors are non-instrusive and passive sensors which measures the acoustic energy or audible sounds generated by vehicular traffic as well as sound produced from the interaction between the roadway and the vehicle [30]. A processing computer afterwards analyzes the noise variation levels recognised by microphones if the vehicle is present[34]. Although they are able to function well on rainy days, it's accuracy can be reduced if they are exposed to cold weather conditions or slower vehicles [13].

Celluar sensors

The overwhelming ubiquitousness of smart phones in every day user's activities has made them a widely used sensor for Smart Parking solutions [29]. They are usually comprised out of several sensors like Accelerometer, Gyroscope, and Magnetometer which are able to detect a persons presence in the car, vehicle motion, direction and orientation [32]. This makes them suitable for both outdoor and indoor parking areas.

2.1.1. Occupancy sensing accuracy

It was considered important to discuss and compare different parking sensors in terms of the accuracy of detection. Over the years, scientific literature has provided insight into sensor technologies like the ones presented in [10, 13], where authors elaborated extensively on Smart Parking solutions and technologies that are incorporated in such solutions. However, they do not report nor discuss or provide their own extensive research in terms of comparison of accuracy of occupancy detection of most frequently applied sensors other then providing a comparison table. What is more, in a rather novel research presented in [37], authors also provide an overview of sensor technologies and methodologies for determining the occupancy of parking spaces. They present some form of comparison of sensors discussing several open challenges in parking occupancy detection. One such open issue is exactly the lack of a comprehensive quantitative comparison and benchmarking of the accuracy and reliability of parking occupancy sensors.

A good approach of performance evaluation for parking sensors was recently presented in [6], but it was rather oriented on power consumption and battery life extension. The authors have utilized the following sensors for testing: magnetometer,1 IR sensor, Time-of-flight WAVGAT VL53L0X, Light Dependent Resistor, Photodiode and Ultrasound sensor. Although the authors point out that the objective of their research was to analyze off-the-shelf sensor devices that can be used for building the smart parking node devices in terms of their detection accuracy and power consumption, the do not provide an elaborated numerical comparison of tested sensors in terms of accuracy of detection. In contrast, they provide a descriptive analyses of how each of the tested senors behaved for different experimental scenarios. For instance, their experimental results indicate that LIDAR showed good occupancy sensing accuracy, since the the absence of a vehicle was explicitly shown by the sensors sending a message of “Out of range” for empty parking lots as shown in Figure 2.1.

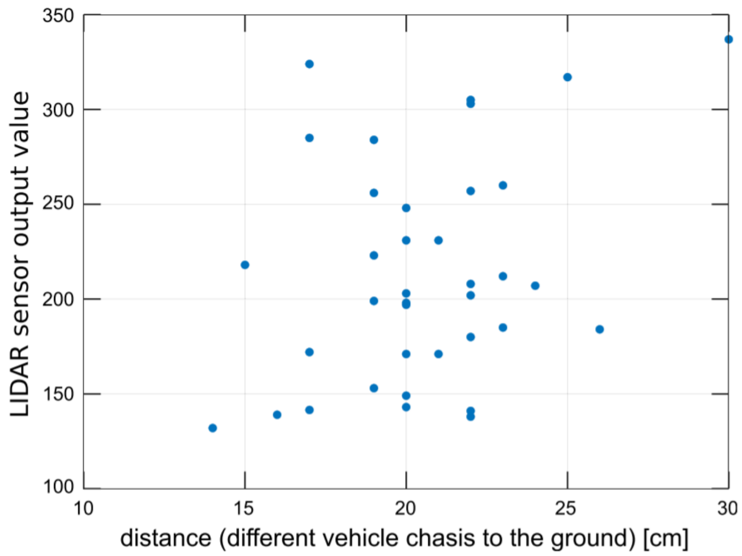

Figure 2.1. Sensing vehicle presence by LIDAR. The read message via LIDAR is “Out of Range” in any open lot [6].

In contrast to LIDAR, the tested ultrasound sensor showed false predictions (smaller than the threshold value) during the experiments in realistic scenario, as depicted in Figure 2.2. The authors state that the tested ultrasound sensor can not be reliable in every vehicle detection. From the data obtained from their graph it can be seen that the ultrasound sensor provides a detection accuracy (for their experiment) of 76%.

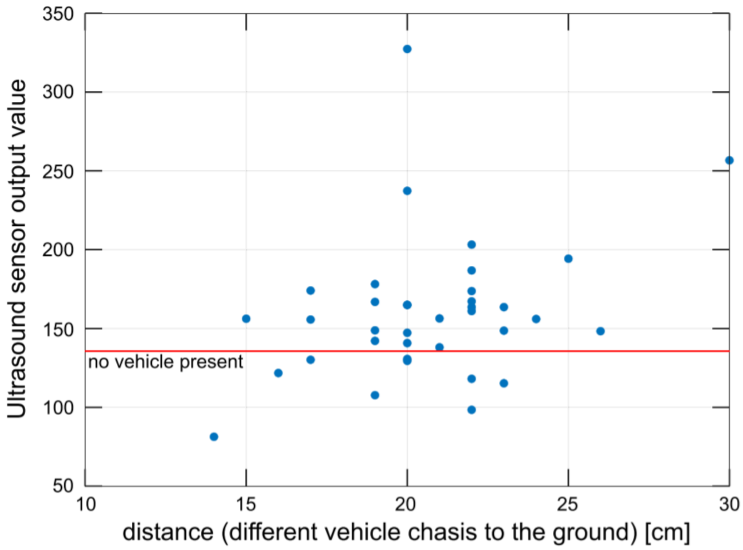

Figure 2.2. Sensing vehicle presence by Ultrasound detector [6].

Furthermore, the authors point out that the measurement results from the magnetometer and infrared sensor in some scenarios also indicate a non-occupied parking lot although the space is occupied. They conclude that the inaccuracies are a result of the distance between the chassis and the ground, along with metallic structure of the chassis.

The authors in [37] point out that, although in scientific literature diverse sensors have been tested in terms of accuracy of detection, different settings on sample sets of different sizes and experimental environments makes it hard to compare and benchmark the performance of different parking occupancy detection sensors. What is more, other scientific literature surveys regarding smart parking systems like ones in [29, 7] do not discuss this issue it at all. Therefore, based on the information about accuracy presented in [10, 13, 37, 6] this paper provides comparison of parking occupancy accuracy detection for previously elaborated sensors presented in Table 2.1. As stated in [13] one star (*) means poor and the 5 stars (*****) means excellent detection accuracy.

Table 2.1. Comparison of parking occupancy accuracy detection for different sensor technologies.

Sensing Device	**Accuracy**
Infrared (passive and active)	**
Ultrasonic	***
Camera	****
RFID	***
Magnetometers	****
Inductive loop detector	****
RADAR	****
LIDAR	***
Acoustic	*
Celluar	unknown

Based on presented table, cameras, magnetometers, inductive loop detectors and RADAR sensors show high accuracy of occupancy detection, which could be indicative for future employment in Smart Parking solutions.

2.2. Communication protocols

This Section gives an a short insight into most commonly used communication protocols within Smart Parking solutions with brief introduction of basic concepts and terminology.

Different modes of communication have been proposed to support communication from the sensors delivering data to the processing unit's and on-wards to the end users. Networking serves a bridge between all of these parts therefore being one of the crucial parts of Smart Parking solutions [32]. Generally, two types of network protocols are distinguished within these solutions: one for the users and one for the sensors [29]. Scientific literature has recognized and dived these into long-range i. e. low power wide area networks (LPWAN) and short-range wireless networks. Among the short-range ones, most commonly used are Zigbee, Bluetooth/BLE and Wi-Fi. whereas for the long-range, these are SigFox, LoRa and Narrow-Band IoT (NB-IoT) [32, 13, 29, 38]. Distinguishing features among all of these are network size, data rate, cost, power consumption, as well as distance coverage and security. Due to specific requirements of IoT applications in general, namely long communication range, very low energy consumption, and cost effectiveness, LPWAN have been considered better adapted for IoT implementation in general [39]. Although the widely used short range technologies support high data rate, one of their main disadvantages is high power consumption, which makes them unattractive to employ in low-power applications [40]. Figure 2.3 exhibits how short range technologies like BLE and ZigBee have bigger data rate and battery life at the expense of connection range; LPWA technologies such as NB-IoT, provide superior battery life and coverage, but low data rate on the downside, whereas in comparison traditional cellular technologies have big data rate (mostly 4G, 5G) and range with complex designs optimised for mass consumer voice and data service [41].

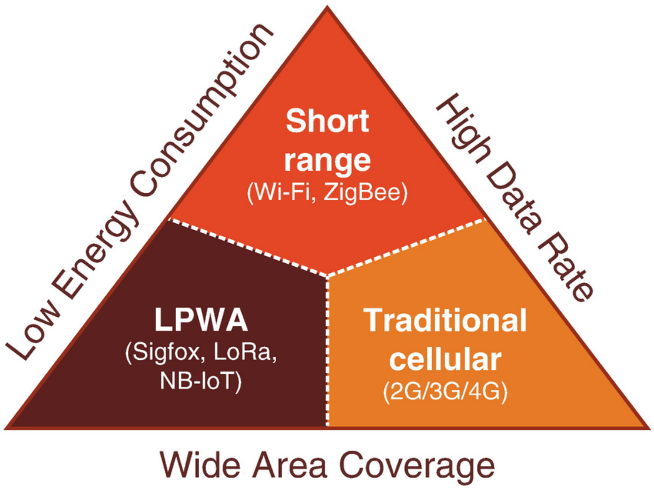

Figure 2.3. Comparison of some of the distinguishing features and trade-off amongst different network technologies [41].

However, recent research, as ones presented in [42] and [40] have started to explore how short-range technologies could compete with LPWA solutions. With regards to Smart Parking solutions researches in [42] have developed a prototype that uses a magnetometer to verify the vehicle presence upon trigger generation and BLE 5.0 technology for status change update, The BLE 5.0 technology was selected for employment as the most promising protocols in terms of communication distance, throughput, and power consumption, in comparison to other technologies as depicted in Figure 2.4. They argue that BLE 5.0 data range up to a couple of hundred meters makes it rather fitting to challenge the LPWA technology in cases like Smart Parking solutions.

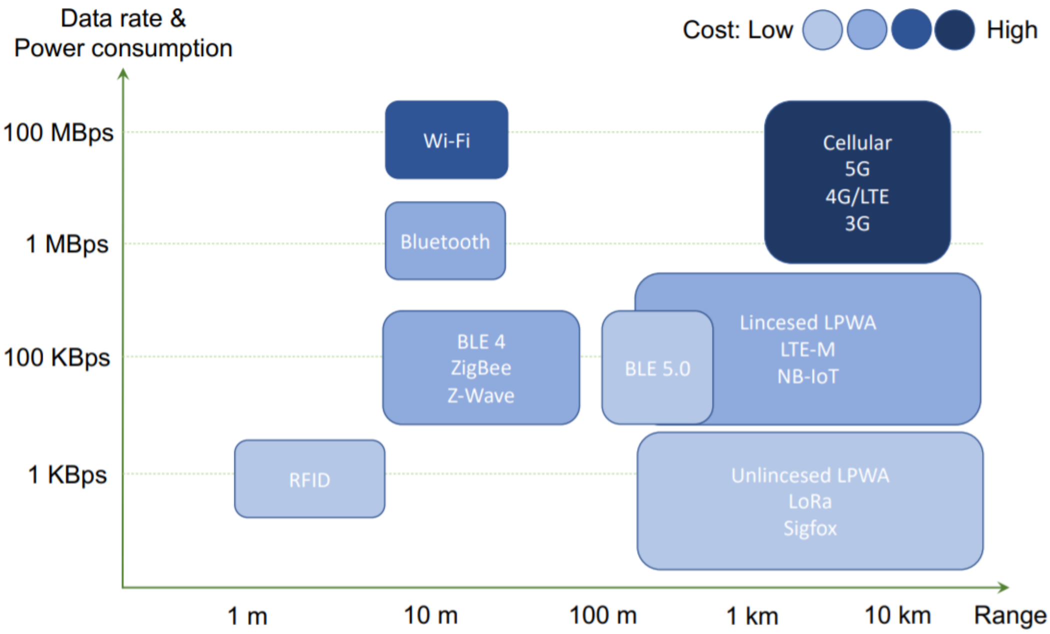

Figure 2.4. Data rate and power consumption vs distance for the most diffused wireless communication technologies for IoT [42].

In the following, a brief discussion on the existing and most commonly applied wireless technologies for Smart Parking solutions obtained from scientific researches is presented.

2.2.1. Short-Range Technologies

1. Bluetooth and BLE

In the late 90s Nokia created Bluetooth as an internal project which swiftly became a favored technology that substituted cables for connection of computers, printers, keyboards and other portable devices which were scattered within a small area of a maximum 100 m range [43]. By the 2020 it was ratified as Institute of Electrical and Electronics Engineers (IEEE) 802.15.1 standard. The Bluetooth standard uses short-wavelength UHF (ultra-high frequency) radio waves in the range of 2.400 and 2.485 GHz, where the data rate varies from 1Mbps to 3Mbps [44]. Communication amongst Bluetooth devices is arranged in a master-slave structure, having a maximum of eight devices — seven active slaves and one master — working together form a *Piconet* as presented in Figure 2.5, thus making the simplest configuration of a Bluetooth network [45]. If Piconets may are connected together they form a *Scatternet*.

