Internet of Intelligent Things (IoIT): A Large-Scale Evaluation

Antreas Dionysiou[1]

[1]Department of Computer Science, University of Cyprus, P.O. Box 20537, 1678 Nicosia, Cyprus

adiony01@cs.ucy.ac.cy

Abstract. Internet of Things (IoT) and Machine Learning (ML) have been two among the most popular research topics for the last two decades. The benefits that these two technologies offer are indeed prominent. Nevertheless, the combination of these two breakthrough technologies can even bring more groundbreaking advantages to society, also transforming the classic IoT to an enhanced version called Internet of Intelligent Things (IoIT). In this paper, a large-scale evaluation of this enhanced concept is conducted, analyzing all of its core aspects, as well as explaining the advantages and potentials of this groundbreaking concept. Nonetheless, many challenges, that may act as an impediment on the benefits received through the IoIT, exist. In our large-scale evaluation, these challenges are detected and carefully examined, also suggesting ways to effectively overcome them. Data Mining (DM) is the process of extracting useful insights from large volumes of data. In this paper, we explain how ML-based DM techniques and methodologies could be utilized for the effective and efficient extraction of insights and valuable information from complex sequential data volumes.

Keywords: Internet of Intelligent Things, Big Data, Machine Learning, Data Mining.

Table of Contents

1 Introduction

Internet has certainly changed the way that people communicate. Over the last couple of decades, Internet has been in a constant state of evolution [1]. The Internet has been evolved from a network of linked HTML documents that resided on top of the Internet architecture, to Web 2.0, which enabled two-way communication, user participation, collaboration and interaction, to the under construction Semantic Web and sometimes referred as Web 3.0. The main goal of the Semantic Web is to mark up web content in a way that makes it understandable by machines, allowing devices and search engines to behave more intelligently (as machines will be able to process and share data on their own, without the need for human intervention). Internet-based technologies, such as social networking services, blogs, and wikis became essential to modern social interaction as well as for global business [1]. The next wave in the era of computing will be outside the realm of the traditional desktop. In the Internet of Things (IoT) paradigm, many of the objects that surround us will be on the network in one form or another [2].

Machine-to-machine communication concept has been the main concern of the scientific community for the last decades. The possibility of having a framework that will enable the aforementioned concept (machine-to-machine communication) over the Internet has led researchers to envision the benefits of bringing more machines online and allowing them to participate in the web as a vast network of autonomous, self-organizing devices. Machine-to-machine communication is the basic building block of Internet and IoT.

As there is not a universal definition for the IoT, the scientific community struggles to think or find one that best describes this breakthrough technology. After exploring the massive, in terms of size, literature related to IoT we found a well descriptive definition. As stated in [1], the core concept for *"IoT, is that everyday objects can be equipped with identifying, sensing, networking and processing capabilities that will allow them to communicate with one another and with other devices and services over the Internet to achieve some useful objectives"*. Due exactly to the massive scientific interest on IoT, the definition and the core objectives of IoT will continue to change the lives of people worldwide, whether its effects are obvious to the user or not. However, it has to be noted, that the core concepts underlying IoT and machine-to-machine communication, are not new. For example, Radio Frequency IDentification (RFID) and Wireless Sensor Networks (WSNs) have been excessively used in industrial and manufacturing contexts for tracking large-ticket items, such as cranes and livestock. Furthermore, machine-to-machine communication, is the core idea that Internet is built upon and in which clients, servers, and routers communicate with each other.

What is new about IoT, is the evolution of these technologies (in terms of the number and kinds of devices) as well as the interconnection of networks of these devices across the Internet [1]. The term "Internet of Things" was coined by Kevin Ashton in a presentation to Proctor and Gamble in 1999. In paper he published in 2009 [3], with title: That 'Internet of Things' Thing, explained how IoT concept came in life, also mentioning that we need to empower computers with their own means of gathering information, so they can *"sense"* the world for themselves, in all its random glory. He also states that RFID and sensor technologies enable machines to observe the environment and understand the world, without the limitations of human-entered data. It concludes his one-page paper by saying that the IoT has the potential to change the world, just as the Internet did, and maybe even more [3].

RFID and sensor network technologies will rise to meet IoT challenges, in which information and communication systems are invisibly embedded in the environment around us [2]. As a result, enormous amounts of data will be produced by IoT that have to be stored, processed and presented in a seamless, efficient, and easily interpretable form. Having such amounts of data coming from different sensors, different Data Mining (DM) algorithms could be deployed in order to extract valuable information. Due to the massive amounts of cheap and different information type sensing IoT devices, such as mobile devices, aerial (remote sensing), software logs, cameras, microphones, RFID readers and WSNs, the already big amounts of data (Big Data) keeps multiplying as we speak [4]. The world's technological capacity for information storing is doubled approximately every 4 years. According to Makrufa et al. [5], the global data volume will grow exponentially from 4.4 zettabytes to 44 zettabytes between 2013 and 2020. By 2025, IDC predicts that 163 zettabytes of data will exist [6]. The main concern of any company that wants to make an impact is how to process this massive amount of data and produce valuable information that could be used for the company's benefit. Joe Kaeser, CEO of Siemens, who took part in a technology forum in Stockholm said that *"Data is the oil, some say the gold, of the 21st century - the raw material that our economies, societies and democracies are increasingly being built on"*. Nowadays, it is (or it should be) crystal clear, that data analytics (the engine for analysing this massive amounts of data) could lead organisations and companies to valuable information and insights that will be used for making serious money. Relational database management systems and software packages used to visualize data often have difficulty handling Big Data [7]. Analysing such an enormous amount of data will require an intense amount of computation power provided by thousands of servers. These massive computation requirements could be satisfied through Cloud Computing [8] which integrates monitoring devices, storage devices, analytics tools, visualization platforms and client delivery [2]. Cloud Computing will enable in this way an end-to-end service provisioning for businesses and users to access applications on demand from anywhere.

Fifth generation (5G) of cellular mobile communications, is currently the under development latest technology succeeding 4G (LTE/LTE Advanced), 3G (UMTS) and 2G (GSM) systems. Some basic 5G cellular networks promises are: (a) high data rate, (b) reduced latency, (c) energy saving, (d) cost reduction, (e) higher system capacity, and (f) massive device connectivity. As a result, 5G cellular networks are expected to massively expand today's IoT in terms of boosting cellular operations, IoT security, minimizing latencies, facing existing network challenges and driving the Internet future to the edge.

Artificial Intelligence (AI) and Machine Learning (ML) received great interest in the last two decades. ML is the study of algorithms and mathematical statistical models for effectively learning or extracting features from massive datasets known as “training data”. Learning from training data, will lead to intelligent machines that are capable of solving complex sequential data classification problems based on their training experience, ideally with high accuracy. As mentioned before a couple of paragraphs, IoT produces a massive amount of data that if they effectively been processed, precious conclusions will be gathered. Furthermore, deploying trained ML algorithms on any kind of IoT device leads on what is said to be Internet of Intelligent Things (IoIT). IoIT consists of intelligent devices that can perform classification or prediction actions based on sensed input data and by exploiting their integrated intelligence (ML trained models). In this paper, we provide an extensive analysis of what IoIT is, carefully studying each of its main components and underlying technologies that will actually bring IoIT in life. Different applications of IoIT, potential key enabling technologies (e.g., 5G cellular networks, Bluetooth, Wifi, etc.), and the ML concept will be carefully and extensively examined as they play a critical role in IoIT’s future.

The rest of this paper is organized as follows. The core aspects of IoT are discussed in Section 2; these aspects include a brief explanation of IoT as a concept, as well as an providing details regarding the most prominent enabling technologies for the effective deployment and operation of IoT. In Section 3, we discuss the IoT’s Big Data era aspects, firstly describing the characteristics of Big Data and then explaining the different challenges that should be effectively faced for the successful operation of IoT. In Section 4, we stress the role of advances in ML, briefly explaining the core categories and characteristics of different ML algorithms, as well as discussing the role of datasets and performance metrics used for evaluating the accuracy of a proposed ML-based model, and, in Section 5, we provide a detailed explanation of the different ways and methodologies that this novel combination of IoT and ML could be performed, also giving specific directions for specific fields and application areas. Later on, in Section 6, we discuss the application of DM tools for extracting useful information from enormous complex sequential data volumes, generated by the massive amounts of devices participating in IoT, also describing a typical DM process as well as providing specific DM application areas where the use of ML models will contribute to the rise of the revenue or the minimization of the cost of particular organization. Finally, we discuss our future research directions and conclusions regarding this work in Section 7, also mentioning the implications of our work.

2 The Internet of Things (IoT)

2.1 Understanding Internet of Things as a Concept

IoT has been excessively studied. Since the term IoT was coined by Kevin Ashton in 1999 [3], the scientific community has shown a great interest on studying this concept and examining the underlying technologies that IoT will be based on. The basic concept of IoT is that *every day devices such as vehicles, home appliances, mobile phones and every other electronic device, will have the ability to connect, interact and exchange data.* Due to the massive number of interconnected electronic devices that have (or will have) networking capabilities, IoT essentially comes in life. As already mentioned, the IoT definition, core objectives, and underlying technologies will continue to evolve as long as the scientific community will continue to study IoT-related aspects. IoT extends Internet connectivity to the edge (i.e., beyond standard devices such as laptops, desktops, smartphones and tablets), making all electronic devices accessible through Internet for remote monitoring and controlling. However, it has to be noted that the IoT became possible due to the emergence of multiple technologies, such as wireless technologies, microelectromechanical systems, microservices, commodity sensors, and the evolution of internet's underlying technologies.