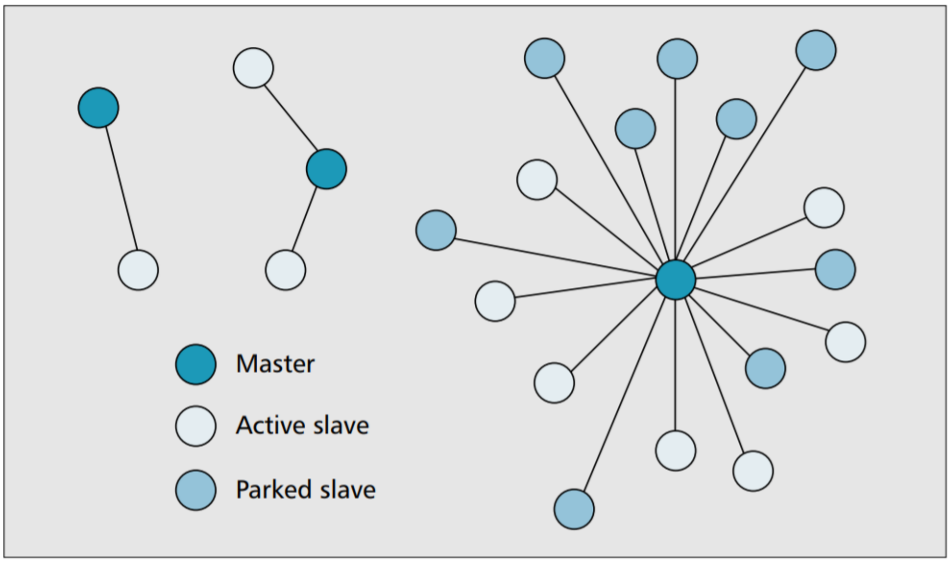

Figure 2.5. Piconet configurations[45]

Classical Bluetooth is able to exchange generally all types of data such as text or multimedia, but its high power consumption makes it impractical for usage in IoT scenarios that depend upon low-power transmissions for small and battery-limited devices [46], [43]. Therefore, in the last two decades Bluetooth has technologically evolved trough various versions, namely, Bluetooth 1.2, 2.0, 2.1, 3.0, 4.0, 4.1, 4.2, and 5.0, where with each version improvements and benefits were made in terms of enhanced data rate, speed and finally energy efficiency [47], as depicted in Figure 2.6.

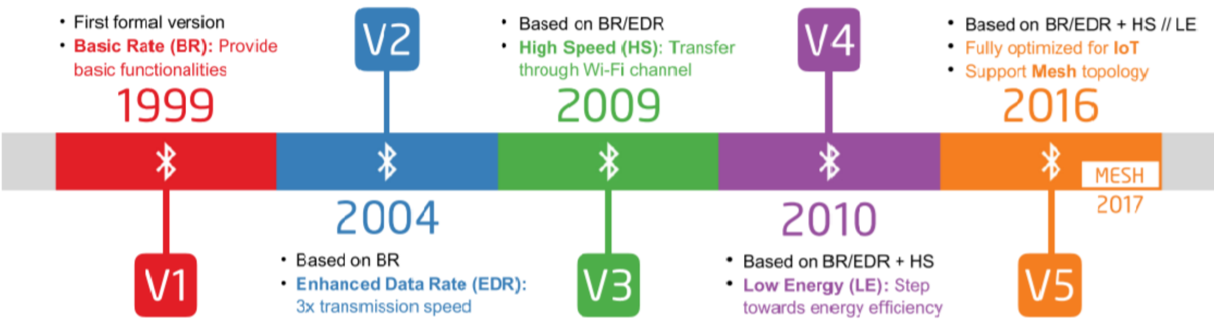

Figure 2.6. A brief history of Bluetooth [47].

The version 4.0 has introduced Bluetooth Low Energy (BLE) specifically designed as low power solution contrary to classic Bluetooth [46]. In contrast to previous versions which were optimized for continuous data streaming, BLE is optimized for short burst data transmissions (low data rate applications) having longer battery life time [43]. Latest enhancements regarding BLEs data rates and range were brought within Bluetooth 5.0 by using increased transmit power or coded physical layer, achieving a maximum data rate of 2Mbps (as twice as fast), four time times the transmission range, and eight times the broadcasting capacity of Bluetooth 4.2 [48]. In order to sustain many-to-many device communications within large-scale IoT device networks, BLE mesh topology has been adopted in 2017 operating on a managed flood routing principle for forwarding messages from one device to another [43], [47].

2. ZigBee

The ZigBee protocol, yet another short-range wireless technology for low-data rate monitoring application, is managed and issued by a association companies under the name of the ZigBee Alliance [43]. The ZigBee protocol aims to enable a steady, low- power, low-cost that is easy to maintain and install [49]. Built upon the established IEEE 802.15.4 standard for packet based wireless transport, Zigbee utilizes IEEE 802.15.4 specifications for the physical layer (PHY) and Media Access Control (MAC) layers (as depicted in Figure 2.7) and provides specifications for the upper layers by enhancing the functionality of IEEE 802.15.4 and providing flexible, extendable network topologies that have integrated set-up and routing intelligence to expedite easy installation and high resilience to failure [50].

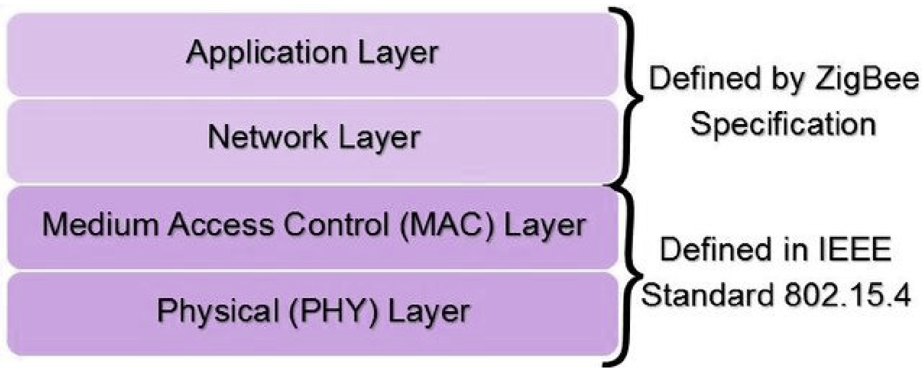

Figure 2.7. ZigBee protocol architecture built upon IEEE 802.15.4 standard.

Today, ZigBee has been broadly utilized within IoT applications that range from health care, home automation to industrial monitoring, due to its low-power technology operating in the unlicensed bands, i.e., usually at 2.4GHz and optionally at 868MHz or 915MHz, with the default operation mode being at 2.4GHz [43], as depicted in Figure 2.8.

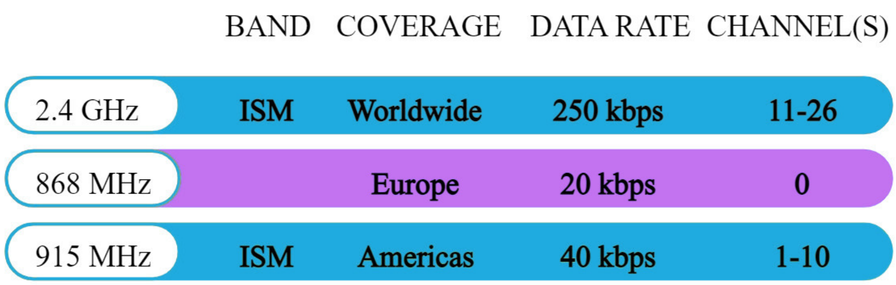

Figure 2.8. ZigBee frequency bands.

Zigbee supports different network topologies such as Star, Mesh, and Tree, illustrated in Figure 2.9, with three device types: the network coordinator, router and end device that vary in terms of resources, capabilities and cost [50]. The coordinator usually requires the most memory and computing power and along with the router is mains-powered whereas the end-device can be battery-powered [43]. The router performs application functions and, in the mesh and tree topologies, serves as an intermediate router to communicate data between connected nodes [49]. The end-devices are unable to straightforwardly communicate amongst each other and are therefore logically connected to a coordinator or routers [43]. Depending on the application demands ZigBee based networks can be centralized and/or decentralized allowing up to 65,000 nodes on a network with the direct spread spectrum sequence (DSSS) transmission technique that offers up to 250 kbps of data rate in 2.4 GHz frequency band [46]. Although ZigBee is highly efficient due to long battery life and simple installation and implementation, in comparison to BLE, ZigBee has been shown to be inferior with regards to bit rate and dedicated data channels as well as energy consumption [43].

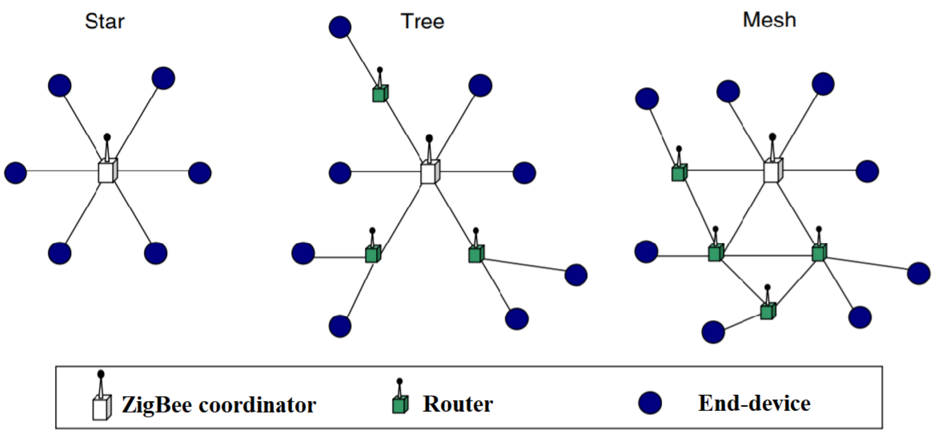

Figure 2.9. ZigBee network topologies.

3. Wi-Fi

Wi-Fi technology has been considered as one of the most immense applied technology of the modern era that has been greatly exploited by the world's population for both personal, commercial and professional purposes [51]. In general, Wi-Fi is a family of technologies utilized for wireless local area networks (WLAN) and standardized by IEEE 802.11 [43]. IEEE 802.11 specifies the Media Access Control and physical layer protocols for WLAN implementation operating in frequency band of 900 MHz, 2.4GHz, 3.6GHz, 5GHz and 60 GHz, out of which the most used ones in WiFi networks are 2.4GHz and 5GHz, with the former having a higher usage percentage [46]. In order to prevent interference from other wireless technologies such as 2.4GHz ZigBee and Bluetooth that are also co-located on the 2.4 GHz industrial, scientific and medical (ISM) frequency band, Wi-Fi uses Direct DSSS radio technology [52]. WiFi has advantages over ZigBee and Bluetooth in terms of the data rate and coverage distance, but has much more lower latency and higher power consumption [53]. In order to support higher throughputs, WiFi has been evolving over the years and its generations from the IEEE 802.11a and IEEE 802.11b that were introduced in 1999. up to IEEE 802.11ax known as High Efficiency WLAN, as depicted in Figure 2.10.

IEEE Standard	802.11a	802.11b	802.11g	802.11n	802.11ac	802.11ax
Year Released	1999	1999	2003	2009	2014	2019
Frequency	5Ghz	2.4GHz	2.4GHz	2.4Ghz & 5GHz	2.4Ghz & 5GHz	2.4Ghz & 5GHz
Maximum Data Rate	54Mbps	11Mbps	54Mbps	600Mbps	1.3Gbps	10-12Gbps

Figure 2.10. The evolution of Wi-Fi standards

With regards to networking topologies, Wi-Fi supports two distinguishing ones; namely the Peer-to-Peer (ad-hoc) topology and Access point-based topology[52], as illustrated in Figure 2.11.

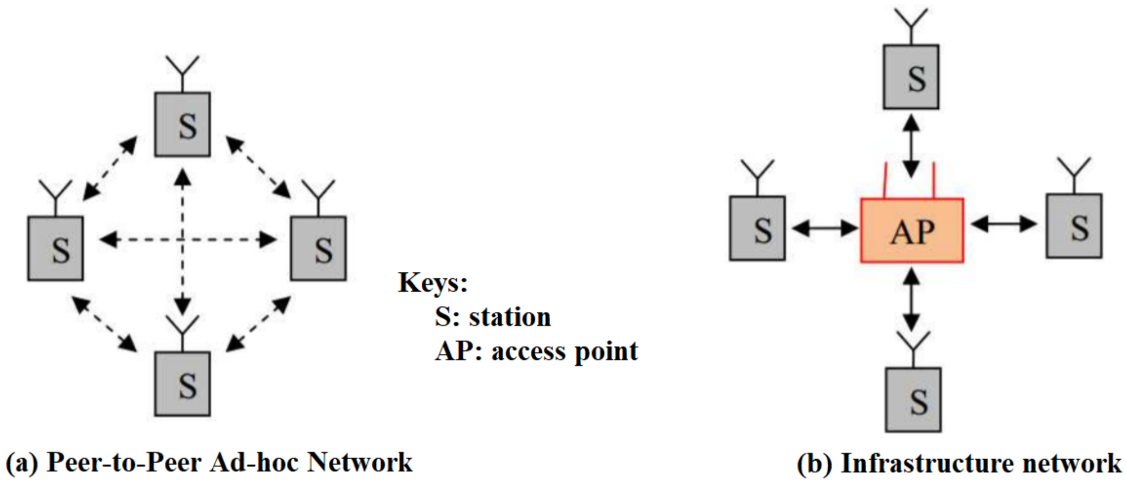

Figure 2.11. Examples of two possible types of Wi-Fi topologies [52].

In the first case, the access point is usually a router that is employed for connecting the devices and enabling data sharing, where as in in ad-hoc case, two Wi-Fi enabled devices can communicate in a point-to point topology without requiring an intermediate device [49]. Although, Wi-Fi has been able to expand the communication range and decrease delay (at the expense of power consumption), the number of supported devices has lingered as challenge to be overcome for its proper utilization within IoT scenarios [53].

To conclude, the current ZigBee, Bluetooth and WiFi that have been employed for connecting numerous wireless devices are still challenged by the requirements of present IoT applications in terms of network range, capacity and power efficiency, which emphasizes the need for usage of other technologies [53]. These technologies are presented in the following.

2.2.2. Long-Range Technologies

To meet the needs of overgrowing IoT demands and applications, especially in terms of lower consumption, cost- effectiveness and long communication range and distances, LPWANs have been considered as the ultimate solution [54]. To this day, LPWAN has been directed to accomplish all of the emerging IoT demands and has broadly been classified as unlicensed and licensed technology [55]. The LPWANs obtain low power and wide coverage range by using the sub-1 GHz unlicensed, industrial, scientific and medical frequency band, high processing gains, narrow bandwidths, and by periodically transmitting packets at low data rates [56].

1. SigFox

Founded in the 2009, the SigFox technology is on of the dominant unlicensed LPWAN solution on the market [43]. By using Binary Phase Shift Keying (BPSK) as Ultra Narrow Band (UNB) modulation (its patented) with a bit rate of 100 bps and operating in the unlicensed sub-GHz ISM bands (e.g. 868MHz in Europe, 915MHz in North America, and 433MHz in Asia), SigFox is able to achieve very low noise levels thus obtaining high receiver sensitivity, lower power consumption as well as low cost antenna design [39]. The Gaussian frequency shift keying (GFSK) modulation is used to downlink and, commonly, 140 messages of 12 bytes per day and four message of 8 bytes per day can be sent over uplink and downlink, respectively [54]. It is important to point out that the downlink transmission takes place only consequently to an uplink transmission.[39]. SigFox protocol stack is composed of three main layers: Frame, MAC and Physical layers as depicted in Figure 2.12 and the network topology is is a star topology as illustrated in Figure 2.13. The element of the network are the end node (end point), gateway (base station), network server (SigFox cloud) and end user application (device application) where gateways are bridges between end nodes and network server and end nodes are connected to the network server by a single hop wireless communication and are not able to communicate with each other directly [57]. SigFox technology ability to transmit with a reasonable level of power and due to gateways high reception sensitivity, SigFox is able to reach a high link-budget [58]. Developers of the SigFox technology assert that this technology can support a million connected devices in a network allowing the urban coverage of 3–10 km and 30–50 km coverage in rural areas [54].

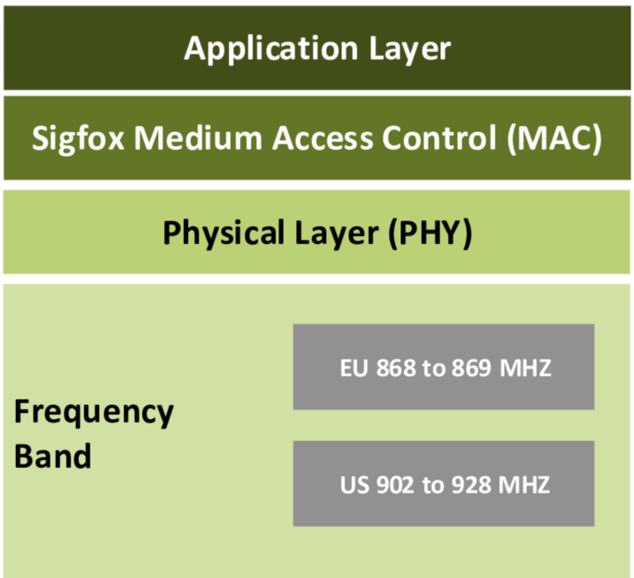

Figure 2.12. Sigfox protocol stack[55]

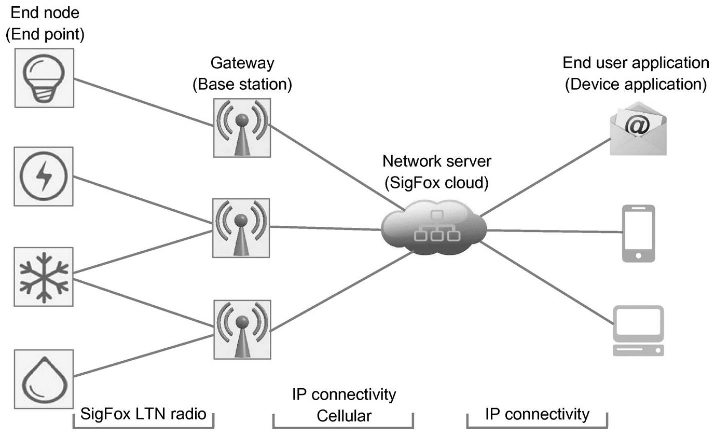

Figure 2.13. SigFox network topology [57]

Research and community has pointed out one large disadvantage of SigFix and that is the fact that it is not an open protocol and only limited to SigFox networks which is not always desirable, especially in occasions where downlink communication and security is important [57], [54]. As a consequence of such restrictions, SigFox has inadvertently turned the interest of academia and industry to its competitor LoRaWAN that has been evaluated as more flexible and open [43].

2. Lora/ LoRaWAN

The LoRa alliance patented the LoRa (standing for long range), a spread spectrum modulation scheme that utilizes Chirp Spread Spectrum (CSS) modulation and which exchanges data rate for sensitivity within a fixed channel bandwidth [59]. It operates within the sub-Gigahertz unlicensed spectrum ISM bandwidths, namely for USA: 915MHz, for EU: 433MHz and 868MHz having a standardized MAC protocol, LoRaWAN, that determines the communication protocol and system architecture of the network for which the LoRa physical layer applies direct sequence spread spectrum with multiple spreading factors (SF) that enable the long-range communication link [60]. LoRa applies six different spreading factors (SF7 to SF12) allowing the adaptation of the data rate and range and thus making it highly resilient to interference, where the generated signal has low noise levels and is difficult to detect or jam [39]. Precisely, a higher spreading factor enables a longer transmission range but at the expense of lower data rate, and vice versa, where the LoRa data rate ranges from 50bps and 300kbps depending on the spreading factor and channel bandwidth [43]. LoRaWAN does not allow device-to-device communications working mainly in the uplink and, if need be, network servers can send downlink data and control packets to end devices [61]. Different functionalities for bidirectional communications lead to the definition of three main classes of LoRaWAN devices, which have different capabilities to cover a wide range of applications and where each class constitutes a trade-off between battery life and network downlink communication latency [62]. These classes are:

- **Class A**- It is the class of LoRaWAN devices that has the lowest power consumption using pure- ALOHA RA protocol for the uplink and requiring only short downlink communication [43]. The node stays most of the time in the sleeping mode initiating communication and transmitting to the gateway when necessary [58].
- **Class B**- In the Class B, the nodes open an additional receive window at a specific period in addition to the random receive windows of class A. The gateway sends beacon frames for synchronization between the nodes in class B [63]. The communication is slotted, synchronized by an external beacon, which allows the server to know when the end device is listening [60].
- **Class C**- Within this class, devices continuously listen for incoming messages, i. e. they are always available to receive downlink messages unless transmitting (no latency), which is why devices from this class are deployed for real-time applications, where power is not constrained. [62].

Figure 2.14 depicts the LoRa and LoRaWAN protocol stacks.

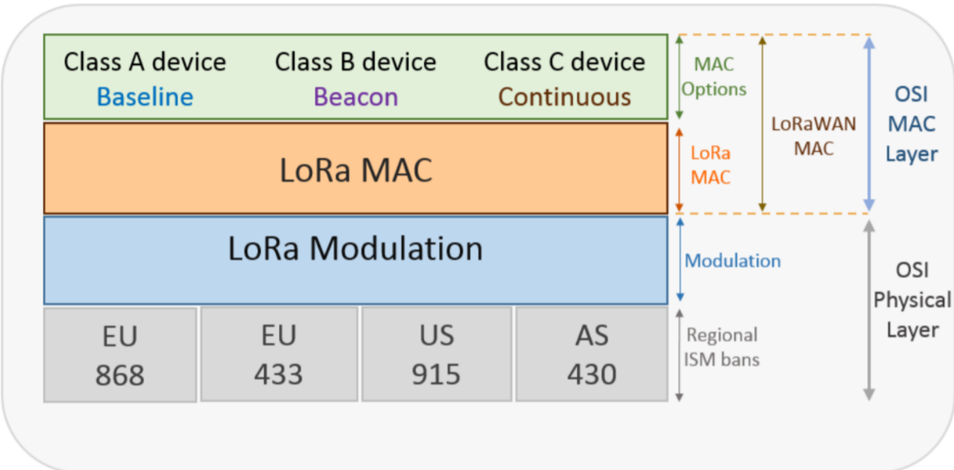

Figure 2.14. LoRa and LoRaWAN protocol stack [58].

LoRaWAN exibits a star-of-stars topology, depicted in Figure 2.15, made out of LoRa modules (end-devices), one (or more) LoRa gateways; and a central network server where the gateway devices relay messages between end-devices and a central network server [43]. The central server further transmits the received packets to the application server, which then processes them for further application usages.

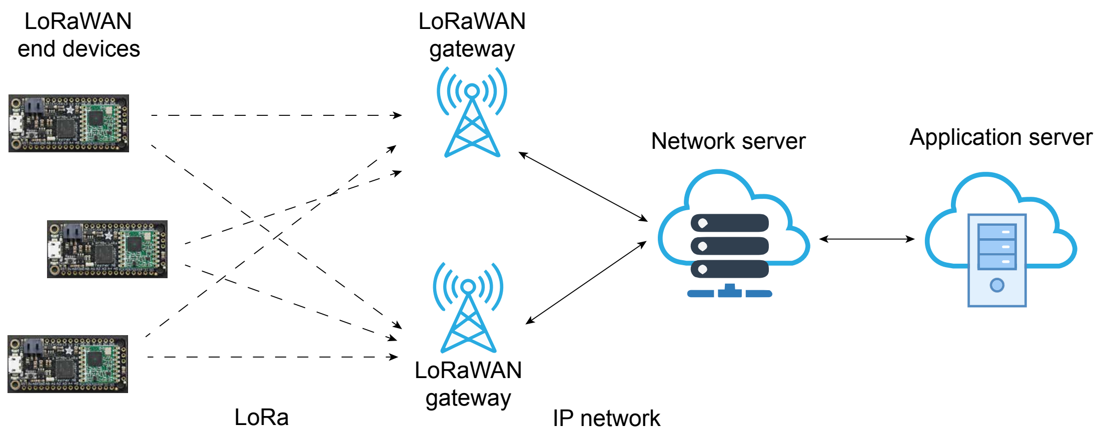

Figure 2.15. LoRaWAN (Long Range Wide Area Network) architecture.

One of the major LoRaWAN advantages are its scalability, since it can reach up to millions of devices depending the scenario, the average message transaction rate, the average size of the transmitted message as well as the the number of used LoRa channels [58]. Another crucial advantage of LoRa it lies within the fact that a single base station can cover hundreds of square kilometers [60]. However, the range may depend on the environment or obstructions.

LoRaWAN will reduce the nodes cost, providing extended battery lifetime and increase the capacity of the network, which makes it suitable for WSN that requires low communication range, low energy consumption and low data rate [63]. What is more, althogh LoRaWAN ensures data rates from 0.3 kbps up to 50 kbps, with the maximum payload length for each message of 243 bytes, which is considered sufficient for transmission of real-time sensor data in the IoT, Machine-to-Machine or industrial applications, the transmission of real-time image data, or anything that requires high bandwidth may not be suitable on LoRa networks [60]. LoRa technology has been compared in-depth with other LPWAN technologies in terms of architecture, battery lifetime, network capacity, device classes and was rated as advantageous, but, interestingly, the security issues in LoRa were mentioned repeatedly in several studies, pointing out to the potential security vulnerabilities of LoRa which may expose the LoRa network to jamming attacks [60].

3. NB-IoT

NB-IoT is a narrowband LPWAN technology operating under licensed frequency bands used in Long-Term Evolution (LTE) and released by the Third Generation Partnership Project (3GPP) with the aim of scaling the WSN devices to be usable and more dependable [63]. Due to the fact that NB-IoT is a 3GPP technology it can exist alongside with global system for mobile communications (GSM) and LTE in licensed frequency bands of 700 MHz, 800 MHz, and 900 MHz, which can utilize the existing network hardware and reduce the deployment cost, supporting bi-directional communication using orthogonal frequency division multiple access (OFDMA) for downlink and and single carrier frequency division multiple access (SC-FDMA) is for uplink [64]. In downlink a maximum throughput rate is 200 kbps and 20 kbps in uplink, where each message has a 1600 bytes of payload size [39]. NB-IoT design optimizes and reduces functionalities of LTE enabling its employment for sporadic data transmissions and with low power requirements achieving 10 years of battery lifetime [64]. With respect to the spectrum occupied within a LTE carrier, three different deployments, illustrated in Figure 2.16, are possible:

- **Stand-alone operation mode**: employs some of the available spectrum, such as GSM channel with 200 kHz and 10kHz guard interval on both sides of the spectrum [54].
- **Guard band operation mode**: exploits the unemployed resource blocks within an LTE carrier's guard-band not disturbing its capacity [43].
- **In-band operation mode** exploits one or more LTE physical resource blocks within an LTE carrier [39].

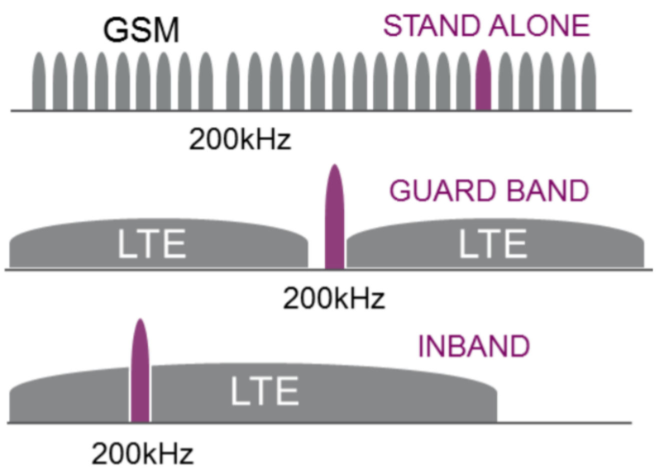

Figure 2.16. NB-IoT Deployment Modes [62].

In order to extend battery life, NB-IoT suports two main power efficiency mechanisms: the power saving mode (PSM) and expanded discontinuous reception (eDRX) [65]. In PSM mode a device will be registered with network but the functions like paging listening and link quality measurements will be turned off, whereas in the eDRX mode the device will negotiate a sleeping period in which the receiving functionality will not be turned on [43].

Figure 2.17 outlines the key parameters of the NB-IoT technology.