Traditional fields of embedded systems, WSNs, control systems, automation (including home and building automation), and others, all contribute to enabling IoT. The main reason why IoT received great interest from the scientific community the last two decades, is the high impact that IoT will have on several aspects of everyday life, from healthcare to environment monitoring, to whatever anyone can think of [9]. The numerous applications that could be developed based on IoT led the scientific community on envisioning the advantages and the potentials of this concept. Domotics (i.e., smart homes), assisted living, e-health, enhanced learning, environment controlling and nano-particles measuring are only a few examples of possible application scenarios in which the new paradigm will play a leading role in the near future. Furthermore, from the business perspective the benefits and consequences of IoT operation are equally visible affecting various aspects of industry such as manufacturing, logistics, process management and enhancing of transportation of people and goods [9]. In addition to the above, US National Intelligence Council included IoT in the top six “Disruptive Civil Technologies” with potential impacts on US national power, noting that “by 2025 Internet nodes may reside in everyday things – food packages, furniture, paper documents, and more”. The potentials and the enormous advantages of successfully employing such an advanced technological framework (IoT) will surely enhance the quality of life and improve the worldwide economy [10]. Nevertheless, many threats that coexist with IoT should be effectively tackled. Security and privacy related risks are the most common, as this technology distributes security risks to everyday objects, extending in this way the range of those risks far more widely than before. In addition, many technological challenges,

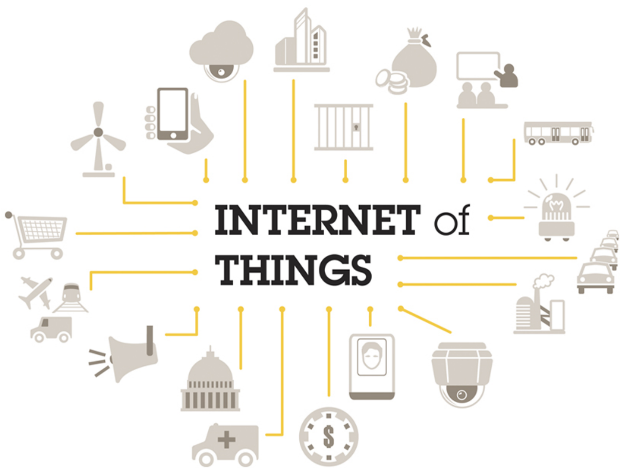

Fig. 1. In this figure, the *Internet of Things (IoT)* concept, is shown.

such as the interoperability, adaptation, and autonomous behaviour of interconnected devices should also be tackled. Furthermore, scalability and resource efficiency issues exist, as the “things” composing the IoT are mainly low resource devices in terms of computation power and energy capacity.

In order for someone to understand the capabilities and limitations of IoT, multiple survey papers related to IoT aspects should be carefully examined to perceive the current status of research progress in this particular field. In [1], authors provided a classification/distribution of literature (shown in Figure 2) in six (6) major categories: (a) technology, (b) applications, (c) challenges, (d) business models, (e) future directions and (f) overview/surveys, receiving 42%, 25%, 17%, 3%, 2% and 11% respectively, of the total percentage of the articles studied [1]. From the aforementioned results, it is obvious that the larger amount of literature related to IoT, is mainly focused on the technology aspects that will enable this concept called IoT. The 2nd larger portion of the literature is related to different applications that would be based on IoT to achieve certain goals. I bet that you can easily think of a bunch of applications that will provide high value and solve some serious everyday problems or make peoples' lives easier. In [1], many of the papers studied are related to application areas and they are heavily focused on supply chains and social applications due to the established role of specific IoT key enabling technologies technologies like RFID in supply chains and the way big interest of humanity on social media. The 3rd larger portion of the literature is concerned about the different challenges that the IoT will face so to find a way to tackle them before they even happen. Again, as you can easily imagine, there are plenty of challenges, mainly focused on information security and privacy, that need to be tackled in order for the

IoT to take place. As the IoT extends internet's reachability to the edge, new privacy policies as well as different information security algorithms and suites that will protect users' data are considered critical, especially in the *GDPR [11] age* that we live today. It is worth mentioning, that legal and accountability issues received the least coverage in the challenges category, perhaps because these are also unresolved issues in the classic Internet paradigm.

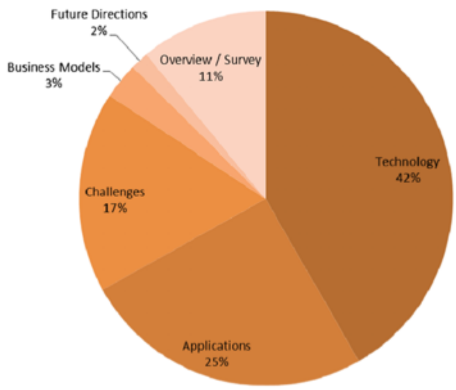

Fig. 2. Distribution of articles by major category [1].

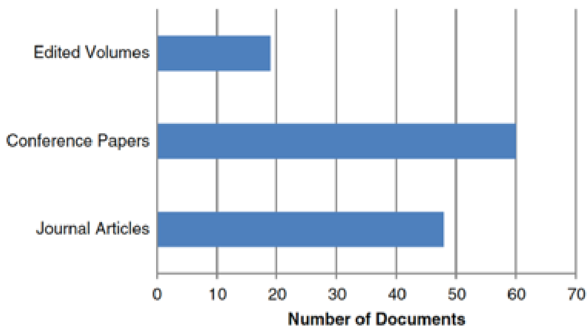

Fig. 3. Reviewed literature by publication type [1].

Observing the results shown in Figure 3, much of the work being done on IoT is through technical and engineering conference papers and edited volumes, something which is much more commonplace and encouraged than it is in other fields.

When we refer to IoT term we essentially mean billions and trillions of interconnected devices that interact with each other, sense the environment and operate in an autonomous way. The *addressing* of such an enormous volume of devices is still an open question. The scientific community should develop effective and efficient –in all terms– addressing schemes for the successful communication of the devices participating in IoT. Thus, *smart connectivity* with existing networks and *context-aware computation* using network resources is an indispensable part of IoT [2]. Based on the massive and continuous growth of wireless technologies, such as Bluetooth, Wi-Fi, and 5G, the ubiquitous information and communication networks is already evident. In later sections, a brief explanation on how these technologies contribute to the realization of IoT and IoIT, will be given.

The evolution of these technologies as well as the large amounts of interconnected devices that adopt them, has led to a rapid growth of IoT. As clearly stated in [2], in 2011 the number of interconnected devices has overtaken the actual number of people in planet earth. By the time the article [2] has been written, 9 billion interconnected devices existed and that number expected to reach 24 billion devices by 2020. According to the GSMA, this amounts to $1.3 trillion revenue opportunities for mobile network operators alone spanning vertical segments, such as health, automotive, utilities and consumer electronics. In Figure 4, the interconnection of different sectors and objects in real-life aspects are shown, also giving some application domains based solely to the scale of the impact of the data generated and the value derived from that data. As already mentioned, IoT builds upon existing technologies, such as RFID and Wireless Sensor Networks along with standards and protocols to support machine-to-machine communication, such as those envisioned for the semantic web [1]. In the next section, the technologies that will enable and boost IoT are explained in detail.

Fig. 4. Internet of Things schematic showing the end users and application domains based on the scale of impact of the data gathered [2].

2.2 IoT Key Enabling Technologies

There are plenty of IoT key enabling technologies that were designed considering IoT objectives (e.g., Zigbee) and others that emerged in order to fulfil IoT requirements (e.g., Bluetooth 4.1 and 5). The combination of these technologies will lead to the interconnection of heterogeneous systems and devices and thus allow ubiquitous computing, one of the main aspects of IoT. Nonetheless, it has to be noted, that these different standards and protocols should be interoperable allowing devices deploying different protocols and created from different vendors to seamlessly communicate with each other. Furthermore, these standards and solutions should emerge and properly combined together in order to meet the IoT technical Key Performance Indicators (KPIs) [12]. In the subsections below, the state-of-the-art IoT key enabling technologies are explained in depth.

2.2.1 First forms of IoT connectivity and identification: The first forms of IoT connectivity and identification standards and protocols have been proposed a long time ago, with the legacy Radio Frequency Identification (RFID) technology and later, the Wireless Sensor Networks (WSNs) to be the most popular ones [12]. As the number of potential IoT applications and their impact on the industry and the society in general was realised in the very early stages, the industry as well as any Standards Developing Organizations (SDOs) struggled to invent and develop new standardized low power IoT enabling solutions. RFID, barcode, and intelligent sensors were mainly deployed as the identification and tracking technologies. RFID uses electromagnetic fields to automatically identify and track tags attached to objects. These tags contain electronically-stored information that mainly serves the identification process. There are two types of RFID tags namely: (a) Passive, and (b) Active. Passive tags collect energy from a nearby RFID reader interrogating radio waves. Active tags have a local power source (e.g., battery) and may operate hundreds of meters away from the RFID reader. In contrast with a barcode, the RFID tag does not have to be in line of sight with the reader, so it may be embedded in the tracked object.

Due to RFID's low-cost and its ability to identify, trace, and track devices and physical objects, the RFID system has been heavily deployed in industries, such as logistics, supply chain management, and healthcare service monitoring [13,14]. The aforementioned advantages of RFID system combined with other derived benefits, such as: (a) providing precise real-time information about involved devices, (b) massively reducing labor cost, (c) simplifying business process, (d) increasing the accuracy of inventory information, as well as (e) improving business efficiency and control, have led this technology to be adopted and used by numerous manufactures, distributors, and retailers across a large scale of industries. According to [15], recent development of the RFID technology focuses on (a) active RFID systems with spread-spectrum transmission; and the underlying (b) technology of managing RFID applications. RFID and WSNs could be integrated to improve the real-time tracking and tracing technologies. The different emerging wireless intelligent sensor technologies further facilitate the implementation and deployment of industrial services and applications. To give you a trailer about the sections explaining how IoT and ML could be integrated to produce IoIT, processing and integrating the data (Big Data) acquired by intelligent sensors and RFID data, more powerful IoT based applications can be developed, bringing intelligence to the edge of the IoT infrastructure (i.e., to the devices), and converting in this way the "things" term in IoT to "intelligent things" in IoIT.

2.2.2 Bluetooth Low Energy (BLE): Bluetooth is a standard wire-replacement (wireless) communications protocol primarily designed for low power consumption technology and adopted by numerous companies for short distance and low data rate requirements communication purposes. Bluetooth, was originally conceived as a wireless alternative to RS-232 data cables. Many applications and different devices rely on Bluetooth connectivity technology, some of them including: (a) wireless speakers, (b) wireless headphones, (c) connecting smart phones to cars, (d) wireless networking between PCs where little bandwidth is required, (e) wireless communication with PC input and output devices, the most common being the mouse, keyboard and printer, and many others. One advantage of Bluetooth technology over the infrared [16], is that the devices that communicate with each other, do not have to be in visual line-of-sight of each other as they make use of radio (broadcast) communication system. However, if not a direct, an indirect wireless path must exist for the radio waves to propagate from transmitter to receiver [17].