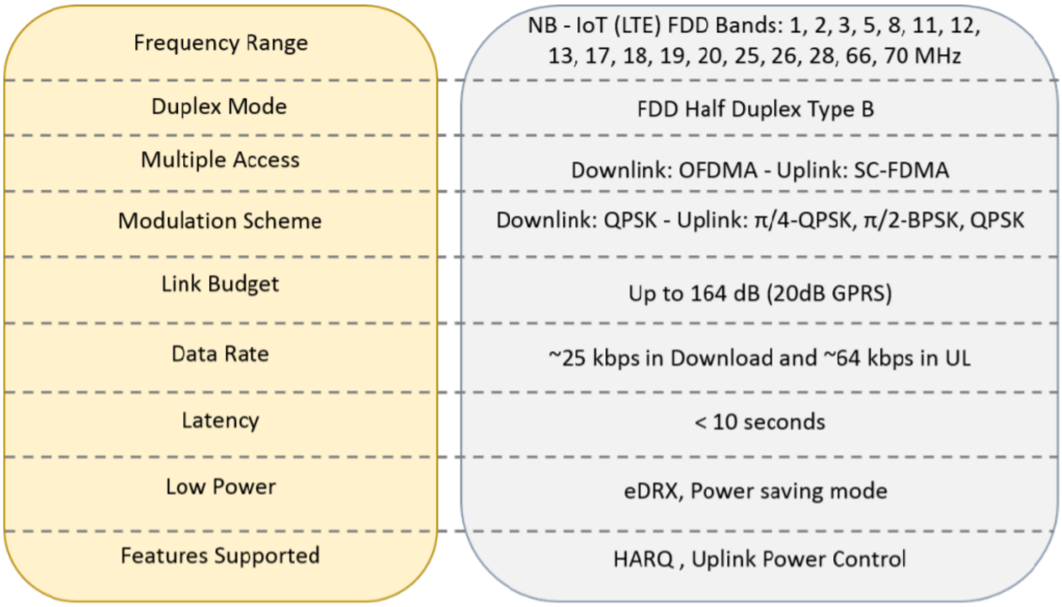

Figure 2.17. NB-IoT key parameters [58]

The NB-IoT technology advantages are emphasized within its characteristics like enhanced indoor coverage, low power consumption, latency insensitivity and ability to connect more than 50k devices per cell, making it a fair candidate in the LPWA market [66]. Through LTE optimization, NB-IoT aims to meed the demands of cost efficiency, low data transfer and high network device density and in line with the ongoing 3GPP plan, NB-IoT will be extended to include multicast services (e.g. end-device software update and messages concerning a whole group of end-devices), mobility, as well as further technical details to enhance the applications field of NB-IoT technology [39]

2.3. Machine Learning: a general overview

In the IoT paradigm of numerous smart connected devices, Machine Learning has emerged as an essential field of research and application aiming at providing computer programs the ability to automatically improve through experience [67]. The most distinguished attribute of a learning machine is that the trainer of learning machine is ignorant of the processes within it [68]. Machine learning generally includes data processing, training, and testing phases with the aim of making the system able to carry out decisions based on the input received from the training phase [17]. In order to archive the learning process, systems use various algorithms and statistical models to analyze the data and gain information about the correlation between the data features [16]. The algorithms that are used in these processes can be divided into four distinctive groups, as Supervised, Unsupervised, Semi-supervised, and Reinforcement learning algorithms:

- Supervised learning algorithms demand external monitoring by a supervisor with the goal of learning how to map input values to the output values where the accurate values are given by a supervisor [69].
- Unsupervised learning algorithms make computers learn how to perform a specific task only with the provided unlabeled data. These types of algorithms need to find existing relationships, irregularities, similarities, and regularities in provided input data [70].
- Semi-supervised learning is a hybrid approach of the previous two categories that uses both labeled data and unlabeled data. These algorithms generally act like the unsupervised learning algorithms with the improvements that are brought from a portion of labeled data [71].
- Reinforcement learning algorithms operate with a restricted insight of the environment and with limited feedback on the quality of the decisions. In order to operate effectively and provide the most positive outcome, these algorithms have the ability to selectively ignore irrelevant details [72].

ML has been ideally suited for various types of problems, such as as classification, clustering, predictions, pattern recognition, etc. The most appropriate ML algorithm is chosen based on the swiftness of the technique and its computational intensity, depending on the application type [16].

Nowadays, Deep Learning has become one of the leading Machine Learning techniques efficient in solving complex problems that have otherwise been impossible to solve while using more traditional ML approaches [17]. Deep Learning has been recognized as one of the ten breakthrough technologies of 2013 and fastest-growing trend in big data analysis [73]. Deep Learning applications have achieved remarkable accuracy and popularity in various fields, especially in image and audio related domains [17]. Deep Learning techniques effectively give insights from the data, comprehend the patterns from the data, and classify or predict the data [74]. Neural networks that involve more than two hidden layers have been considered to be a characterization of DL and the word 'deep' signifies the large number of hidden layers that compose the neural network [73]. Implementations of deep learning technology today is achieving a large success in a variety of engineering and technical problems, including object detection, traffic engineering, traffic classification, and prediction [75, 76, 77, 78].

2.3.1. Algorithms

1. Support Vector Machine

The idea of Support Vector Machine (SVM) was introduced by Vapnik in mid 1990-ties and today this a well known machine learning algorithm used in various applications from classification, forecasting to pattern recognition. The SVM implements the idea of mapping input vectors into a high-dimensional space $\mathcal{F}$, which is furnished with a dot product, using a non-linear mapping selected a priory [79]. This idea has been generalized to become applicable to regression problems using Support Vector Regression (SVR) briefly presented in the following.

Let us consider a training set $T = \{(x_i, y_i) \mid x_i \in \mathbb{R}^n, y_i \in \mathbb{R}, i = 1, \ldots, n\}$, where $X = (x_1, \ldots, x_n)$ are sampling data and $Y = (y_1, \ldots y_n)$ target vaules. The objective of SVR is to find function $f(x)$ that has at most ε- deviation from the observed target y_i for all training data, enforcing flatness. This function can be defined as a linear function

$$f(x) = \omega\Phi(x) + b, \tag{2.1}$$

where $\Phi : \mathbb{R}^n \to \mathcal{F}$ is the map into the higher dimensional feature space, ω represents vector of wights of the linear function and b is the bias. Desired function which is optimal is chosen by minimizing the function

$$\Psi(\omega, \xi) = C \cdot \sum_{i=1}^{n} (\xi_i + \xi_i^*) + \frac{1}{2} \|\omega\|^2, \tag{2.2}$$

where ξ, ξ^* are non negative slack variables that measure the upper and lower excess deviation, $\|.\|$ is the Euclidean norm ($\frac{1}{2} \|\omega\|^2$ represents regularization term), C is a regularization parameter which allows the tune of the trade-off between tolerance to empirical errors and regularization term. $\Psi(\omega, \xi)$ must satisfy following constraints:

$$\begin{cases} y_i - \omega\Phi(x_i) + b_i \leq \varepsilon + \xi_i \\ \omega\Phi(x_i) + b_i - y_i \leq \varepsilon + \xi_i^* \\ \quad \xi, \xi^* \geq 0,\ i = 1, .., n \end{cases} . \tag{2.3}$$

Furthermore, the most prominent feature of SVR is the ability to establish correlation between data using non-linear mapping. This is achieved using kernel functions for generating the inner products, know as kernels, which satisfy Mercer's theorem. One of the broadly used kernels are polynomial and Gaussian radial basis function (RBF) kernels. The RBF kernel is given with the formula:

$$K_\gamma(|x - x_i|) = \exp\left\{-\gamma \cdot |x - x_i|^2\right\} \tag{2.4}$$

The necessary parameters γ, C and ε can be selected with grid search process of performing hyper parameter tuning in order to determine the optimal values for a given model.

2. Neural Networks

Neural Networks, or Artificial Neural Networks (ANN), have gained large attention in the last two decades as a Machine Learning technique in a variety of areas for prediction and classification task [16]. Inspiration for their architecture was taken from the brain nervous system in a form of a mathematical model designed to mimic the structure and functionalities of the real biological neural networks [80]. They have been applied in many divers areas of scientific research such as pattern recognition [81], image classification [82], language processing [83], computer vision [84] as well as time series forecasting [85].

Generally, the neural network consists out of three basic layers as shown in Figure 2.18, namely the input layer, the hidden layers, and the output layer. The neural network can have more than one hidden layer, which represents the depth of the neural network. The imitation of the brain learning processes is done by searching the hidden links between a series of input data using hidden layers of neurons, where the output of a neuron of a layer becomes the input of a neuron of the next layer. An artificial neuron y_i can be defined as a function

$$y_i = f_i(x) = \varphi(\langle w_i, x \rangle + b_i), \tag{2.5}$$

which acts on a linear combination of the input vector $x = (x_1, ..., x_n)$ and a neuron bias b_i [86].

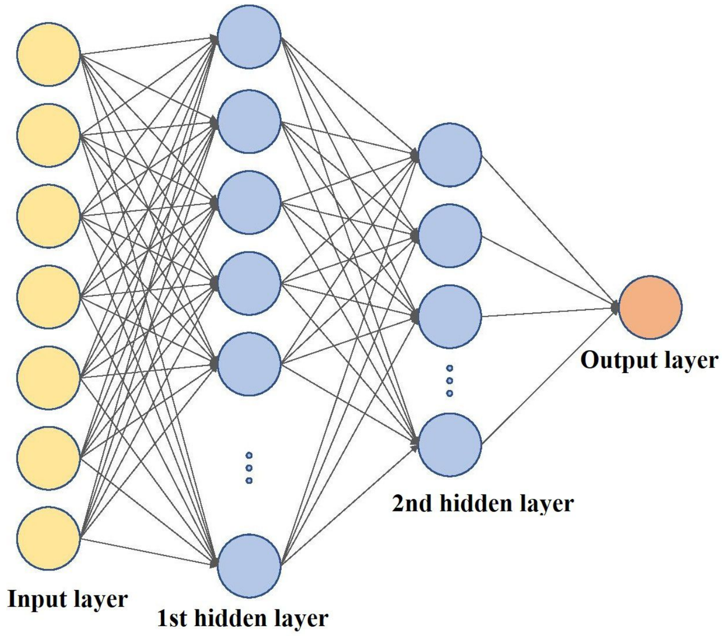

Figure 2.18. Example of a Neural Network Architecture

Input vector is weighted with the connection weight vector $w_i = (w_{1,i}, ..., w_{n,i})$ and the φ is called activation function. Performance of the training process and estimation (or prediction) accuracy of the NN is highly influenced by the weight initialization and the activation function [87]. The activation function will control the amplitude of the output of the neuron keeping it in a usually acceptable range of $[0,1]$ or $[-1,1]$ [88]. Activation functions are divided into linear and non-linear activation function and non-linear ones are most commonly used. Some of most frequently applied non-linear activation functions are Sigmoid, Rectified Linear Unit (ReLU) and Tanh function. Sigmoind function can be defined as $S(x) : \mathbb{R} \to [0,1]$

$$S(x) = \frac{1}{1+e^{-x}}.$$

The Sigmoid function is continuously differentiable but suffers from gradient vanishing [87], which can significantly slow down the learning process. This problem has been resolved using ReLU activation function.

ReLU function can be defined as $\phi : \mathbb{R} \to \mathbb{R}^+$

$$\phi(x) = \begin{cases} \lambda x, x > 0 \\ \beta x, x \leq 0 \end{cases},$$

where commonly $\lambda = 1$ and $\beta = 0$. As can be seen from the function's definition, the derivative of the function will be quite simple, 1 for positive values and 0 otherwise. Therefore, the average derivative is rarely close to 0, which allows gradient descent to keep progressing. Hence, ReLU has been mainly used as an activation function for the neurons placed in hidden layers [87], while Sigmoid has been used as a activation function for the neurons placed in the output layer.

As seen, layers comprise artificial neurons, where every neuron has multiple weights and some form of transfer or activation function. Neural network is a supervised learning algorithm in which the weight of the neurons is calculated during the training process. Because of the training procedure, the input data to the network should cause the output as close to the ground truth. To accomplish this, during the training procedure, which is an iterative procedure, a loss (cost) function is used to determine the quality of the network with specific weights. For a binary classification problem, such as parking lot occupancy, Binary Cross-Entropy Loss, as one of the commonly used loss functions is often utilized. To minimize loss function during the training phase in which the weight of neurons is determined, a good deal of optimization algorithms have been implemented, many of which are first-order iterative optimization algorithms such as: Stochastic Gradient Descent (SGD), Adaptive Moment Optimization (Adam), and Root Mean Square Propagation (RMSProp).

3. Long-Short Term Memory (LSTM) neural network

Recurrent Neural Networks are based on the recursive structure in which the one-step model with a time-step is trained first and then recursively used to return the multi-step prediction [89]. A special type of RNN is Long-Short Term Memory (LSTM) neural network constituted out of a set of recurrently connected memory blocks – LSTM cells (depicted in Figure 2.19). LSTM cell consists out of four layers, main layer and three layers which are gate controllers each computing values between 0 and 1 based on their input [22].

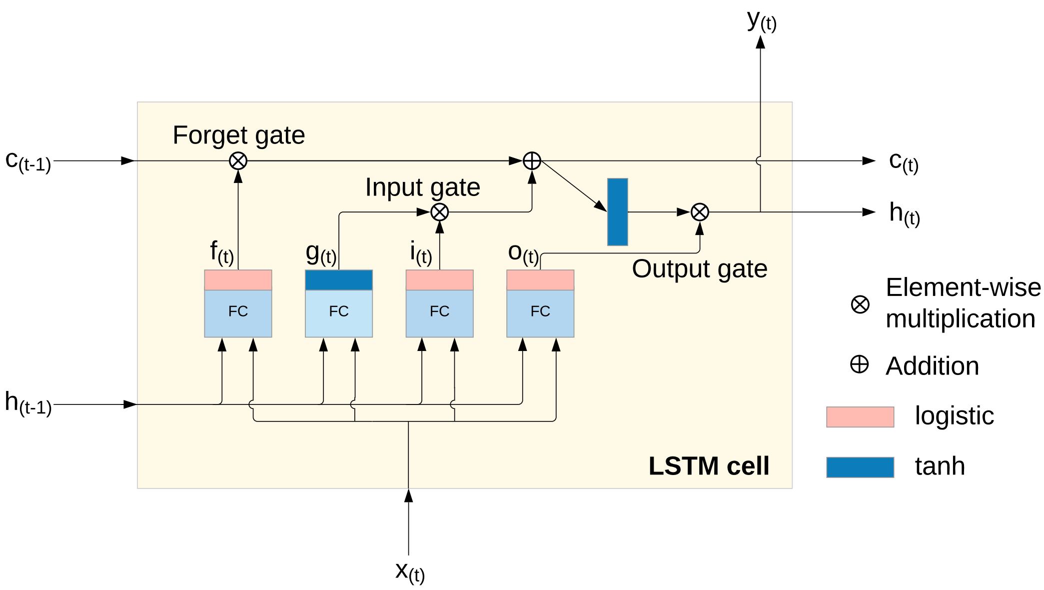

Figure 2.19. Long Short-Term Memory (LSTM) cell.