Bluetooth operates at frequencies between 2402 and 2480 MHz, or 2400 and 2483.5 MHz including 2 MHz wide guard bands at the bottom end and 3.5 MHz wide guard bands at the top. Thus, Bluetooth frequency bands are unlicensed (2.4 GHz short-range Industrial Scientific Medical (ISM) radio frequency band) but not unregulated. Bluetooth, makes use of a technology to preserve its signal quality and deal with any interference and noise at specific frequency bands that may destroy the carriers (signal's) useful information, called Frequency Hopping Spread Spectrum (FHSS). FHSS, is a method of transmitting radio signals by rapidly switching a carrier among many frequency channels, using a pseudorandom sequence known to both transmitter and receiver [18]. Bluetooth divides transmitted data into packets, and transmits each packet on one of 79 designated Bluetooth channels, each channel having a bandwidth of 1 MHz. Bluetooth, usually performs 1600 hops per second, with adaptive frequency-hopping (AFH) enabled [19] which improves resistance to radio frequency interference by avoiding crowded frequencies in the hopping sequence.

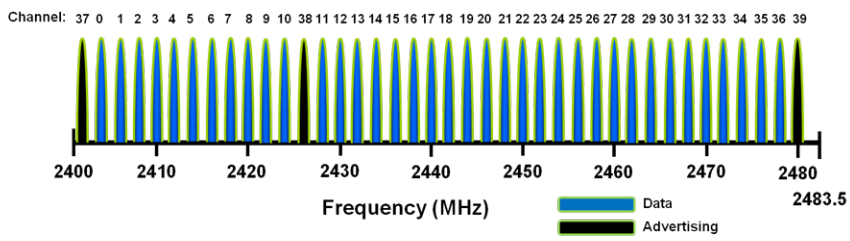

Fig. 5. BLE's frequency bands used for exchanging data (blue) and advertising (black).

Bluetooth Low Energy (version 4.1) is an updated, smart, low-energy version of classic Bluetooth (version 4) that uses 2 MHz spacing, which accommodates 40 channels [14,21]. In other words, BLE is intended to provide considerably reduced power consumption and cost while maintaining a similar communication range with its previous version (up to 50m), and at the same time aiming at many novel applications that require low-energy consumption devices.

To achieve low power consumption, BLE scans only 3 separate channels (frequencies), for device discovery, connection set up, and broadcast transmission [20], where the advertising device sends a packet on at least one of these three channels, with a repetition period called the *advertising interval*. As shown in Figure 5, for the advertising frequencies the BLE's centre frequencies have been assigned to minimize interference with the widely used IEEE802.11 channels 1, 6, and 11. Furthermore, the remaining 37 channels are dedicated for bidirectional exchange of data between the communicating devices. It has to be noted, that BLE quickly sets up new connections for further minimizing: (a) the interference on the 3 dedicated advertising channels, and (b) the power consumption required for new connection set ups [14,21]. BLE makes use of the AFH [19] mentioned above to reduce sensitivity to interference and multi-path fading [17]. Other low power-solutions, such as ZigBee, 6LoWPAN, and Z-Wave, have been emerging the same time period as BLE, targeting applications with multi-hop topology scenarios (Figure 7). On the other hand, BLE currently supports only single-hop topology (Figure 6), namely Piconets, having one master node (in Figure 6 the center blue circle) communicating with several slave nodes (in Figure 6 the light blue circles), and a broadcast group topology, with an advertiser node broadcasting to several scanners.

In 2015, the Bluetooth SIG formed a working group mainly focused on the formation of Bluetooth Smart Mesh to define the architecture for BLE's mesh networking. This, will lead to an extended communication range and simplification of BLE networks for IoT.

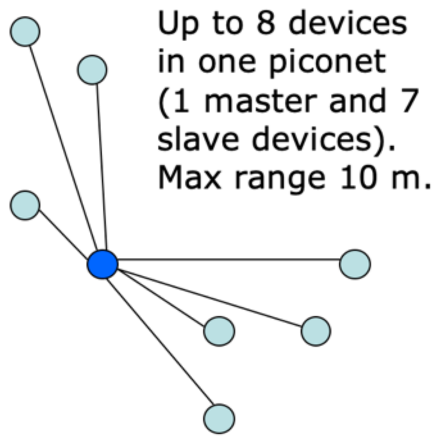

Fig. 6. BLE's single-hop topology.

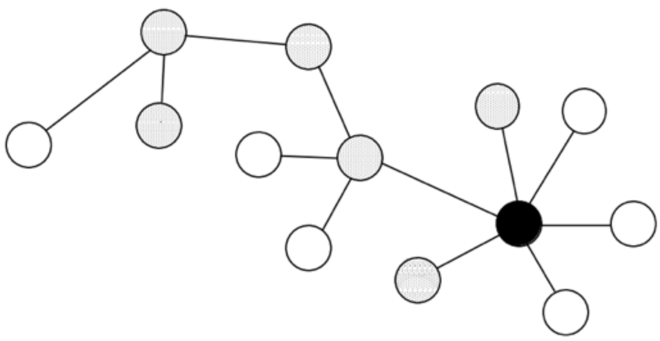

Fig. 7. ZigBee's multi-hop topology.

Considering all the information given above, regarding BLE, one can say that BLE was designed keeping in mind the emergence of IoT concept. The low-energy requirements and cost for devices deploying BLE as well as the struggle of Bluetooth SIG to standardize a mesh networking architecture for BLE, clearly shows that BLE is destined to be a key enabling technology for some short-range IoT applications, such as in healthcare, smart energy, and smart home domains [21]. BLE is expected to become a *de facto* standard for short-range IoT services [22]. As a matter of fact, all nowadays smartphones shipped worldwide are equipped with BLE interfaces. As a result, BLE will become the most common communication technology used from consumer applications, further decreasing the cost of BLE hardware, also allowing devices equipped with BLE to participate in all those applications (i.e., smart living, health care, smart building, and so forth).

2.2.3 ZigBee: Similar to Bluetooth technology (Section 2.2.2) , ZigBee is a low-cost and low-power standard –supporting wireless tree, star, and mesh network topologies (Figure 8)– which has been widely applied in WSNs, also being the first that was deployed and designed for industrial IoT applications (e.g., for control and monitoring) [22]. ZigBee, was conceived in 1998, standardized in 2003, and revised in 2006. It builds on the IEEE802.15.4-2006 Physical (PHY) and Medium Access Control (MAC) standard specifications [23]. The name refers to the waggle dance of honey bees after their return to the beehive [24]. ZigBee demonstrated high energy efficiency based on real-world deployments compared to other standards, as it minimizes the energy needed to transmit a given information bit maintaining at the same time the signal's quality. ZigBee, was designed to be the core standard for the emerging IoT. However, many IoT applications are expected to exchange only a few bits, and thus, these ultra rate transmission requirements lead to an enormous link budget and considerably larger distances of signal propagation and enhanced devices' (adopting ZigBee standard) coverage [25].

The IEEE802.15.4-2006 MAC layer(s) did not suffice the needs of IoT applications as its single-channel nature makes it unreliable, especially in multihop scenarios, where it incurs in a high level of interference and fading [22]. Furthermore, the IEEE802.15.4-2006 MAC layer(s) have high energy requirements regardless of the actual traffic [25]. As a result, the IEEE802.15 Task Group 4e (TG4e) (created in 2008) redesigned the existing IEEE802.15.4-2006 MAC standard and obtain a low-power multi-hop MAC better suitable for emerging embedded industrial applications. The redesigned version of IEEE802.15.4-2006 MAC, namely IEEE802.15.4e standard [23], defined three new MACs, where the Timeslotted Channel Hopping (TSCH) mode is the most promising one, facilitating energy efficient multi-hop communications, while at the same time reducing fading and interference [22]. Finally, another defining feature of Zigbee is the provided facilities suite –that builds on the basic security framework defined in IEEE 802.15.4– for carrying out secure communications, protecting establishment and transport of cryptographic keys, ciphering frames, and controlling device. Current ZigBee standard allows for the following three types of devices:

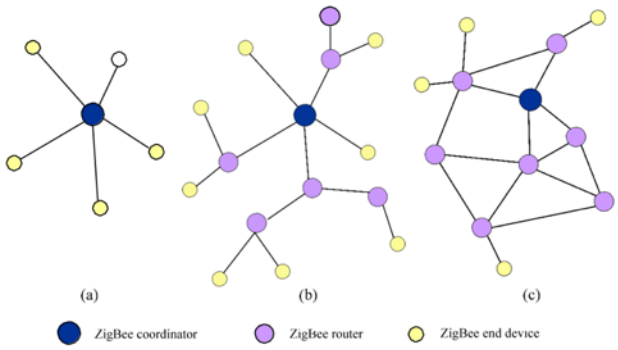

Fig. 8. Network topologies supported by ZigBee.

- **Coordinator (ZC):** The Coordinator device (Figure 8(a)) forms the root of the network tree and might act as a bridge to other neighbouring networks. There is exactly one Coordinator in each network since it is the device that started the network originally (LightLink specification also allows operation without a Zigbee Coordinator, increasing the usability of off-the-shelf home products). Coordinator stores different kind of information about the network formed, also acting as the Trust Center and repository for security keys.
- **Router (ZR):** As well as running an application function, a Router (Figure 8(b)) can act as an intermediate router, passing on data from other devices and forming in this way the network backbone.
- **End Device (ZED):** An End Device (Figure 8(c)), is able to communicate with the parent node (which may be either Coordinator or Router), but cannot relay data from other devices. The specifications of End Devices, allows these nodes to be asleep a significant amount of the time thereby giving long battery life. A ZED requires the least amount

of memory and therefore, can be less expensive to manufacture than a ZR or ZC.

2.2.4 Wifi and Low-Power Wifi (LP-Wifi): The first version of IEEE802.11 standard (Wifi), was released in 1997 without having the IoT concept in mind. Instead, the main aim of this technology was to provide high data rates to short distanced devices. The main reason that Wifi has not been a key enabling technology until nowadays, is the higher energy consumption and its low energy efficiency compared to other standards, like BLE that offers shorter propagation distances but has way too lower power consumption requirements, and ZigBee that supports fairly long range but has much lower data rate. In order for the Wifi to overcome the high power consumption requirements that directly affect the battery life of devices (large drawback for IoT devices), IEEE802.11 community proposed duty cycling and hardware optimizations achieving in this way extremely energy efficient solutions. Nevertheless, Wifi's poor mobility and roaming support, as well as the fact that its prone to interference by other standards sharing the same unlicensed 2.4 GHz band (e.g., ZigBee, Bluetooth, etc.), still prevented it from being one among the most popular IoT's key enabling technologies. As a consequence, the use of sub 1 GHz (S1G) license-exempt bands have been proposed for use and deployment, by the IEEE 802 LAN/MAN Standards Committee (LMSC). These bands can propagate to longer distances and are are less prone to noise and interference, especially in outdoor scenarios, compared to traditional Wifi. Finally, considering the main objectives of IoT, LMSC proposed the *Low-*

Power Wifi (LP-Wifi) for: (a) supporting a large number of devices, (b) increasing the coverage ranges, and (c) improving the energy efficiency (and increase as a consequence devices' battery life) of traditional Wifi standard.

Considering the IoT objectives and goals, a Wireless Access Point (WAP) must support hundreds, if not thousands of devices (e.g., sensors and actuators). Legacy IEEE802.11, was limited by the number of stations that could be simultaneously supported. IEEE802.11ah, overcomes this devices densification limit by introducing a novel hierarchical method which defines groups of stations and allows the support of a large number of devices [26]. Performance studies regarding IEEE802.11ah, showed that it is able to support a large set of machine-to-machine scenarios (e.g., agriculture monitoring, smart metering, industrial automation), also providing a Quality of Service (QoS) higher than the QoS provisioned in mobile networks, enabling scalable and cost-effective solutions [22]. Concluding all of the above, LP-Wifi can now serve as a key enabling technology for IoT successfully meeting the concept's requirements.

2.2.5 5th Generation Cellular Networks (5G): Cellular networks standards, like Long-Term Evolution (LTE) have been proposed for increasing the data rates and minimizing the latency of mobile communication systems. Nevertheless, these technologies have not been designed keeping IoT in mind. This, means that they are not well suited for low-power and low data rate devices such as the devices participating in IoT, leading to the invention of a large number of new IoT standards. Fifth Generation

(5G) mobile cellular networks, as well as enhancements of 5G like 5G ultra-dense cellular networks, aim to provide tremendous higher data rates, supporting higher capacity demands, further minimizing latencies, and at the same time aiming to address the limitations of previous cellular standards, in order for the 5G to become a potential key enabling and boosting technology for the future of IoT [22]. As clearly stated in [22], the advent of 5G cellular systems, with the availability of a connectivity technology which is at once truly ubiquitous, reliable, scalable, and cost-efficient, is considered to be as the most popular potential key enabling technology for the global emergence of IoT.

3 Internet of Things and Big Data

3.1 IoT's Big Data Era

According to [27], the rapid developments in hardware, software, and communication technologies will lead to a total number of 20-25 billion interconnected devices by 2020. In addition, as the number of interconnected devices rises and the technologies become more mature the volume of data published will increase. As a result, the IoT generates Big Data characterized by velocity in terms of time and location dependency, with a variety of multiple modalities and varying data quality. The process of extracting useful information from this enormous amounts of data, created daily by participating in IoT devices, is not an easy task. Imagine the enormous amount of data that a number of sensors gathering different measurements produces in a daily basis. Business, governments and even

Non-Government Organisations (NGOs), can benefit by leveraging the insights offered by Big Data analysis.

Today, data is in fact everywhere. The access in data and information from just anywhere is also a fact nowadays. The Google searches that users perform as well as any second they spend on different social media applications, everything, is converted into data. With the growth of smart devices (e.g., smart watches, glasses, toothbrushes, etc.) the world has become a data creation station. As the volume of data grows different problems about storing, processing, and generally controlling this massive amounts of data, rise. Before we continue describing Big Data and any challenges that have to be faced, we have to explain the problems that rise when it comes to data produced from devices and systems participating in IoT. According to [28], the key characteristics of the data in IoT era can be considered as Big Data; and they are as follows:

- **Enormous volumes of data** (in size of Terabytes, Petabytes, and even Zettabytes) to be processed, so new effective and efficient mechanisms, for processing these large amounts data, should be invented.
- **Large heterogeneity of data sources and data types** to be processed and integrated (e.g., sensors data, cameras data, social media data, and so on and all these data being different in format, byte, binary, string, number, and so forth.), so there is the need for automatically communicate with different types of devices and different systems also automating the data extraction process from web pages. This goal will be largely realized when the interoperability issue is effectively tackled.

- **Immense complexity of data** for knowledge extraction. The valuable knowledge hidden in this large volumes of data is very difficult to be successfully extracted. As a result, different data analytics practises should be exploited for effectively analysing the properties of data and finding any associations and correlations between them that maybe exist.

In order for the IoT to be effectively applied, the various challenges related to Big Data and acting as impediments to the successful operation of IoT, should be effectively eliminated. As one can easily imagine there are plenty of challenges when IoT and Big data come together, as the quantity of data volumes becomes enormous, the quality remains low, and various different data sources (devices) should easily communicate and share information with each other. In addition, the data collected form the devices participating in IoT is heterogeneous, semi-structured, and many times even completely unstructured. Before mentioning the main challenges that need to be tackled for the IoT to be operational, we shall first give a brief definition of the characteristics of Big Data, according to the field experts. Most experts define Big Data in terms of the *three Vs.* You have Big Data if your data meets the following criteria and characteristics:

- **Volume:** Big Data is any set of data that is so large that the organization that owns it faces challenges related to storing or processing it. In reality, trends like ecommerce, mobility, social media and the Internet of Things (IoT) are generating so much information, that nearly every organization probably meets this criterion.

- **Velocity:** If your organizations is generating new data at a rapid pace and needs to respond in real time, you have the velocity associated with Big Data. Most organizations that are involved in e-commerce, social media or IoT satisfy this criterion for Big Data.
- **Variety:** If your data resides in many different formats, it has the variety associated with Big Data. For example, Big Data typically include email messages, word processing documents, images, video and presentations, as well as data that resides in structured relational database management systems (RDBMSes).

Characteristics of Big Data	
Volume	Big data requires a large amount of storage space, and organizations must constantly scale their hardware and software in order to accommodate increases.
Velocity	New data is being created quickly, and organizations need to respond in real time.
Variety	Data resides in a variety of different formats, including text, images, video, spreadsheets and databases.

Fig. 9. In this table a brief explanation of the three main characteristics of Big Data, namely Volume, Velocity and Variety, are shown.

3.2 IoT's Big Data Challenges

Considering the above characteristics and criteria describing Big Data we came up with the following list that briefly describes some major challenges rising from IoT's Big Data era.

3.2.1 Dealing With Data Growth:

Considering the massive amounts of data that devices and systems participating in IoT create, one can easily say that the most obvious challenge associated with Big Data is the storing and analysing these large volumes of data to produce valuable information. The amount of information stored in worlds data centres seems to be approximately doubled every year. Originally, data scientists maintained that the volume of data would double every two years thus reaching the 40 ZB point by 2020. That number was later bumped to 44ZB when the impact of IoT was brought into consideration. It has to be noted, that the larger volume of the data produced is unstructured, meaning that they do not have a predefined structure according to a database or a protocol's format standards. For example, documents, photos, audio, and videos (as well as other unstructured data) can be difficult to search and analyse. In order to deal with Big Data, organizations are turning to a number of different technologies. In particular, technologies like compression, deduplication and tiering can effectively reduce the amount of space required as well as the cost associated with the Big Data storage. For the management and analysis side, tools like NoSQL databases, Hadoop, Spark, and different Big Data analytics software as well as business intelligence applications (mainly based on Artificial Intelligence and Machine Learning) have been developed to extract the valuable information and insights behind these large volumes of data (Big Data).

3.2.2 Extract Valuable Information in a Timely Manner: There is no point on storing Big Data unless there is an underlying purpose for this action. Organisations and companies store Big Data so to process them, in a later stage, and produce valuable information and insights to make a specific prediction about something or –from the business side– achieve some business goal (e.g., decreasing expenses through operational cost efficiencies, establishing a data-driven culture, creating new avenues for innovation and disruption, accelerating the speed with which new capabilities and services are deployed, launching new product and service offerings, etc.). There are many valuable insights hidden in Big Data that can help organizations to become more and more competitive. Nevertheless, effectiveness and efficiency on data processing is a major aspect. If insights not extracted within a period of time it would be too late for taking action on a particular extracted insight. In order to achieve high speed of insights extraction from Big Data, different organizations and companies are working on the development of tools that can dramatically reduce the data processing and report generation times. For example, a framework proposed to process massive amounts of data in a distributed manner is the well-known Map Reduce framework [29]. Many organisations are investing large amounts of money to real-time analytics platforms that will offer them the capability of immediately responding to different developments in the marketplace.

3.2.3 Heterogeneity of Data and Data Sources: A large number of vendors and companies have stepped-up their game in order to participate in the upcoming IoT market. Standards describing specific data formats and protocols for exchanging data between different types of devices do not exist. As a result, any vendor that produces IoT enabled devices stores, processes, and shares information with other devices in its own preferred way. This variety of storage and sharing information ways leads to challenges in data integration and communication. As data comes form a lot of different places (e.g., social media streams, email systems, enterprise applications, etc.) and different vendors, combining all that data and sharing it among different vendor devices can be an incredibly challenging task. Despite the existence of many data integration tools, trying to tackle this problem, the data integration and communication between different vendor devices problem still remains unsolved.

3.2.4 Data Validation: As data is collected from different sources and with different formats, validating these data –in terms of correctness and duplication– is a critical task. For example, in healthcare a hospital's Electronic Health Record (EHR) system may have a phone number for a specific patient, while a partner pharmacy has a different phone number for the same patient. The process on trying to getting those records to agree, as well as making sure that data collected from different sources is accurate, usable, and secure, is called *data governance*. To solve data governance challenges policies, protocols, and standards have to be developed covering different aspects of data such as the aforementioned data heterogeneity and data sharing across devices and systems from different vendors and companies. Ensuring data validation, has a direct impact on the insights derived from them. Thus, this challenge is considered among the most important challenges to be faced for Big Data.

3.2.5 Security of Big Data: Security has always been a major concern when it comes to data and information. As we nowadays live in the GDPR-age [11], security is among the most critical objectives to be met when trying to develop any kind of application. In addition, some Big Data centres can be attractive targets for hackers or advanced persistent threats (APTs) due to the monetized value of the assets being stored. Information security algorithms and suites exist that could be used to ensure the integrity and privacy of any kind of data. However, the implementation of the security algorithms has to be carefully examined as the most attacks are heavily based on bugs in the source code. Most organizations nowadays are forced to deploy identity and access control techniques, data encryption (e.g., Advanced Encryption Standard – AES), and data segregation (i.e., separating the data in different places for resisting and minimizing the impact of potential data leakage). The security aspect of data produced by the IoT participating devices should be of great concern as numerous attacks on non-secured devices have been detected [30].