Layers operate in the following way:

- Main layer - analyses the current inputs $x_{(t)}$ and the previous (short-term) state $h_{(t-1)}$ then outputs the $g_{(t)}$ vector;
- Forget gate $f_{(t)}$ decides parts of the long-term state $c(t-1)$ that need to be erased;
- Input gate $i_{(t)}$ controls parts of $g_{(t)}$ that are added to the long-term state $c_{(t)}$;
- Output gate $o_{(t)}$ determines which parts of long-term state should be read $c_{(t-1)}$ and given to the output y(t) and short-term state $h_{(t)}$ at the current time step(t).

The states of the cell are calculated using equations given below:

$$i_{(t)} = \sigma(W_{xi}^T \cdot x_{(t)} + W_{hi}^T \cdot h_{(t-1)} + b_i) \tag{2.6}$$

$$f_{(t)} = \sigma(W_{xf}^T \cdot x_{(t)} + W_{hf}^T \cdot h_{(t-1)} + b_f) \tag{2.7}$$

$$o_{(t)} = \sigma(W_{xo}^T \cdot x_{(t)} + W_{ho}^T \cdot h_{(t-1)} + b_o) \tag{2.8}$$

$$g_{(t)} = tanh(W_{xg}^T \cdot x_{(t)} + W_{hg}^T \cdot h_{(t-1)} + b_g) \tag{2.9}$$

$$c_{(t)} = f_{(t)} \otimes c_{(t-1)} + i_{(t)} \otimes g_{(t)} \tag{2.10}$$

$$y_{(t)} = h_{(t)} = o_{(t)} \otimes tanh(c_{(t)}) \tag{2.11}$$

where σ represents logistic activation function, *tanh* is hyperbolic tangent function, $W_{(x)}$ are weight matrices for each of the four layers for input vector $x_{(t)}$, and $W_{(h)}$ are matrices of the previous short-term state $h_{(t-1)}$. Finally, b denotes the bias term of each layer. Difference between the LSTM and the standard RNN is within their structure to memorize. With traditional RNN parts of information are lost in the process of each feedback resulting in RNN not being able to have long time memory in contrast to LSTM which has a long term memory. LSTM is able to remove or add information to the cell state, unlike the mechanism that completely overrides cell states like in standard RNN [90]. Long dependency in time can be observed in IoT applications such as environmental monitoring, human activity recognition, or machine translation and LSTM models have proven to perform better than RNN for such data [22]. LSTM cells are very successful at capturing long-term patterns in time series data and that was one the reasons for their selection as Deep Learning approach for prediction.

4. Random Forest

Random Forest (RF) as an ensemble learning Machine Learning approach to classification and regression was first introduced by Breiman in 2001. [91]. It has successfully been utilized in many research and application domains and has become a standard in non-parametric classification and regression Machine Learning technique for making predictions based on different types of variables without making any prior assumption of how they are associated with the target variables [92]. Its application ranges from bioinformatics [93], intrusion detection systems [94] computer vision [95], RS land cover classification [96], as well traffic accident detection [97], crop classification based on object-based image analysis [98] and DDoS attack detection [99].

Formally, RF can be defined as a classifier constructed out of a collection of tree-structured classifiers $\{c_k(x,T_k)\}, k = 1,...,L$, where T_k are independent identically distributed random samples (vectors) and for a input x, each of the trees casts a unit vote for the most popular class [100] as depicted in Figure 2.20.

The trees are generated using a bagging approach, that is by producing random samples of training sets through replacement, where some samples can be taken several times and others may not be taken at all [101]. For a given training set T constructed classifiers $\{c_k(x,T_k)\}$ cast a vote and make the *bagged* predictor and for each y,x in the train set the votes from classifiers for which the T_k did not contain y,x are stored as *out-of-the- bag* classifiers [91]. Generally, samples used for training the trees are taken from two thirds of the instances and the remaining one third are used in an inner cross-validation technique that estimates the resulting RF model performance [101]. The *out-of-the-bag* estimate for the generalization error is the error rate of the *out-of-the- bag* classifier on the training set and this estimate is as accurate as using a test set of the same size as the training set, thus removing the need for a set aside test set [91]. Com-

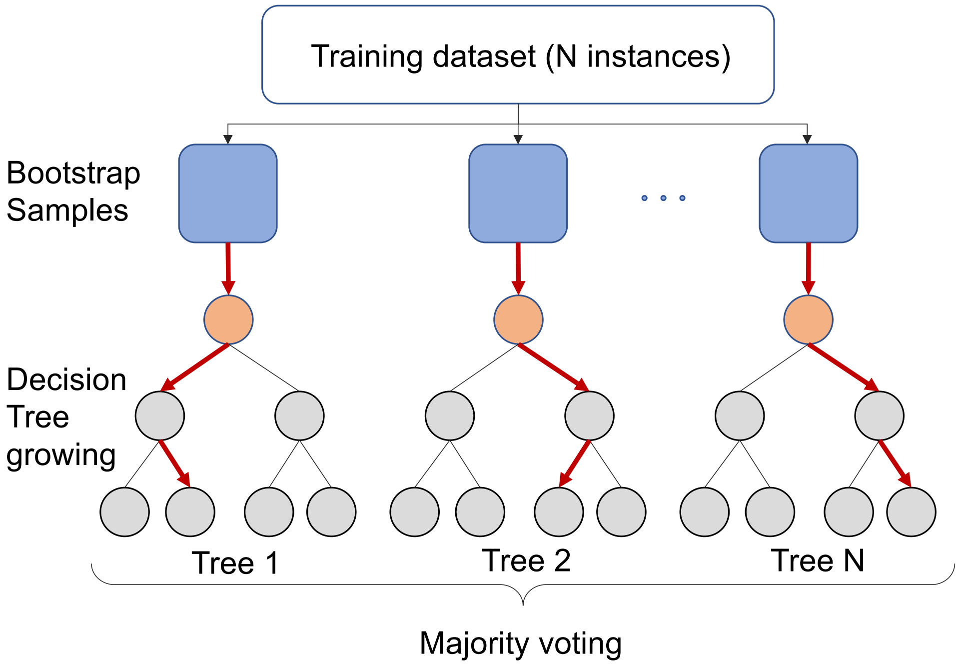

Figure 2.20. Example of an Architecture of Random forest model.

monly, user defines the number of trees and the algorithm creates trees that have high variance and low bias where each decision tree is independently produced without any pruning, and each node is split using a user-defined number of features that are randomly selected [101]. The error rate will decrease as the number of combinations increases and therefore the *out-of-the-bag* estimates will tend to overestimate the current error rate and therefore it is necessary to run past the point where the test set error converges [91]. Final classification is done by taking the average of class assigned probabilities calculated by all generated trees and new data given as an input is accordingly evaluated against all decision trees produced in the ensemble and each tree votes for a class membership [101]. The class which has the biggest overall number of votes is the one that in chosen in the end.

5. Hidden Markov Models

Hidden Markov Models (HMMs) have been known for decades and today are making a large impact with regard to their applications, especially in form of Machine Learning models and applications in reinforcement learning. They are widely being used for pattern recognition [102], i.e. namely speech recognition [103] as well as in biological sequence analysis [104], gene sequence modeling, activity recognition [105] and analyses of ECG signal [106, 107]. Markov Chains and process were introduced by the Russian mathematician Markov in 1906 when he obtained a theoretical result for a stochastic process. Markov process can be considered a time-varying random phenomenon for which Markov properties are attained. It's practical importance is the use of the hypothesis that the Markov property holds for a certain random process in order to build a stochastic model for that process [108]. Such a process has a fixed number of states, and it randomly evolves from one state to another at each step. The probability for it to evolve from state *a* to a state *b* is fixed, and it depends only on the pair (*a*,*b*), not on past states (the system has no memory) [109].

In the broadest sense, a Hidden Markov model (HMM) is a Markov process that can be divided into two parts: an **observable** component and an unobservable or **hidden** component. The observation is a probabilistic function of the state, i.e. the resulting model is a doubly embedded stochastic process, which is not necessarily observable, but can be observed through another set of stochastic processes that produce the sequence of observations like illustrated in Figure 2.21.

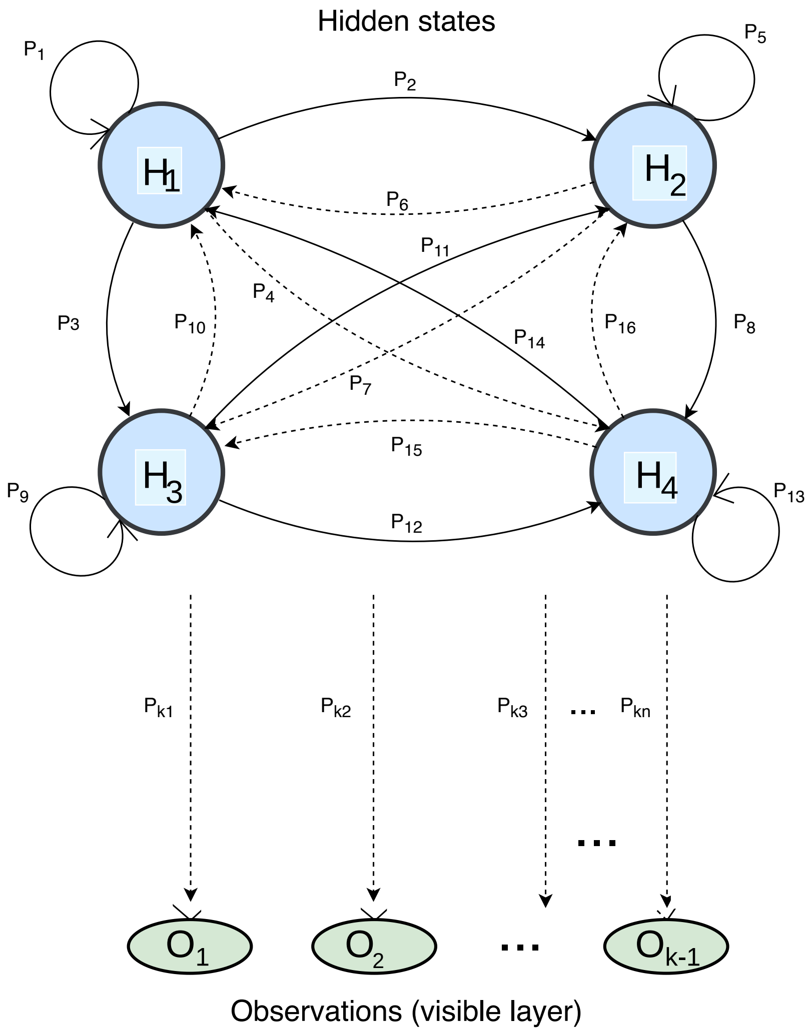

Figure 2.21. Example of Hidden Markov Model for four hidden states

A machine learning algorithm can apply Markov models to decision making processes regarding the prediction of an outcome.

In 1986 Rabiner and Juang [110] gave the structure of the first order Hidden Markov Model denoted as $\lambda(A,B,\pi)$, where $A = \{a_{ij}\}$ is the matrix of transition probabilities, $B = \{b_j(k)\}$ is the matrix of observation probability distribution in each state and π is the initial state distribution. Rabiner (1989) presented [111] three different types of problems in HMM: The Evaluation Problem, Decoding problem and Learning.

1. **The Evaluation Problem.** Given the observation sequence $O = o_1, o_2, \ldots, o_T$, and the model $\lambda(A,B,\pi)$, how to compute $\mathbb{P}(O \mid \lambda)$, the probability of the observation sequence.

2. **Decoding.** What is the most likely state sequence in the given model that produced the given observations.

3. **Learning.** How to adjust the model parameters $\lambda(A,B,\pi)$ to maximize $\mathbb{P}(O \mid \lambda)$.

The first problem is commonly solved by using the Forward or Backward algorithm, where as the last problem is, the most difficult of the three problems, usually solved using Baum-Welch method. With regards to the second problem the central issue is to find the optimal sequence of states to a given observation sequence and model used. Most common method to this is by using the **Viterbi algorithm**, introduced by Andrew Viterbi in 1967 as a decoding algorithm for convolution codes over noisy digital communication links. It is the answer to the decoding problem resulting in the Viterbi path, since the algorithm can be interpreted as a search in a graph whose nodes are formed by the states of the HMM in each of the time instant [108]. Let $\lambda(A,B,\pi)$ be a HMM and $O = (o_1, o_2, \ldots, o_T)$ given observations. The Viterbi algorithm finds single best state sequence $q = (q_1, q_2, \ldots, q_T)$ for the given model and observations. The probability of observing $o_1, o_2, \ldots, o_t$ using the best path that ends in state i at the time i given the model λ is:

$$\delta_t(i) = \max_{q_1,q_2,\cdots,q_{t-1}} \mathbb{P}(q_1, q_2, \ldots, q_{t-i}, q_t = i, o_2, o_2, \ldots, o_t \mid \lambda) \tag{2.12}$$

$\delta_{t+1}(i)$ can be found using induction as:

$$\delta_{t+1}(i) = b_j(o_{t+1}) \max_{1 \leq i \leq N} [\delta_t(i) a_{ij}] \tag{2.13}$$

To return the state sequence, the argument that maximizes Equation (2) for every t and every j is stored in a array $\psi_t(j)$ [110]. It is important to point out that The Viterbi algorithm can be implemented directly as a computer algorithm. Moreover, the algorithm succeeds in splitting up a global optimization problem so that the optimum can be computed recursively: in each step we maximize over one variable only, rather than maximizing over all n variables simultaneously.

Hidden Markov models have been used now for decades in signal-processing applications, such as speech recognition, but the interest in models has been broaden to fields of all kind of recognition, bioinformatics, finance etc. [112].

With regards the first order Markov model, if the past and the present information of the process is known, the statistical behaviour of the future evolution of the process is determined by the present state. Thus, the past and the future are conditionally independent (the system has no memory) [113]. Therefore, it is reasonable to ask can there be a model which can gather and somewhat keep information from the past. The answer lies within a higher-order Markov models, where the hidden process is a higher order Markov chain and it is dependent on previous states. This gives memory to the model and such a modeling is more appropriate for processes in which memory is evident and important, for example a stock market time series.

6. *k*- Nearest Neighbour (*k*-NN)

One of the most straightforward, fundamental and extensively used algorithms for classification (although it can be applied for regression as well) is the *k*- Nearest Neighbour algorithm. It was first introduced by Fix and Hodges in 1951 as non-parametric method for pattern classification and was later formally elaborated and defined by Cover and Hart in 1967 [114]. For almost half a century, *k*-NN has been explored and implemented in numerous problems related to pattern classification such as pattern recognition, ranking models, text categorization as well as object recognition and has been recognized as one of the top ten data mining techniques [115]. *k*-NN needs no prior knowledge about data distribution and has been labeled as as a "lazy learning" or "instance-based learning" algorithm [71]. The algorithm will use raw training instances to make decision and no learning of the model is needed, i. e. it will not construct a mapping function or an internal model- the computational outcome will be derived directly from training data set stored in the memory [116].

The basic operation of the *k*-NN is founded on the calculation of distances among the tested and the training data samples for identification of its nearest neighbours thus assigning the tested instance to a particular class of its nearest neighbour[117]. One of the *k*-NN advantages are simplicity of implementation, robustness to noisy training data and its ability to effectively process large training data [118]. In the following some formal definitions will be provided alongside with the mathematical concepts for *k*- Nearest Neighbour that employs distance as a method for classifying data.

Definition 2.3.1. Let S be a set. A **metric** on S is a function $d : S \times S \to \mathbb{R}$ that satisfies the following properties :

i) (Positivity) For all $x, y \in S$, $d(x,y) \geq 0$; equality holds if and only if $x = y$;

ii) (Simetry) For all $x, y \in S$, $d(x,y) = d(y,x)$;

iii) (Triangle inequality) For all $x, y, z \in S$, $d(x,y) \leq d(x,z) + d(z,y)$.

The couple (S,d) is called a **metric space**, the elements of S are called **points** and the number $d(x,y)$ is called the **distance** between x and y.

Commonly used metrics for k- Nearest Neighbour technique are Euclidean, Manhattan, Minkowsky and Chebyshev distances with Euclidean distance being is the most frequently applied [117]. Some of these are defined in the following.

Definition 2.3.2. Let $x = (x_1, x_2, .., x_n)$ and $y = (y_1, y_2, ..., y_n)$ be points in the $n-$dimensional metric space (X,d).

- The Minkowski distance, commonly know as the L_p norm is defined as:

$$L_p = \sqrt[p]{\sum_{i=1}^{n} |x_i - y_i|^p}. \tag{2.14}$$

- The Euclidean distance norm, also known as the L_2 norm is defined as:

$$L_2 = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2}. \tag{2.15}$$

- The Manhattan distance or the City block distance, otherwise known as the L_1 norm is the special case of Minkowski distance for $p = 1$ and is given with formula:

$$L_1 = \sum_{i=1}^{n} |x_i - y_i|. \tag{2.16}$$

- The Chebyshev distance, also known as chessboard distance or maximum value distance is defined as:

$$D_{Chebyshev}(x,y) = \max_i |x_i - y_i|. \tag{2.17}$$

From the two above formulas it can be seen that the Euclidean distance is just a special case of the Minkowski distance for $p = 2$.

Principle of operation: Let k be a positive integer and let set C be a set of different classes $C = C_1, ..., C_l\}$. For a given $m-$dimensional metric space (X, d) let $\{(x_1, y_1), ..., (x_n, y_n)\}$ be a set of points $x_i \in X$ with their appropriate classses, i.e. $y_i \in C, \forall i = 1, ..., n$, (or in regresssion case let $y_i \in \mathbb{R}$). For a given query point $x \in X$ the k-NN algorithm determines the k closests points to x with respect to metric d, permutates the values y_i and orderes them with respect to the given metric obtaining an ordered set $\{(x_{1'}, y_{1'}), ..., (x_{n'}, y_{k'})\}$. In the case of classification, the corresponding class $y(x)$ of the point x will be determined by majority voting rule, where as in the regression case, $y(x)$ is calculated using formula:

$$y(x) = \sum_{i'=1}^{k} \omega_{i'} y_{i'}, \tag{2.18}$$

where number $\omega_{i'}$ represents weight of each point, commonly calculated as $\omega_{i'} = \frac{1}{d(x, x_{i'})}$.

The majority voting rule for classification problems can also be expressed using Formula 2.18, where all weights are set to be $\frac{1}{k}$ and

$$y(x) = \begin{cases} 1, \text{ if } \sum_{i=1}^{k} y_{i'} > \frac{1}{2} \\ 0, \text{ if } \sum_{i=1}^{k} y_{i'} < \frac{1}{2} \\ \text{a tie otherwise.} \end{cases} \tag{2.19}$$

Figure 2.22 represents an example of k- Nearest Neighbour classification. The test sample (the green star within the two circles) needs to be classified as class 1 of purple squares or class 2 of red circles. For $k = 1$ it is assigned to class 1 since there is only one square within that circle. For $k = 3$ (outside the first circle) it is assigned to the second class since there are 2 red circles and only 1 purple square inside the inner circle. For the case of $k = 5$ the green star will be classified belonging to the first class since there are 3 purple squares vs. 2 red circles outside the outer circle.

The main disadvantages of k- Nearest Neighbour algorithm are its dependence of the appropriate selection of distance (metric), high computational time since for every new instance, all the distances from k-neighbors need to be calculated all over [118], [115]. What is more, the k-NN inherits instability with respect to the order in which the data are presented to the algorithm which is not desirable and can be avoided by labeling the data, but at the cost of expanding the computational time [119]. What is more, if the class probability estimation is based on a simple voting, it can be a drawback if the nearest neighbors vary extensively in their distance and the closer neighbors more reliably indicate the class of the points, indicating that it may be prudent to give weight to each of the points based on their distance [120].

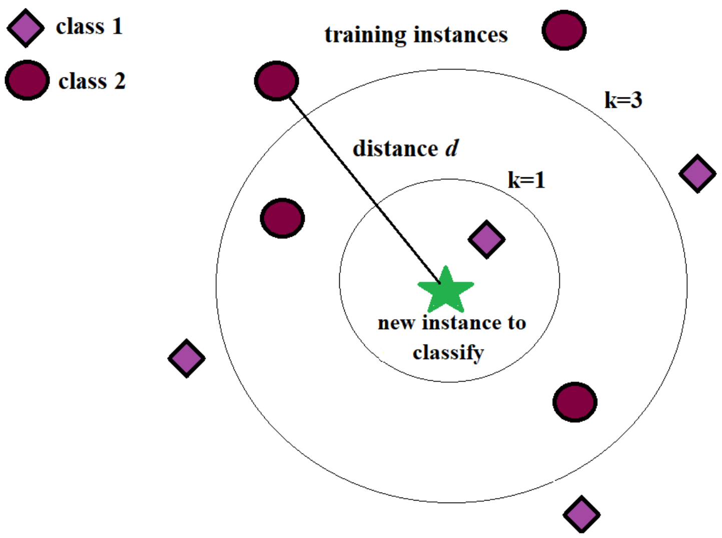

Figure 2.22. Example of k- Nearest Neighbour classification.

2.3.2. Algorithm evaluation techniques

Finally, it is important to address some of the most common evaluation techniques that are being employed for performance testing of particular prediction or classification algorithms. If the predictive algorithms most frequently used evaluation metrics are Mean Squared Error (MSE) and Mean Absolute Error (MAE), defined as:

$$MSE = \frac{1}{2m}\sum_{i=1}^{m}(\hat{y}^{(i)} - y^{(i)})^2. \tag{2.20}$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|\hat{y}^{(i)} - y^{(i)}|. \tag{2.21}$$

MSE is usually the loss function used for estimation of error. Smaller MSE implies higher estimation accuracy. MSE gives average squared difference between the estimation and expected results whereas MAE measures the average magnitude of errors in a group of estimations. Moreover, validation loss represents how well or poorly the model behaves during training.

In binary classification problems like classification of free or occupied parking space, a particular set of evaluation metrics has been used by the research community to evaluate different characteristics of the classifier. Namely, the metrics used are Accuracy, F1 score, Area under the Receiver Operating Characteristic Curve Accuracy (ROC AUC) and Average Precision (AP).

- **Accuracy**—it is defined as the overall accuracy or proportion of correct predictions of the model and it is given with the formula:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}, \tag{2.22}$$

where TP and TN denote the number of positive and negative instances that are correctly classified. FP and FN denote the number of misclassified negative and positive instances, respectively.

- **F1 score**—F1 score is the harmonic mean of the Precision and Recall. Precision is defined as the number of correct predictions out of all the predictions based on the positive class, whereas Recall is the number of instances of the positive class that were correctly predicted [17]. F1 score is calculated while using formula:

$$F1\ score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}. \tag{2.23}$$

  The F1 score takes values from the $[0, 1]$ interval, reaching minimum for TP = 0, that is, when all the positive samples are misclassified, and the maximum for FN = FP = 0, which is for perfect classification [121].

- **ROC AUC**—the Receiver Operator Characteristic (ROC) curve is an evaluation metric for binary classification problems and it is a probability curve that is created by plotting the True Positive Rate (TPR) versus the False Positive Rate (FPR) [17]. The Area Under the Curve (AUC) represents a separability measure of classifiers, i.e., the ability of the classifier to distinguish between classes [122]. The ideal classifier will have the unit area under the curve and a worst case classifier will have FPR = 100% and TPR = 0 [17].

- **Average Precision**—it is the measure that considers both Recall and Precision and can be expressed as a function $p(r)$ of the recall and it is given with [123]:

$$Average\ Precision = \int_0^1 p(r)dr. \tag{2.24}$$

3. State of the art

This Chapter gives State of the art for Smart Parking solutions, providing an insight into scientific literature that has employed the technological architecture elaborated in Chapter 2. It presents various solution laid by researches aiming to improve parking space detection and future occupancy prediction for further utilization. Finally, this Chapter brings a particular emphasis on solutions that have elaborated and tested in detail all of the three distinguishing components of Smart Parking Solutions: sensor type, communication protocol and Machine Learning employment.

3.1. Literature overview

An IoT based smart parking system presented in research [124] exhibits a solution that provides parking lot occupancy information, parking slot reservation and payments using a mobile app. The solution is based on the Passive Infrared and Ultrasonic Sensors to sense parking slot availability where information is send using Wi-Fi and a raspberry pi acts as an intermediate between the sensors and cloud allowing communication with the cloud to process collected data. Finally, the mobile application serves as an interaction interface between the end user and the system.

In [125], the authors designed a prototype of a parking occupancy monitoring and visualization system that uses an ultrasonic sensor being controlled by an Arduino Uno which uses a Wireless XBee shield and an XBee Series 2 module for communication. The data collected from the sensor is then given as an input to a algorithm that detects parking space statues and reports to a database in a real-time basis.

Research presented in [126] describes a system based on ultrasonic sensors for detection of parking spaces. Information about occupancy is then sent via Zigbee protocol to an information center, where as a Bluetooth station is employed to identify a user within the parking lot. By employing a proposed "Shortest path search algorithm", the user will be able to find the swiftest ways to a free parking space. All the collected data is onwards sent via Wi-Fi to a parking a management menu.

In [127], the authors used a light detection and ranging optical sensor in order to measure the distance between a car and an object next to it. They have combined this sensor with a GPS receiver to determine the speed of a vehicle in a particular pair of geographic coordinates and a web camera to track tests. The information were then sent to a Raspberry Pi connected to the cloud via LTE-IEEE 802.11p protocol for further data processing and analyses. Parking situations were estimated by applying machine learning (not explicit which one) obtaining accuracy above 95%.

Research that was conducted in [128] uses video camera sensors for detecting multiple parking space occupancy. Using image processing techniques: the Histogram of oriented Gradient (HOG) descriptor, the Scale-invariant feature transform (SIFT) corner detector, and Metrics on Color Spaces YUV, HSV, and YCrCb authors achieved an accuracy rate of over 93% for parking lot occupancy detection.

Employment of RFID sensors in a smart parking scenario has been explored in [129]. The solution is based on RFID readers, passive RFID tags, barriers, retractable bollards, Wi-Fi spots and a database. Readers are placed at the entrance and exit of the parking area allowing entrance to cars that have RFID tags, where the parking space is assigned with the same identification number as the passive RFID tag. This way, information about parking occupation is collected at the entrance along with the time of occupancy as well as exit time. Gathered data is sent through Wi-Fi to a cloud server that saves it in a database for future study. The main novelty of the proposed solution is the adoption of RFID tag-to-tag communication, which can support a more energy-efficient collection of information from the RFID tags compared to the conventional direct type of communication. Research presented in [130] demonstrates a proof-of-concept of a smart parking solution based on Ultra-High Frequency (UHF) RFID and WSN technologies. The infrastructure of the system consists of Zigbee network, Smart Gateway (SG), Central Server (CS) and two different mobile applications, named Parking App and Policeman App, designed for vehicle drivers and traffic cops, respectively. The information about occupancy is collected using RFID tags, where CS receives the information about occupancy if an appropriate RFID tag has been read by the reader that is placed on poles located near the reserved parking spaces. The system onwards directs the drivers to the nearest empty parking space by using a customized software application.