3.2.6 Energy Efficiency: Energy efficiency is a challenge directly connected to IoT. However, the problem becomes extremely critical when being in the IoT's Big Data era. Devices participating in IoT can be of any size and ideally the size of a grain of sand. The energy capacity of these nano-scale devices is extremely limited so the processing as well as the forwarding of data should be preserved in the lowest possible levels. For this reasons, the scientific community has to invent smart routing algorithms for forwarding this massive amounts of data, depending on application specific domains (i.e., applications where energy is limited, such as WSNs). In IoT the topology of a particular network in not stable in any perspective. Thus, the scientific community has to develop different protocols and tactics for forming and ad-hoc network and configuring the addressing and settings of any node (device), and at the same time minimizing the required power consumption. For example, in ZigBee the addressing as well as the coordinator, router, and end-node configuration has to be done in a way that minimizes the power consumption required. Nevertheless, many techniques and methods have been proposed for recharging the nodes in a WSN using drones [31], robots, etc. In addition, as 5G cellular networks is going to be an enabling technology for IoT, the scientific community is extremely concerned about its energy efficiency. Thus, numerous studies trying to optimize the energy efficiency aspects in 5G –as well as other IoT enabling technologies– have been conducted [32, 33]. Finally, a recent approach requires nodes participating in IoT to perform most computations within the node, only forwarding the most critical information and thus, minimizing the power consumption required in small-scale and nano-scale devices.

4 Machine Learning

4.1 Machine Learning Core Aspects

Machine Learning (ML) has been one of the most interesting topics for the last two decades. An enormous amount of related literature and companies exclusively specialized in ML literally exist. Nowadays, ML (and especially Deep Learning) has revolutionized peoples' everyday lives by offering different kinds of intelligent technologies, such as smart voice assistants, self driving cars, medical diagnosis, statistical arbitrage, etc. Machine learning scientists and engineers aim to replicate the learning process as the human mind does. Machine learning imagines the human brain as a powerful computer, with a combination of a number of external signals as inputs, a summation of these signals being the outputs. For the human mind, the same input as signals would not always result in the same output in terms of action, behaviour or process. The human physical neural pathways are adapting and changing as per the experience and feedback received. While in machine, learning happens when algorithms are updated independently through calculating input signals and how the output is determined. Inspired from the interdisciplinary nature of ML field, we below give a formal definition in order to clearly explain what exactly ML, is as well as the impact that may have in many difficult and unsolved problems.

ML is the study and development of algorithms and statistical models that could be effectively and efficiently used by computer systems to perform specific tasks (e.g., prediction, classification, etc.), without the need of *explicit instructions, but rather based on learned patterns and features from a specific dataset.* ML field is under Artificial Intelligence (AI) umbrella. In particular, ML algorithms are either based on mathematical/statistical models or Artificial Neural Networks (ANNs), where the later is considered to be a more powerful approach. Moreover, ML-based models try to infer information from the sample data given, also known as *training data*, in order to perform a prediction or a classification without being explicitly programmed for that specific task. As already mentioned, ML algorithms are widely deployed to solve different kinds of problems, such as email filtering and computer vision, where the development of specific algorithms is considered impractical due to the variety and diversity of the problem instances to be solved. It is worth to be mentioned that ML is closely related to computational statistics, which focuses on making predictions and forecasting, using classic computer systems. The study of mathematical optimization delivers methods, theory, and application domains to the field of ML. For example, *Data Mining* is a field of study within ML, and focuses on exploratory data analysis through different algorithms belonging to ML family.

In many cases, ML is refereed as *predictive analytics* when it's being applied across different business problems. ML has also been used in tackling many complex sequential data classification problems. For example, ML has been excessively used and deployed in order to tackle one of the most difficult problems in bioinformatics namely *Protein Structure Prediction (PSP)* problem. PSP is one of the most important goals pursued by bioinformatics and theoretical chemistry; it is highly important in medicine (e.g., in drug design) and biotechnology (e.g., in the design of novel enzymes). For the sake of reference, Dionysiou et al. [34], have proposed a hybrid ML approach on trying to solve *Protein Secondary Structure Prediction (PSSP)* problem. In particular, the authors combined two supervised learning algorithms namely (a) Convolutional Neural Networks (CNNs - ANN-based) and (b) Support Vector Machines (SVMs – Mathematical/Statistical-based) in order to tackle PSSP problem.

A Convolutional Neural Network (CNN) is a class of deep, feedforward ANNs that has successfully been applied to analyzing visual imagery [35,36]. CNNs were inspired by the human visual system, where individual cortical neurons respond to stimuli, only in a restricted region of the visual field, known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field. CNNs have enjoyed a great success in large-scale image and video recognition [37]. This has become possible due to the large public image repositories, such as ImageNet [36], and high-performance computing systems, such as GPUs or large-scale distributed clusters [38]. Overall, CNNs are in general a good option for feature extraction, immense complexity sequence and pattern recognition problems [34].

Support Vector Machines (SVMs) were introduced by Cortes & Vapnik [39] in 1995, initially for binary classification problems. SVMs are a powerful technique for linearly and non-linearly separable classification problems, regression, and outlier detection, with an intuitive model representation [39]. SVMs are mathematical/statistical models that try to maximize a gap between the different classes. After that, based on the gap created between the instances of different classes the middle line is taken as the optimal separation/decision hyperplane. Both, CNNs and SVMs belong to supervised learning algorithms which means that the actual category that each sample belongs in, is given. In the following subsections (4.3, 4.4, and 4.5) we firstly discuss about the datasets and different performance metrics used in ML field, and then briefly explain the three main ML algorithms' categories.

4.2 Datasets and Performance Metrics

In ML field, it is a common practise to divide the dataset into two subsets called: (a) *training set*, and (b) *testing set*. The (a) is used during the training process for tuning the parameters of the deployed ML algorithm, and the (b) is used for testing the actual accuracy of the trained model, so to conclude about different performance aspects of the proposed ML model, such as the *precision*[1], *recall*[2], and the well-known *F1-score*. The F1-score is the harmonic average of the precision and recall, where an F1-score reaches its best value at 1 (perfect precision and recall) and worst at 0. Thus, *F1-Score might be a better measure to use* if we need to seek a balance between precision and recall and there is an uneven class distribution (large number of actual negatives). Validation is probably one of most important techniques that data scientists use in an attempt to validate the stability of a proposed ML model (i.e., how well it would generalize to new data). We need to be sure that out ML-based model

[1] Precision is the number of correct positive results divided by the number of all positive results returned by the classifier.

[2] Recall is the number of correct positive results divided by the number of all relevant samples (all samples that should have been identified as positive).

has perceived most of the patterns from the training data correct, and its not picking up too much on the noise, or in other words its low on bias and variance. As a result, in addition to all of the aforementioned metrics (i.e., precision, recall, and F1-score), it is nowadays commonplace to used an extra validation technique called *k-fold cross-validation*.

Cross-validation is a technique to evaluate ML models by partitioning the original dataset into a training set to train the model, and a test set to evaluate it. In *k-fold cross-validation*, the original dataset is randomly partitioned into k equal size subsets. Of the k subsets, a *single subset* is retained as the validation data for testing the model, and the remaining *k-1 subsets* are used as training data. The cross-validation process is then repeated k times (the folds), with each of the k subsets used exactly once as the validation data. The k results from the folds can then be averaged (or otherwise combined) to produce a single estimation. The advantage of this method is that all observations are used for both training and validation, and each observation is used for validation exactly once. For classification problems, one typically uses stratified k-fold cross-validation, in which the folds are selected so that each fold contains roughly the same proportions of class labels. In most cased though, 10-fold cross-validation is used for validating the performance of a proposed ML algorithm.

4.3 Supervised Learning

In Supervised Learning (SL), the ML algorithm is trained to solve a specific problem, also having the actual results (i.e., the correct answer) for each training sample. Supervised (as well as Unsupervised learning) algorithms, require a dataset to be trained on. In particular, a dataset containing the training samples as well as the label (i.e., correct prediction/classification) for each sample is given to the algorithm [40]. For this reason, supervised learning algorithms are sometimes refereed as learning with a teacher. As a result, the SL-based algorithm tries to optimize its model representation so as to minimize an error notion between the output of the network and the actual/correct answer. SL is mainly a method for function approximation as a proposed SL-based algorithm tries to tune its own parameters with respect to the aforementioned error notion for each training sample. Nevertheless, after successfully training a SL-based algorithm it should be able to generalize its *learned knowledge* to completely new/unknown samples that the algorithm has not seen before [40]. Some algorithms belonging to SL category are: (a) K-Nearest Neighbours (KNN), (b) Decision Trees, (c) Linear Regression, (d) Support Vector Machines (SVMs), (e) Multi-Layer Perceptrons (MLPs), and (f) Convolutional Neural Networks (CNNs).

4.4 Unsupervised Learning

In Unsupervised Learning (UL), the ML algorithm is trained to group the samples given in the training set according to different similarity measures (e.g., euclidean distance, manhattan distance, cosine similarity, etc.), without having the labels (i.e., actual/correct answer) for each training sample. Thus, UL-based algorithms try to *create clusters or groups with similar instances* without any guidance (i.e., without knowing the correct answer). As UL algorithms create clusters containing the samples that are similar according to algorithm's eyes, the result is detecting different correlations and dependencies between the training samples. UL

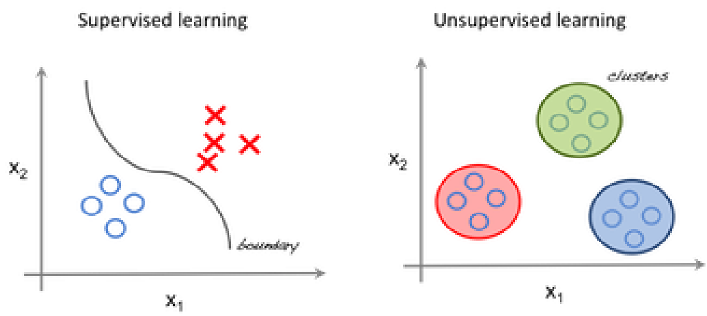

Fig. 10. In this figure, the way that SL (left) and UL (right) algorithms form the separation hyperplane and clusters, respectively. The image to the left is an example of supervised learning; we use regression techniques to find the best fit line between the features. While in unsupervised learning the inputs are segregated based on features and the prediction is based on which cluster it belonged.

algorithms are not as popular as SL algorithms mainly due to three reasons: (a) the range of applications of UL-based algorithms is limited, (b) UL-based algorithms require larger training times, and (c) the accuracy results of UL-based algorithms are often lower. For the (a), UL-based algorithms cannot be used for problems such as forecasting or prediction. This, is due to the fact that there is not the notion of prediction in the nature of UL algorithms. Moving forward, UL algorithms require larger training times (b) as the algorithm itself has to perform some excessive computation for each new training sample, to compare it with the already-processed grouped samples or the clusters' representative nodes, to conclude about the most similar cluster to assign the new training sample. The (c) is a little bit ambiguous as UL algorithms perform better in clustering problems whereas SL algorithms perform well across all kinds of problems.

Nonetheless, as UL algorithms do not perform well across the same range of problems as SL algorithms do, it is generally accepted that SL algorithms accuracy results are higher than UL algorithms.

Some algorithms belonging to UL category are: (a) K-Means, (b) Kohonen Self-Organizing Map [41], and (c) Autoencoders [42]. In many cases, UL algorithms are referred as compression algorithms as they mathematically perform dimensionality reduction of the problem instances (i.e., the number of training samples) to the number of final clusters.

4.5 Reinforcement Learning

If SL is learning with a teacher, then Reinforcement Learning (RL) is learning with a critic. In particular, RL is an area of ML mainly concerned with developing models and more specifically agents that take actions in a specified environment –which may be static or dynamic– so as to maximize some notion of cumulative reward [43]. RL is considered as one of the three ML paradigms, alongside supervised learning and unsupervised learning.

RL algorithms do not have the labels (i.e., correct answers) for each training samples, but instead they receive a penalty or reward for each action performed. Thus, the main concern of an agent in RL is to focus on finding a balance between exploration (i.e., perform an action that the received reward/penalty in not known) and exploitation (i.e., perform the action that returns the higher reward based on the agent's current knowledge) [43]. The environment is typically formulated as a Markov Decision Process (MDP) [44], as many RL algorithms for this context utilize dynamic programming techniques [45]. The main difference between

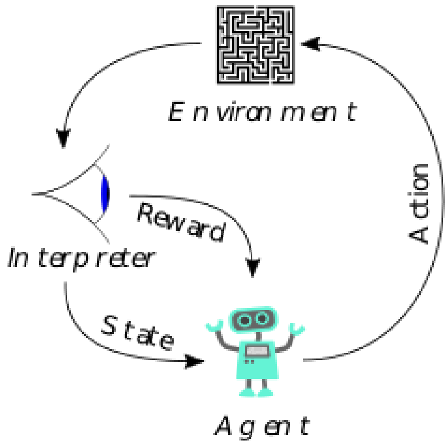

Fig. 11. In this figure, the typical framing of a RL scenario is shown. An agent takes actions in an environment, which is interpreted into a reward and a representation of the state, which are fed back into the agent.

the classical dynamic programming methods and RL algorithms is that the latter do not assume knowledge of an exact mathematical model of the MDP and they target large MDPs where exact methods become infeasible.

4.6 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) have received great interest in the last two decades. According to [46], *ANNs or connectionist systems are computing systems inspired by the biological neural networks that constitute animal brains.* As the *neural* part of their name suggests, they are brain-inspired systems which are intended to replicate the way that humans learn. ANNs consist of input, hidden and output layers. Hidden layers, usually consist of units that raise a non-linearly separable problem to a higher dimension/order so as to become linearly separable. ANNs are ideal for finding patterns which are far too complex or numerous for a human programmer to extract and teach the machine to recognize. ANNs' ability to learn from the training samples is also inspired by the humans' brain neurons plasticity [47] and resides in the weights which are the connections between the artificial neurons. Each weight/connection, like the synapses in a biological brain, can transmit a signal from one artificial neuron to another. The weight increases or decreases the strength of the signal at a connection. An artificial neuron that receives a signal can process it and then signal additional artificial neurons connected to it. In addition, artificial neurons may have a threshold such that the *signal is only sent if the aggregate signal crosses that threshold*. ANNs are most of the times the best option when trying to develop effective and efficient ML algorithms.

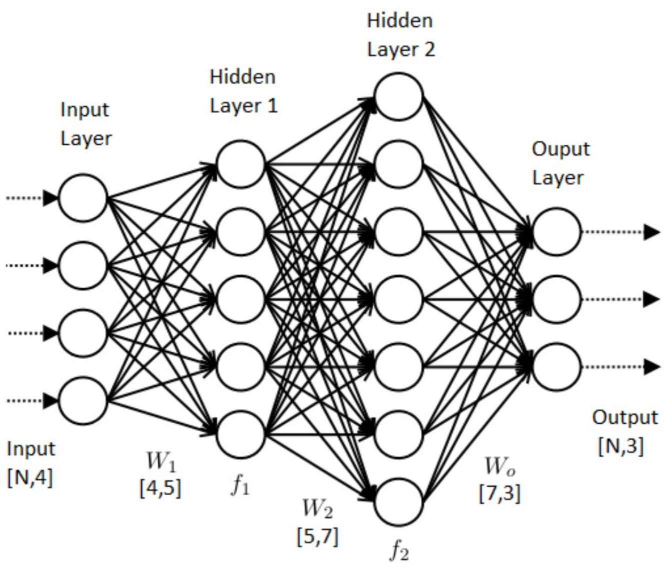

Fig. 12. In this figure an ANN having one input, one output, and two hidden layers, is shown.

As all ML algorithms, ANNs learn to perform tasks and solve specific problems by considering examples, generally without being programmed with any task-specific rules. For example, in image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labelled as *cat* or *no cat* and using the results to identify cats in other images. They do this without any prior knowledge about cats, for example, that they have fur, tails, whiskers and cat-like faces. Instead, they automatically generate identifying characteristics from the learning material that they process. In most ANN implementations, the signal at a connection between artificial neurons is a real number, and the output of each artificial neuron is computed by some non-linear function (e.g., softmax, relu, etc.) of the sum of its inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the hidden layers multiple times. Similar to mathematical/statistical ML algorithms, ANNs can be trained on solving specific complex problems using the data (in case of IoT Big Data) collected by the numerous sensing devices participating in the classic IoT. Next, the trained ML models can be employed in the devices (i.e., the *things*) participating in IoT and thus receiving as a result an enhanced concept namely Internet of Intelligent Things (IoIT). In this case, *energy efficiency is not a problem, as these trained ML models require minimum power consumption for classification or prediction purposes.*

5 Applying Machine Learning on Internet of Things

Artificial intelligence plays a crucial role in IoT applications and deployments. ML and AI have the ability to drive transformative value from the flood of data generated by IoT devices. Where AI has the ability to quickly extract valuable insights from the data, ML brings the ability to automatically identify patterns and detects anomalies in the data, such as temperature, pressure, humidity, air quality, vibration, sound, etc., derived from smart sensors and other sensing devices.

We are already living our everyday lives using devices that are offering technologies based on ML and ANNs. For example, Apple company has integrated to their products' central processing unit (cpu) a chip that is mainly based on ML and ANNs models, namely Neural Engine. Apple's designed Neural Engine is built for advanced, real-time ML. This means that the smart devices incorporating this technology can recognize patterns, make predictions, and learn from experience, similar to the way that humans do. The Neural Engine is: (a) incredibly fast, able to perform five trillion operations per second, (b) incredibly efficient, which enables it to do all kinds of new things in real time, and (c) incredibly smart, so users can do things like jump right into immersive AR experiences. This neural engine also allows for smart searching capabilities, so finding all of my pictures with cats or dogs will be as easy as typing *"cats or dogs"* in the search bar. Furthermore, Apples latest Face ID technology used for various purposes, such as unlocking or paying with Apple pay, is heavily based on this Neural Engine as the devices adopting this technology (Face ID) can recognize your face even if you put on a hat, grow a beard, or wear glasses. The ANN deployed for Face ID is modifying its own weights for training and adopting its knowledge as our face changes. The whole recognizing and training of the neural engine happens in literally no time. The same process should be adopted by all vendors and companies that develop devices that are IoT-enabled. Face ID, smart cities, smart homes, and smart sensors are just some examples of the potential of this novel combination of ML with IoT.

Keeping all of the above in mind, some ways that ML can help IoT industry to succeed its objectives and goals are shown in the below subsections:

5.1 Automating and Enhancing Data Analysis

As briefly explained above, ML can be effectively and efficiently deployed for classification, prediction, and analysis processes. One of the biggest advantages that ML brings to IoT is the automation of analysis of the enormous amounts of data generated and exchanged. Instead of a human data analyst going through the tedious process of manually analysing all these data, looking for patterns and anomalies, a well programmed and implemented ML algorithm can make this task easy by deploying completely reversed top-down approach in analysis. In other words, given a desired output or outcome, the machine can find the factors and variables that are supposed to lead to this desired output. Thus, data correlations and dependencies can be easily discovered and tracked by ML models, where a human analyst wouldn't have a chance.

A field that is primarily concerned about how these valuable insights could be extracted from this massive volume of data (Big Data) created by the enormous devices participating in IoT, is *Data Mining*. In Section 6, more details on this field will be given.

5.2 Machine Learning Models for Predictive Analysis

Through an understanding of regular patterns and algorithm updates, the software becomes self-sufficient to be able to predict the future desired or undesired events. A system, which is often supervised by a human engineer or scientist, is automatically triggered by the relevant input data, through the formula that it came up with all by itself. The software programme can easily recognize inconsistencies and anomalies that may have taken human eye ages to discover by just looking at the raw data. In addition, as explained to Supervised Learning subsection (4.3), the SL-based algorithms perform a function approximation process that results in a trained model capable of performing predictions about the future. These trained models could be easily deployed in data centres and servers receiving data from sensing devices, to conclude about future situations that the society may face. Nevertheless, a ML system is not there just to recognize any abnormal behaviour, but additionally to help the organisations understand and establish long-term trends bringing together a huge job of processing, selecting, recognizing, sorting and associating a vast amount of data collected to make comprehensive and meaningful predictions. Moreover, predictive ML models could be deployed in IoT sensor scale devices specialized for minimizing power consumption and thus extend the battery life of the small battery capacity devices participating in IoT. For example in [48], the authors present a solution that employs ML on the edge device and performs low power transmission through LoRa. More specifically, the authors mention that by implementing embedded ML with LoRa they could compress the transmitted data by 512 times and extend the battery life by three times.

Finally, foreseeing when a machine needs maintenance is unimaginably important, converting into a huge number of dollars in spared costs. Companies are now using ML to predict with over 90% accuracy when machines will need maintenance, meaning huge cost cuttings.