A novel vehicle detection sensor design based on a dual microwave Doppler radar transceiver modules is presented in [131]. By employing a motion recognition algorithm for vehicle behavior identification and parking occupancy detection, the proposed sensor is able to detected the vehicle movement clearly with the parking space occupancy detection accuracy higher than 98%. Research elaborated in [132] provided a radar based real-time algorithm, which detects, classifies, and evaluates parking spaces in a vehicle's immediate vicinity. Their approach processed data obtained from radar in a form of a particularly designed target list of

2D vectors. Using this method, computation burden was decreased and quantization errors were evaded. Experimental results show that more than 95% of all parking spaces were classified correctly in several test drives, indicating that the proposed algorithm is suited for both parallel and perpendicular parking spaces in urban scenarios.

Recently, an extensive research elaborated in [133] presented an IoT-driven vehicle detection method by combining the data feature of magnetic signals with that of Ultra-wideband (UWB) radio channels aiming to improve wireless vehicle detectors that are based based on the IoT technology and magnetic sensor. The proposed method obtains vehicle detection by examining the length of the propagation path and signature of the channel impulse response with respect to the vehicles, which can be obtained from UWB modules. The experimental results indicate that the sensor can achieve a detection accuracy of 98.81% when the sampling rate of the magnetic sensor is 1 Hz. Research presented in [134] provides a comparison between inductive loop and magnetic sensors for vehicle detection that can be employed for traffic or parking systems. The overall measurements provided good comparison results between the two technologies and when considering all the values gathered, the inductive loop detector reported a total of 13,713 vehicles, while the magnetic sensor reported 13,407 vehicles, resulting in an overall detection difference of 306 vehicles (2,28%). Furthermore, a street parking system proposed in [135], employs a magnetic sensor node on the space to monitor the state of every parking space. Authors of the study propose a vehicle detection algorithm based on the magnetic signal along with a an adaptive sampling mechanism to reduce energy consumption. Evaluation of the system was preformed on a street parking spaces where eighty-two sensor nodes were implemented and collected the data for over a year. Their results indicate a vehicle detection accuracy of over 98% and the lifetime of the sensor node of more than 5 years with a pair of 2500mAh Li batteries.

Implementation of an acoustic senors parking space surveillance system is exhibited in [136]. Authors elaborate on the design, implementation, and evaluation of the system equipped with low-cost microphones that are able to localize acoustic events. The system is constituted out of the Acoustic Source Localization (ASL) system, the surveillance camera system, and the server system. One an a acoustic event occurs, the ASL sends estimated position of the acoustic event to the server, which than displays the estimated position on the map and sounds an alarm. The camera surveillance system than rearranges the cameras pointing to the estimated position to capture the event scene and onward performs motion detection to locate a more precise position. The data is transmitted over 802.15.4 wireless network protocol. The proposed system can efficiently supervises a large parking lot of 100 vehicles using only a dozen sensor nodes. Feasibility of the system was validated in a real parking lot, where experimental results show that detection rate in the region with the alarm using a camera is 94.29%.

Research presented in [137] proposes a smart parking solution based on the advantages of NB-IoT technology. The system is comprised of the sensor node made geomagnetic vehicle detectors , smart parking cloud server, application for mobile device and the third-party payment platform. The cloud server implements basic information management, charge management, sensor node surveillance, task management and business intelligence modules. The proposed system has already been deployed two cities in Zhejiang province,China. The author however, do not discuss the accuracy of detection of the proposed system.

Rather recently, authors in [138] presented an smart parking system based on ultrasonic sensors and the received signal strength indicator (RSSI) in Bluetooth communication. Parking occupancy is determined by using sensor motes located in the parking spaces whereas the parked vehicle location is based on the BLE communication between the user's smartphone and the sensor motes. What is more, the authors have done RSSI transformation into a distance range using triangulation in order to improve the location awareness for users. System was further evaluated by employing the sensor motes for the ultrasonic sensor and the BLE modules in parking spaces. Experimental results confirmed that the ultrasonic sensors successfully detected the available parking spaces with the 83% accuracy. A similar idea was explored in work presented in [139]. Authors present a smart parking solution for both indoor an outdoor parking areas that is based Bluetooth low energy beacons and which uses particle filtering to improve its accuracy with the goal to develop a smartphone application for parking users enable them to securely and easily find and pay for parking, while also providing management capabilities for the parking facility owners. The system builds an RSSI path loss model for the desired parking region and further implements the RSSI-based distance estimation on the smartphone. Based on the experimental results, the solution has achieved accuracy ranging from 87% to 100% for outdoor and 74% to 100% accuracy in indoor parking availability estimation.

Employment of LoRa technology for smart parking solution was examined in research [140]. Authors propose a smart vehicle parking system architecture is made out of four layers: sensor nodes, edge gateway, LoRa gateway and Cloud and provide a proof-of-concept with a specific realization. Employed senors were accelerometer, magnetometer and temperature, humidity and barometric pressure sensor for weather conditions. Sensor data is sent over to the edge layer before transmitting it to the cloud layer, and consequently to the end users. The LoRa gateway layer provided communication to ensure robust connection between the edge and cloud layers. The authors examined the latest LoRa and nRF communication technology to effectively increase the energy-efficiency and coverage area. They also propose a dynamic pricing algorithm for maximizing profit for the parking management authorities. Although the presented system is energy-efficient, secure, and provides a multi-parametric data about the parking slots the authors do not discuss the accuracy of detection.

In the last decade, a number of solutions aiming at predicting the occupancy in the future have emerged with the goal of simplifying the search of free parking spaces. These solutions are based on Machine Learning techniques that involve learning, predicting, and the exploiting of cloud based architectures for data storage [141]. Generally, data regarding occupancy are the history of occupancy for a parking lot, containing date-time information with a specific occupancy status. For instance, in the work [142], while using ML, the authors present two smart car parking scenarios based on real-time car parking information that has been collected from sensors in the City of San Francisco, USA, and the City of Melbourne, Australia. The historic data contained features, like area name, street name, side of street, street marker, arrival time, departure time, duration of parking events (in seconds), sign, in violation, street ID, and device ID. From these data, the occupancy rate was calculated. The evaluation revealed that the Regression Tree, when compared to NN and SVR, using a feature set that includes the history of the occupancy rates along with the time and the day of the week performed best for prediction of a free parking space on both the data sets. Moreover, in research [141], the authors applied a Recurrent Neural Network-based approach for the prediction of the number of free parking spaces. They have used parking data of Birmingham, U.K., which contained the parking occupancy rate for each parking area given the time and date. They achieved the median of mean absolute error of 0.077 for prediction of occupancy. The results show that the approach used is accurate to the point of being useful for being utilized in Smart Parking solutions. In [143], the authors discuss the problem of predicting the number of available parking spaces in a parking lot by regarding the vehicle's arrival as a Poisson distribution process. They model the parking lot as a continuous-time Markov chain. With the predicted occupancy status, each parking lot can provide availability information to the drivers via vehicular networks.

Research presented in [144] proposes an urban smart parking management platform based on the NB-IoT and wireless sensor network. The presented solution employees automatic license plate recognition (LPR) device to obtain images from the video stream and determine the license plate information whereas the vehicle location within the parking space is acquired by geomagnetic sensors. The employed image recognition algorithm for LPR is the Back Propagation (BP) Neural Network Algorithm. In the overall architecture of the system a personal digital adaptor (PDA)/mobile app acts as the management tool, and the NB-IoT wireless communication is used for data transmission. The authors elaborate and compare power consumption of NB-IoT with that of Zigbee to verify the performance of the proposed platform, concluding that the NB-IoT consumed less energy than Zigbee, indicating that the technique is cheaper to maintain, considering the long-term maintenance cost. The authors do not comment or discuss the system performance in terms of accuracy of detection of a free parking space.

A recent study exhibited in [145] attempted to realize a low-cost smart parking system utilizing several BLE beacon devices, a smartphone owned by a pedestrian/driver, a gateway, and a server. The idea is that a pedestrian's smartphone measures the received signal strength when it receives radio waves transmitted from the beacon device, and then estimates its own position in the parking lot by inputting the time series data to a learning model of the machine learning based on deep learning . Once the server gets the status of each slot in the parking space from the gateway, it would provide a driver outside the parking lot information about parking availability. What is more, the server has a function of constructing a new learning model based on the measurement results of the smartphones, and applying the updated learning model to the smartphones. The authors utilized Deep Neural Networks (DNN) and Convolutional Neural Network (CNN) as deep learning approaches for parking occupancy estimation. Experimental results show that DNN obtained 98% accuracy in parking slot estimation in contrast to CCN that had 99% estimation accuracy. What is more, estimation accuracy of the pedestrian's position is around 70% and the system is able to position of vehicles / pedestrians and to send the estimation results in the parking lot in less than 0.1 seconds. A similar idea of employment BLE beacon devices (a mesh network topology) and localization technique based on radio fingerprinting was presented in research [146]. Author propose a smart parking solution in which nodes listen for broadcasts of RSSI values from a custom beacon placed in every vehicle that parks in the lot. The RSSI values are then validated, encrypted, and sent back to a designated central node where space prediction occurs using ML; namely Decision Tree, Random Forest, Naive Bayes, Support Vector Machines and k-Nearest Neighbors were employed. Experimental results indicate prediction model obtains a high accuracy using radio training data (90.7% correctly identified) where the evaluation shows a promising result of 69.17% accuracy up to and including 3 spaces away), even without employing tuning and data filtering techniques for the RF classifier.

Two possible solutions for a smart parking deployment are presented in a research exhibited in [147]. Authors propose a design of an adaptable and affordable smart parking system using distributed cameras, LIDAR sensors edge computing, data analyses, and utilization of advanced deep learning algorithms. One solution would use a network of cameras as a sensing technique and the other network of LIDAR sensors, where the data is sent for further processing via Wi-Fi mesh technology. Both solution utilize three types of Neural Networks, namely Standard AlexNet, AlexNet with two convolution and a custom designed network model with one convolution layer. Their results show that camera model obtained 99.8584 % accuracy of detection of empty parking spots, wheras for the LIDAR model result vary depending of the spot from 30% to up to 93% of accuracy.

Moreover, in [148], the authors presented a novel system for detecting the cruising behavior in vehicle journeys and developed a real-time parking information system. The system uses GPS sensors as an application that sends the user's location and allows for the system to create a heat map with the acquired information showing free and unavailable parking lots. The proposed method relies on the principle of detecting a significant local minimum in the GPS trace with respect to the distance from the destination. In addition to GPS data, other sensing data from the driver's smartphone, such as accelerometer, gyroscope, and magnetometer, were also collected. Classification using Decision Trees, Support Vector Machines and *k*-Nearest Neighbors is used to detect cruising behavior. The system then automatically annotates parking availability on road segments based on the classified data and displays this information as a heat-map of parking availability information on the user's smartphone. Using this approach, the researches were able to detect cruising on average 81% of the time.

The work presented in [149] investigates the changing characteristics of short-term available parking spaces. The availability data were collected from parking in several off-street parking garages in Newcastle. This forecasting model is based on the Wavelet Neural Network (WNN) method and it is compared with the largest Lyapunov exponents (LEs) method in the aspects of accuracy, efficiency, and robustness. They conclude that WNN gives a more accurate short-term forecasting prediction with a average mean square error (MSE) is 6.4 ± 3.1.

More recently, the authors in [150] presented a framework that is based on LSTM in order to predict the availability of parking space with the integration of Internet of Things. They have also used the previously mentioned Birmingham parking sensors data set for performance evaluation of free parking space prediction that is based on location, days of a week, and working hours of a day. The authors show that, from all performance measurement parameters, the minimum prediction accuracy is 93.2% and maximum prediction accuracy is 99.8% . They present the experimental results that show that their proposed model outperforms the state-of-the-art prediction models. Finally, they point to some limitations of the study regarding the decision support system: it predicts the availability of parking lots only considering the parking occupancy information.

Recent works of researches incorporated Markov models for parking space occupancy predictions. For instance, in [75], the authors propose a model-based framework in order to predict future occupancy from historical occupancy data. The foundation of this predictive framework is continuous-time Markov queuing model, which is employed to describe the stochastic occupancy change of a parking facility. The model was evaluated while using a mean absolute relative error (MARE), ranging from 5.23% to 1.86% for different case studies. Furthermore, in [151], an agent-based service combined with a learning and prediction system that uses a time varying Markov chain to predict parking availability is proposed. Agents predict the parking availability in a given parking garage and communicate with other agents in order to produce a cumulative prediction achieving prediction accuracy of about 83%.

Neural Networks have also been used for in prediction of future occupation of parking space such as in [25, 26]. Researches in [25] have exploited the data concerning the availability of a free parking state depending on the duration of a particular occupancy status. Therefore, they have deployed a long term and short term occupancy prediction system based on neural network that achieves good performance with only a 0.004 Mean Absolute Error. They concluded that temporal changes of parking occupancy status was appropriately encompassed by the NN model that can provide an rather precise occupancy prediction up to thirty minutes ahead.

Authors in [26] have utilized a DL neural network for classification of a free parking space. Their model is based on images of a parking lot and it achieves a exceptionally good classification with 93% accurately classified occupancy status for a particular data set. Work presented in [78] proposed an occupancy prediction model using a deep neural network model which includes various data sources such as weather conditions, traffic conditions as well as parking meter transactions. Using Graph-Convolutional Neural Networks (GCNN) model is able to extract the spatial relations of traffic flow in large-scale networks and further captures the temporal features by applying Recurrent Neural Networks along with Long-Short Term Memory. Evaluation of the model's performance was done on a case study for the downtown area in Pittsburgh and it achieved mean absolute percentage error (MAPE) of 10.6% when predicting block-level parking occupancy half an hour in advance.