5.3 Personalization of Experience

It is many times absent to our knowledge that ML is in our everyday lives. For example, eBay, Amazon, and Netflix make use of ML models for optimizing the items and films or TV shows suggestions to users, based on the knowledge gained from previous purchases or films that a particular user may have watched. Furthermore, the Nest Thermostat is a representative example for the personalization advantages gained from the combination of ML with IoT, as it utilizes ML for figuring out how to take in your inclinations for warming and cooling, ensuring that the house has the correct temperature when you return home from work or when you get up in the morning. In addition to the Nest Thermostat, ML models trained/optimized to control different settings can now be deployed to a wide range of devices participating in IoT, and thus, transform homes to *smart homes*, cities to *smart cities*, vehicles to *smart vehicles*, and in general transform the previously *dump* (i.e., with no particular intelligence) devices to *intelligent devices*. Finally, a ML model trained on each patients biosignals can be constructed for personalizing the healthcare as well as optimizing the monitoring of each patient according to its individual needs.

5.4 Healthcare Optimization

The IoT has opened up a world of possibilities in healthcare sector; when connected to the internet, ordinary medical devices can collect invaluable additional data, give extra insight into symptoms and trends, enable remote care, and generally give patients more control over their lives and treatment. Thus, in this section we focus on explaining the potential benefits of IoT and ML in healthcare optimization process. Some potential applications of the IoT in healthcare sector have been mentioned in previous sections. Nonetheless, the advantages list becomes literally enormous when someone takes account of the capabilities and potentials of ML in addition to IoT.

The IoT in healthcare is a subject that has received great attention the last few years [49–52]. For example, the home environment monitoring in healthcare, is completely different, from the classic perspective of smart home in IoT. A smart home in healthcare, is a system of pervasive information and communication technologies by which both the home environment and residents' interactions with it are unobtrusively monitored by a center of medical care. Numerous sensors of all types (e.g., cameras, microphones, pulse oximeters, etc.) are installed in the patient's house.

The adoption of ML models and algorithms and thus the fusion of ambient intelligence to lets say the central processing unit of each smart home, will provide enhanced signal processing capabilities as well as recognition of activities or events with higher accuracy. For example, video-based monitoring is also an important mean to observe the health condition of patients. An IP camera can send and receive data via a computer network. Therefore, it is capable of monitoring patients in real time and also supporting video communication between patients and doctors whenever needed. In addition, image recognition techniques using ML algorithms could be added so that the system can recognize abnormal behaviour of the patient been monitored. In this way, an enhanced intelligent ML model will immediately inform the patient's doctor if something is not going as expected, and thus, maximizing the performance of smart homes in healthcare.

Moving forward, a particular application that Apple adopted to one of its products (i.e., smart watch series 4) is the fall detection via wearable. Many ambient sensor systems have been applied to address different health issues, such as mental health, emotional state, sleep measures, diabetes, and Alzheimer's disease, monitoring individual daily activities for health assessments and to detect deviation from a user's behavioural patterns. All these applications of IoT in healthcare through ambient sensors can easily be enhanced with the adoption of effectively trained ML models. Moreover, ML models personalized for controlling a specific patient's biosignals and ML models for predicting the demand for medical specialized staff and medical equipment based on a sensible factor (e.g., month), are just some potential applications in IoIT concept. Finally, as clearly stated in [51] some serious interoperability and security issues exist, preventing us from receiving the full benefits of this novel combination of ML with IoT in healthcare sector.

5.5 Intelligent Cities

Over the years, cities are continuously evolving in an attempt to offer enhanced public services and make peoples' lives easier. Nonetheless, the emergence of IoT as a technological concept has made it the core factor where most of recent *smart technologies* are based on. From smart traffic management to smart architecture and energy management and smart waste management systems, IoT is the core enabling technology that brings these applications to life. As mentioned in [53], the smart city vision is about *"exploiting the most advanced communication technologies to support added-value services for the administration of the city and for the citizens"*. Numerous studies have been conducted for analysing and attempting to formally describe and explain the smart city concept [53–55]. Most of them (if not all) have the IoT as their basic building block. The benefits that an *urban IoT* will bring are really motivating, some of them including: (a) management and optimization of traditional public services, (b) salubrity of hospitals and school, and (c) preservation of cultural heritage [53]. For this reason many frameworks (such as the ones presented in [53] and [55]) for effectively designing an urban IoT have been proposed.

Furthermore, Parera et al. [54] underline that the IoT envisions to connect billions of sensors to the Internet and expects to use them for efficient and effective resource management in Smart Cities. Thus, the authors investigate the concept of sensing as a service model in technological, economical and social perspectives and identify the major open challenges and issues [54]. They finally conclude that the sensing as a service can be a sustainable, scalable and powerful model as it creates a win-win situation for all the parties involved. Moreover, the basic building blocks of smart city IoT Infrastructure are well explained and examined in various scientific papers. For example, in [55] the sensing Paradigms, addressing schemes, connectivity models, and Quality of Service (QoS) mechanisms are described in depth. Considering all of the above, we nowadays have all the necessary tools and directions for effectively applying IoT in cities so as to receive as a result the enhanced *smart city* concept.

Nonetheless, all of the above applications and examinations of IoT in smart cities do not consider ML as a core intelligence providing technology. Thus, we make this clarification that *if IoT makes previously dump aspects of our everyday life smart, then the combination of IoT with ML offers an enhanced intelligent behaviour*. Imagine the advanced benefits that citizens of a particular smart city will enjoy after all previously smart technologies will be improved in intelligent ones, adopting ML models that optimize the performance, maximize the efficiency, and minimizing the errors of the already good –in terms of performance– IoT technologies. Finally, employing IoT in combination with ML, improves the performance of all possible applications converting in this way the previously smart technologies to intelligent ones.

6 Data Mining for the Internet of Things

ML and Data Mining (DM) have been two among the most interesting research topics in the last two decades. Nevertheless, these two terms must not be confused as they mean two totally different things that are both critical for understanding different fields related to information extraction and decision intelligence, such as Data Science. DM for the IoT has been excessively studied [56–59]. As the volume of data (Big Data) derived from IoT keeps increasing, the use of DM tools becomes a necessity. There is a larger volume of data with different structures and format coming from different vendor devices. As a consequence, data consist not only of traditional discrete data, but also of streaming data (e.g., about location, movement, vibration, temperature, humidity, and even chemical changes in the air) generated from digital sensors in industrial equipment, automobiles, electrical meters, and shipping crates.

DM tools form a valuable resource of information for different organisations' and companies' managers. The effectiveness and efficiency of these DM tools has a direct impact on the revenue as well as on the short-term and long-term business activities of a particular company. Nevertheless, the application of DM tools directly to unstructured data is a very challenging task. Thus, processing incoming data to reformat their structure according to specific standards before issuing the DM tools, is required. Data in IoT can be categorized into several types: RFID data stream, address/unique identifiers, descriptive data, positional data, environment data and sensor network data, etc., [60]. This variety of data brings great challenges for effectively and efficiently managing, analyzing and mining data in the IoT.

For this reason, different multi-layer data mining models for IoT have been proposed. For example, in [57] the authors propose a multi-layer data mining model divided into four layers: (a) data collection layer, (b) data management layer, (c) event processing layer, and (d) data mining service layer. However, this framework does not make use of ML in none of its core basic blocks. In the following subsection (6.1) a typical data mining process (shown in Figure 13) is briefly explained.

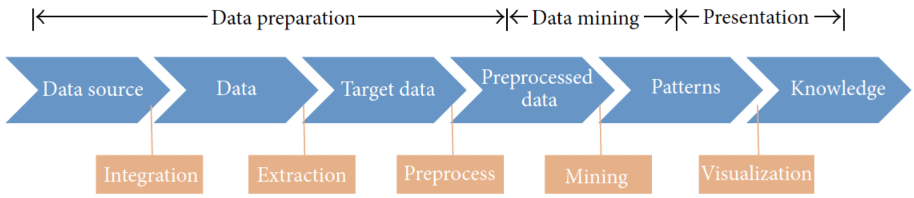

Fig. 13. In this figure a typical data mining process, is shown.

6.1 Typical Data Mining Process

According to [58], a typical DM process includes the following categories (also shown in Figure 13):

1. **Data preparation:** Prepare the data for mining, by integrating data from various data sources, clean the noise from data, and extract some parts of data into DM system.
2. **Data mining:** Apply DM algorithms to the data to find the patterns and evaluate patterns of discovered knowledge.
3. **Data presentation:** Visualize the data and represent mined knowledge to the user.

DM functionalities include classification, clustering, association analysis, time series analysis, and outlier analysis. Thus, in the following subsections the different DM functionalities will be explained in a ML-based context.

6.2 Classification

Classification, is the process of finding a set of models or functions that describe and distinguish data classes or concepts, for the purpose of predicting the class of objects whose class label is unknown. There are plenty of ML methods to classify the data, including decision tree induction, frame-based or rule-based expert systems, hierarchical classification, ANNs, Bayesian network, and SVMs [58].

6.3 Clustering

Clustering, is the process of analyzing data objects without consulting a known class model. In other words, clustering algorithms divide data into meaningful groups so that patterns in the same group are similar in some sense and patterns in different group are dissimilar in the same sense. Again, there are plenty of ML methods for clustering data, such as Hierarchical clustering, Partitioning algorithms (e.g., KNN), and ANN-based clustering algorithms, such as Kohonen Self-Organizing Maps [58].

6.4 Association Analysis

Association analysis, is the discovery of association rules displaying attribute-value conditions that frequently occur together in a given set of data. The association rule mining focuses on the market basket analysis or transaction data analysis, and it targets discovery of rules showing attribute-value associations that occur frequently and also help in the generation of more general and qualitative knowledge which in turn helps in decision making [58].

6.5 Time Series Analysis

Time series analysis, comprises methods and techniques for analyzing time series data in order to extract meaningful statistics and other correlations or characteristics of the data. A time series is a collection of temporal data objects; the characteristics of time series data include large data size, high dimensionality, and updating continuously. ML methods and more specifically ANN-based techniques (e.g., Recurrent Neural Networks, Long-Short Term Memory, etc.) are ideal for processing time series data for prediction or function approximation tasks [58].

6.6 Outlier analysis

Outlier analysis, describes and models regularities or trends for objects whose behavior changes over time. Outlier detection refers to the problem of finding samples in a dataset that are very different/dissimilar from all the other samples contained in the particular dataset based on appropriate similarity metrics, such as cosine similarity, manhattan distance, Euclidean distance, etc. Such dissimilar samples often contain useful information regarding the abnormal behaviour of a system described by the rest of the data. Again, ML models could be deployed for effectively detecting outliers in a specified dataset [58]. For example in [61], UL-based Self-organizing maps are proposed for addressing the problem of multivariate outlier detection.