Researches in [149] have explored the altering properties of parking spaces that available for a short-term period. Data about occupancy in a particular period have been collected in a couple of Newcastle off-street parking garages. A model has been designed based on Wavelet Neural Networks (WNN) and it provides a short- term predictions of occupancy. The proposed model was evaluated in the terms of efficiency, accuracy and robustness and compared with the largest Lyapunov exponents (LEs) method. They conclude that WNN gives a more accurate prediction achieving an average mean square error of 6.4 ± 3.1. More recently, authors in [152] have explored the use of deep convolutional neural networks, namely ResNet, based on the two different data sets containing parking lot images. The have been able to obtain an high accuracy rate raining from $97,36\%$ up to $99,82\%$ for the test set and have optimized the increase of the learning error that occurs when the network becomes deeper thus providing swifter training. Research presented in [153] depicts a parking space occupancy monitoring software solution based on video and image processing and interpretation methods. Authors have employed five different models for classification, namely Logistic Regression, Radial Basis Function Support Vector Machine, Linear Support Vector Machine, Decision Tree and Random Forest. Based on classifier comparison Logistic regression achieved highest classification score of 93.5% outpreforming other classifiers.

Authors in [154] have carried out a study that utilizes several future parking occupancy prediction models such as Multi-Layer Perceptron, k-Nearest Neighbour, Random Forest, Linear Regression and KStar (instance-based model) for the campus location Charles Sturt University (CSU), Australia. The algorithms are based on car park occupancy data collected for a period of five weeks. They have done a performance comparison for all of the algorithms based on the the simple mean as criterion of good performance. Authors conclude that although majority of algorithms provide rather precise prediction in stable conditions, for highly variable conditions the KStar has achieved the best results.

Work presented in [155] explored a concept of using the smartphone's sensors readings such as sound, pressure levels and luminosity to obtain the information about the users transportation mode. By using the pervasive Wi-Fi and cellular infrastructure they were able to automatically detect users which are going out from a parking spot. Researches have utilized the Random Forrest algorithm to classify sensor readings, in real time, and determine which form of the most frequent transportation modes used in city areas the user is applying (for example walking, bus driving, car riding, cycling, train riding etc.) Evaluation was carried out on 7 smartphones and 3 different cities showing an accuracy of over 95% in transportation mode classification and in return-to-vehicle scenarios.

Rather recently, researchers in [156] have proposed a parking space detection system that uses parking lot images captured under different weather conditions as input and detects the empty slots in a particular images. They have employed combination of canny edge detection as well as LUV based colour variation detection methods to accurately derive the edges for each parking slot. Over a 942 images showing 37,680 parking spaces were used and Random Forest classifier has been utilized achieving accuracy of 98.31% compared to the existing methods. Authors point out to RF's good ability to solve the over-fitting problem with regards to training data and conclude this to be the reason of its accuracy. Not long ago, work presented in [157] provided a comparative analysis of Multilayer Perceptron, *k*-NN, Random Forest, Decision Tree, and Voting Classifier for the prediction of parking space availability. Data set used for the analysis was obtained by collecting the measurements of sensors deployed in city of Santander, Spain and it contained information about parking spot ID, day of the week, parking duration and status. Algorithms were evaluated in terms using K-fold cross-validation and numerical results obtained for Accuracy, Precision, Recall and F1-score. Authors conclude that the simpler algorithms such as DT, KNN and RF outperform more complex algorithms like Multilayer Perceptron, achieving higher prediction accuracy, giving better information about the prediction of parking space occupancy that can be compared.

3.2. Discussion

Research of literature presented in this work has revealed some important aspects of current smart parking solutions. Firstly, it can be notices that in the over-viewed literature within this work, majority of solutions only implemented some parts of the smart parking architecture. For instance, works in [124, 125, 126, 127, 129, 130, 136, 137, 139, 140] deployed only sensor and communication technology to obtain/ give information about occupancy status. Amongst these, some do not elaborate on detection rate like in the researches [124, 125, 126, 129, 130, 137]. Some solutions were able to achieve good occupancy detection rate without employing ML data processing like ones in [136], [127], achieving accuracy of 94.29% and 95% respectfully. Moreover, the solutions in [128, 131, 132, 133, 135] are constituted solely on the performance of the applied sensor technology, having no ML or communication protocol elaborated in their research and report of high detection rates generally above 93% up to 98%.

Other papers focused their research in obtaining parking occupancy or availability prediction using the history of occupancy for a specific parking lot, containing date-time information with a specific occupancy status. Some researches do not employ a specific sensing device in order to obtain data, but rather use public data sets that are provided, as presented in researches [75, 141, 142, 150, 151], concentrating the goal of their study in finding the most appropriate Machine Learning technique for prediction or classification of a free parking space. They do not discuss or propose an overall technological architecture of their solution, but rather present a ML model based framework that can be employed in future systems. Moreover, it can be noticed that the majority of research used Neural Networks as a ML technique for the prediction or classification of free parking for a variety of data type. This is due to their ability to learn from complex, large scale structure and unclear information, which provides a high performance result, as shown in researches [25, 26, 127, 149, 150]. These researches point out that Neural networks show high levels of accuracy in the prediction and classification of free parking space out performing other ML algorithms.

Some research did elaborated on the sensors from which they obtained data for Machine Learning employment, like the ones in [148, 152, 156, 153], but not on the communication protocol. Works presented in [154, 157] have evaluated performance analyses of multiple ML classification algorithms that do not include Neural Networks and were able to obtain high accuracy of detection or prediction.

Amongst 41 overall examined researches for Smart Parking solutions, only 8 exhibited all three components of the technological architecture for Smart Parking solutions examined within this paper. Table 3.1 gives a comparison of identified researches regarding the technological architecture of these existing Smart Parking solutions and the concept that is presented in this paper. Within this comparison only researches that have incorporated all three components of the technological architecture for Smart Parking solutions have been considered since only such solutions can be considered equivalent for comparison.

Table 3.1. Comparison table of various sensing technologies and it applications in Smart Parking.

Paper	**Sensing Device (Network Protocol)**	**Data Type**	**Application**	**ML Model**	**Detection Rate**
Ebuchi and Yamamoto[145]	BLE beacon and smarphone(BLE)	RSSI	parking occupancy detection	DNN, CNN	98%, 99%
Seymer et al.[146]	BLE beacon	RSSI	parking occupancy detection	DT,RF, Naive Bayes, SVM, k-NN	69.17%-90.7%
Bura et al.[147]	camera, LIDAR (Wi-Fi mesh)	images, distance	parking occupancy detection	NN	30%-99.8%
Vlahogianni et al. [25]	ferromagnetic parking sensor (802.15.4)	occupancy history	parking occupancy prediction	NN	0.004 MAE
Farag et al. [26]	camera	parking spaces images	parking occupancy classification	NN	93% classification rate
Jones et al. [148]	GPS sensors	location data	detection of cruising behaviour	DT, SVM, k-NN	81% detection accuracy
Hiesmair et al. [127]	LIDAR(LTE-IEEE 802.11p), GPS	distance, speed	estimation of parking situation	NN, DT, k-NN, SVM	95% accuracy
Krieg et al.[155]	smartphone sensor (Wi-Fi)	sound, pressure levels and luminosity	users transportation mode	RF	95%

As can be seen from the table, there is an overwhelming dominance of short range technologies which will be further discussed. Data type used for building the Machine Learning models vary depending on the sensor technologies, which indicates that on a base level, the sensing technology greatly influences the choice of an appropriate Machine Learning model that is further utilized. What is more, the researches report on extremely high accuracy of detection/ prediction of availability of finding a free parking space when ML algorithms are adequately applied. It can also be noticed that traditional classifiers like k- NN or RF are able to compete with deep learning approaches like DNN or CNN.

Second major observation obtained from research of literature is the immense dominance of short-range communication technologies. Only researches presented in [137, 140, 144] have reported to have examined the long-range technologies, which is only 7% of all papers considered in this research. This trend has already been confirmed in a rater recent review of literature presented in [29], that has has elaborated than only 10% of researched papers employed long-range commutation technologies. What is more, amongst these non have employed Sigfox technology within their research. This is rather unusual, since it has been reported by [158, 10] that Libelium [1], a WSN platform provider, has used both LoRaWAN and Sigfox in

[1]Libelium: https://www.libelium.com/iot-products/smart-parking/, (accessed on 8 October 2021)

their Plug & Sense platform, which uses magnetic sensors to detect vehicles in parking spots for commercial purposes. Author in [10] claim that Lora has not yet been popular within smart parking solutions, whereas SigFox has been highly commercially employed in large cities like Moscow and Barcelona, but not explored for scientific purposes.

Thirdly, only some studies have elaborated the cost and energy efficiency of the proposed solutions in general, like the ones presented in [135, 144]. This a rather small percent of research, and such aspects should be examined more. An appropriate solution must consider all technological aspects of a system in terms of accuracy, cost and energy savings. One such good approach was presented in [6], in which the authors have discussed state-of-the-art by a systematic in-depth overview of technologies used for the smart parking detection realization consuming mW of power. The researchers have conducted a real-scenario performances and power consumption of most popular sensor devices and LoRa, Sigfox and NB-IoT communication technology. Based on their results, lowest consumption is for LoRa devices. They have also conducted an analysis of power consumption of commercial LPWA-based Smart parking sensor device along with battery estimation lifetime.

4. Conclusion

Work exhibited in this paper provides an detail insight into overall technological architecture of Smart parking solutions constituted out of different sensors, communication protocols and utilization of Machine Learning techniques for parking occupancy sensing. Furthermore, this paper provides an overview of relevant scientific literature that has employed the previously elaborated technological architecture. Based on the results and analyses of the solutions that were proposed from different reviewed researches and experiments, following conclusions were obtained.

Firstly, a comprehensive analyses of quantitative comparison and benchmarking of the accuracy and reliability of parking occupancy sensor is needed. Such an comparison could be obtained from a thoroughly elaborated experiment of accuracy of detection for different sensors with a proper experimental environment from which better insight could be given to researches. This is a rather important issue, since it has been noticed that the choice of sensor technologies influences the communication and ML deployment.

Secondly, a more elaborated research is needed regarding the employment of long-range communication technologies for Smart Parking solutions. Based on the reviewed scientific literature, only a handful of research have started to explore performance and effectiveness of long-range technologies within this context. Their implementation should be examined particularity in terms of cost-effectiveness and power consumption, as well as different data information that can be obtained from such technologies (like received signal strength for instance). As was presented in literature overview such data seemed indicative for occupancy status detection when short-range technologies were involved in the Smart Parking solution. What is more, such data information might be indicative for future ML algorithms in terms of selection of the appropriate approach for sensing the occupancy status.

Finally, adequate Machine Learning implementation must be regarded with the goal of achieving high accuracy of detection while achieving cost saving by reducing the price of the sensing device. As was seen in the literature, current solutions are rather power hungry due to the consumption of a large number of sensors, microcontrollers (MCUs) and radio communication peripherals. This lagrerly impacts the lifetime of an otherwise battery-powered device. Consequently, the existence of sensing technologies in Smart Parking sensor devices often requires from manufacturer the implementation of circuitry that requires from MCU a state-machine capable methodology, adequate software for sensor activation and sensor readings, decision making about and radio communication upon parking status changes. In addition, such devices are usually implemented with capability to receive communication over the radio from centralized systems / gateways for making updates (e.g., duty cycle period, time synchronization), but also perform online firmware updates. Taking into account additional requirements from end user to calibrate sensors prior installing them, there is a need for an alternative solution based on ML that would be easier to implement as well as cost effective, while achieving high detection accuracy.

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Labels:

IoT	Internet of Things
ML	Machine Learning
DL	Deep learning
LSMT	Long Short Term Memory
AI	Artificial Intelligence
M2M	Machine-to-Machine
ANN	Artificial Neural Networks
NN	Neural Network
WNN	Wavelet Neural Network
RNN	Recurrent Neural Network
GCNN	Graph-Convolutional Neural Networks
IEEE	Institute of Electrical and Electronics Engineers
SVM	Support Vector Machine
SVR	Support Vector Regerssion
RBF	radial basis function
RF	Random Forest
HMM	Hidden Markov Model
k- NN	*k*- Nearest Neighbour
DT	Decision Trees
MSE	Mean Squared Error
MAE	Mean Absoulte Error
MAPE	Mean Absolute Percentage Error
MARE	Mean Absolute Relative Error
ROC	Receiver Operator Characteristic
AUC	Area Under the Curve
TPR	True Positive Rate
FPR	False Positive Rate
ROC AUC	Receiver Operating Characteristic Curve Accuracy
AP	Average Precision
ReLU	Rectified Linear Unit
MCU	Microcontroller

LED	Light Emitting Diode
RFID	Radio-frequency identification
SGD	Stochastic Gradient Descent
Adam	Adaptive Moment Optimization
RMSProp	Root Mean Square Propagation
LIDAR	light detection and ranging optical sensor
HOG	Histogram of oriented Gradient
MAC	Media Access Control
PHY	physical layer
IR	Infrared sensor
BLE	Bluetooth Low Energy
LPWAN	low power wide area network
NB-IoT	Narrow-Band IoT
DSSS	direct spread spectrum sequence
ISM	industrial, scientific and medical
WLAN	wireless local area networks
BPSK	Binary Phase Shift Keying
UNB	Ultra Narrow Band
GFSK	Gaussian frequency shift keying
CSS	Chirp Spread Spectrum
SF	spreading factors
LTE	Long-Term Evolution
3GPP	Third Generation Partnership Project
OFDMA	orthogonal frequency division multiple access
SC-FDMA	single carrier frequency division multiple access
UWB	Ultra-wideband
PSM	power saving mode
eDRX	expanded discontinuous reception
ASL	Acoustic Source Localization
LPR	license plate recognition
BP	Back Propagation
RSSI	received signal strength indicator

SMART PARKING SOLUTIONS FOR OCCUPANCY SENSING

Abstract:

One of the most important infrastructures that enable IoT-based Smart Cities is Smart Parking. Existing parking systems are becoming inadequate in urban city areas due to the rise of inhabitants and cars. Novel smart technologies must provide solutions that will decrease fuel consumption and air pollution, as well as to minimize cost-effective losses and enable power savings. This paper presents an overview of scientific literature about the concepts of Smart Parking solutions within the IoT paradigm, categorizing them based on their architecture. A proper insight into different sensor types employed for different parking status observations is provided along with elaboration of commonly used network protocols for communication and different Machine Learning employments for sensing the occupancy status. Several important open issues for Smart Parking solutions are addressed along with guidelines for future work.

Keywords:
IoT, Smart Parking, parking occupancy, Machine Learning, sensing technologies