6.7 Data Mining Applications

Data Mining in e-Commerce. Many companies nowadays make use of DM tools in order to understand any hidden patterns contained in their past purchase transactions datasets. In this way, new cost-effective marketing campaigns could be planned and launched. Fortunately, plenty of data related to e-commerce exist making it an attractive domain for DM to be applied on. DM in e-commerce is most of the times used for suggesting to customers products *similar* (according to a specified notion of similarity) to those which they have sometime in their life bought. To accomplish this task, the behaviour of users is monitored and analysed when surfing in Internet, searching, as well as selecting different products. Classic recommender systems using collaborative filtering may propose the most popular items that people/customers, similar to a particular user (again leveraging different similarity metrics), bought. In this way, it has been shown experimentally that there was an increment on sales in contrast with suggestion systems that just consider user's preferences. Recommender systems also extends to social network, education area, academic library, and tourism [58].

Data Mining in Health Care. As already mentioned DM in healthcare is an increasingly popular field for the last decade. The various and heterogeneous medical data generated by different healthcare organizations and centres, including payers, medical equipment providers, goverment, pharmaceuttical companies, doctor notes, etc., can be used as datasets for performing DM on them, predictive modelling, survival analysis, clustering, classification and a bunch of other analytics tools for improving the quality of care as well as reduce the cost and wasted resources. Patients' medical data can be *mined* to explore any opportunities for delivering same medical results (i.e., treatment) but at the same time minimizing the required resources. Futhermore, applying DM in medical data can detect unusual patterns and thus potential frauds, as well as detect and understand the high-cost patients suffering from rare diseases [58].

Data Mining in City Governance. DM can be directly applied in public service areas to discover any potential public needs, improve services' performance, and aid decision making systems. Estonia, is popular for its all e-government based approach where the most government-related processes are individually performed by citizens through the Internet. E-government improves quality of government service, cost savings, wider political participation, and more effective policies and programs. Furthermore, DM could be employed in order to assess the impact of different natural disasters on the agricultural production to rank the disaster affected areas objectively and assist governments in disaster preparation and resource allocation. Moreover, the factors that lead a resident's decision to leave the city can be tracked, using data analytic tools through DM platforms. Finally, the government could deploy DM techniques to analyze the growing volume of crime data and detect the highest crime areas so to adapt its law enforcement methodologies according to the new insights gained [58].

7 Conclusion

The IoT concept arises from the need to interconnect, manage, and automate the process of controlling and extracting useful information from the enormous amounts of interconnected devices. Nevertheless, the full benefits of this groundbreaking concept cannot be fully realized without the adoption of ML as the core technology for the devices' intelligence and processing capabilities enhancing, as well as empowering DM tools with increased performance on detecting the underlying insights and valuable information contained in large volumes of data. Employing ML models in devices and sensors participating in IoT will unlock the potential advantages that this novel combination may have.

However, the IoT's key enabling technologies as well as different limitations of the devices that may arise (e.g., battery capacity) should be carefully examined. ML is the key technology that will transform the classic Internet of Things to an enhanced version called *Internet of Intelligent Things*. In this large-scale comprehensive evaluation, we have explained in detail what exactly IoT is (Section 2) also giving some of the most prominent key enabling technologies (Section 2.2). Furthermore, we have explained in-detail why IoT causes the rise of Big Data due the enormous number of IoT's participating devices as well as their continuous operating (and thus, the continuous generation of data), also detecting the major challenges in IoT's Big Data era that need to be effectively tackled (Section 3.2).

Afterwards, we made a deep dive to Machine Learning core aspects (Section 4), also discussing and explaining how different Machine Learning models could be deployed for enhancing the IoT as a concept and transforming it to IoIT (Section 5). Moreover, Data Mining in IoT has been described in detail in order to get the insights behind the strong connection of Machine Learning and Data Mining fields (Section 6). DM and ML are closely working together when trying to effectively extract and discover data correlations and features from complex sequential data arising from the emergence of IoT. ML-based DM in IoT, clearly lead the classic IoT concept to its enhanced version, namely IoIT. Considering all of the above, we have shown in detail how *Internet of Intelligent Things* (i.e., the enhanced version of IoT) can be fully realized by adopting Machine Learning technologies. It is worth to be noted, that the full benefits and potentials can be fully achieved through the *effective and efficient utilization* of the new enhanced concept, namely IoIT. Through IoIT, humanity can achieve goals and objectives, previously seen only as potential *opportunities* [62].

In conclusion, this work aims on briefly explaining the different aspects composing the new, enhanced IoT concept, namely IoIT, also giving the open challenges related to it. In addition, this large-scale evaluation aims on providing directions towards the realization of IoIT, also trying to inspire and motivate researchers to conduct studies in IoIT-related aspects. Finally, in an attempt to define this interdisciplinary concept, we provide the following definition for IoIT. *Internet of Intelligent Things (IoIT), is the act of deploying intelligence on an enormous amount of interconnected devices as well as for extracting useful insights from the Big Data derived from them.*

References

1. A. Whitmore, A. Agarwal, and L. Da Xu, "The internet of things—a survey of topics and trends," *Information Systems Frontiers*, vol. 17, no. 2, pp. 261–274, Apr 2015. [Online]. Available: https://doi.org/10.1007/s10796-014-9489-2
2. J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of things (iot): A vision, architectural elements, and future directions," *Future Generation Computer Systems*, vol. 29, no. 7, pp. 1645 – 1660, 2013, including Special sections: Cyber-enabled Distributed Computing for Ubiquitous Cloud and Network Services & Cloud Computing and Scientific Applications — Big Data, Scalable Analytics, and Beyond. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167739X13000241
3. K. Ashton, "That 'internet of things' thing," *RFID journal*, vol. 22, no. 7, pp. 97–114, 2009.
4. T. Segaran and J. Hammerbacher, *Beautiful data: the stories behind elegant data solutions.* " O'Reilly Media, Inc.", 2009.
5. M. S. Hajirahimova and A. S. Aliyeva, "About big data measurement methodologies and indicators," *International Journal of Modern Education and Computer Science*, vol. 9, no. 10, p. 1, 2017.
6. D. Reinsel, J. Gantz, and J. Rydning, "Data age 2025: The evolution of data to life-critical," *Don't Focus on Big Data*, 2017.
7. J. R. Mashey, "Big data and the next wave of infrastress," in *Computer Science Division Seminar, University of California, Berkeley*, 1997.
8. P. M. Mell and T. Grance, "Sp 800-145. the nist definition of cloud computing," 2011.
9. L. Atzori, A. Iera, and G. Morabito, "The internet of things: A survey," *Computer Networks*, vol. 54, no. 15, pp. 2787 – 2805, 2010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1389128610001568
10. S. C. B. Intelligence, "Disruptive civil technologies–six technologies with potential impacts on us interests out to 2025," *National Intelligence Council (Washington)*, 2008.

11. V. Paul and A. V. D. Bussche, *The EU General Data Protection Regulation (GDPR).* Springer International Publishing, 2017.
12. G. A. Akpakwu, B. J. Silva, G. P. Hancke, and A. M. Abu-Mahfouz, "A survey on 5g networks for the internet of things: Communication technologies and challenges," *IEEE Access*, vol. 6, pp. 3619–3647, 2018.
13. W. Yao, C. Chu, and Z. Li, "The use of rfid in healthcare: Benefits and barriers," in *2010 IEEE International Conference on RFID-Technology and Applications*, June 2010, pp. 128–134.
14. B. Vijayaraman and B. A. Osyk, "An empirical study of rfid implementation in the warehousing industry," *International Journal of Logistics Management, The*, vol. 17, pp. 6–20, 01 2006.
15. Y. Duroc and S. Tedjini, "Rfid: A key technology for humanity," *Comptes Rendus Physique*, vol. 19, no. 1, pp. 64 – 71, 2018, radio science for Humanity / Radiosciences au service de l'humanité Journées scientifiques URSI-France 2017 – SophiaTech, Sophia Antipolis, France, 1–3 February 2017 / 1er–3 mars 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1631070518300124
16. R. D. Hudson, *Infrared system engineering.* Wiley-Interscience New York, 1969, vol. 1.
17. C. Gomez, J. Oller, and J. P. Aspas, "Overview and evaluation of bluetooth low energy: An emerging low-power wireless technology," in *Sensors*, 2012.
18. K. M. Dostert, "Frequency-hopping spread-spectrum modulation for digital communications over electrical power lines," *IEEE Journal on Selected Areas in Communications*, vol. 8, no. 4, pp. 700–710, May 1990.
19. and E. S. Sousa and S. Pasupathy, "Multicarrier cdma with adaptive frequency hopping for mobile radio systems," *IEEE Journal on Selected Areas in Communications*, vol. 14, no. 9, pp. 1852–1858, Dec 1996.
20. P. H. Kindt, D. Yunge, R. Diemer, and S. Chakraborty, "Precise energy modeling for the bluetooth low energy protocol," *CoRR*, vol. abs/1403.2919, 2014.
21. M. Siekkinen, M. Hiienkari, J. K. Nurminen, and J. Nieminen, "How low energy is bluetooth low energy? comparative measurements with zigbee/802.15.4," in *2012*

IEEE Wireless Communications and Networking Conference Workshops (WCNCW), April 2012, pp. 232–237.

22. M. R. Palattella, M. Dohler, A. Grieco, G. Rizzo, J. Torsner, T. Engel, and L. Ladid, "Internet of things in the 5g era: Enablers, architecture, and business models," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 3, pp. 510–527, March 2016.
23. IEEE, "Part 15.4: wireless medium access control (mac) and physical layer (phy) specifications for low-rate wireless personal area networks (lr-wpans), ansi/ieee std 802.15.4," *IEEE Standard 802.15.4*, 01 2001.
24. D. Gislason, *Zigbee Wireless Networking.* Newnes, 01 2008.
25. M. R. Palattella, N. Accettura, X. Vilajosana, T. Watteyne, L. A. Grieco, G. Boggia, and M. Dohler, "Standardized protocol stack for the internet of (important) things," *IEEE Communications Surveys Tutorials*, vol. 15, no. 3, pp. 1389–1406, Third 2013.
26. E. Khorov, A. Lyakhov, A. Krotov, and A. Guschin, "A survey on ieee 802.11ah: An enabling networking technology for smart cities," *Computer Communications*, vol. 58, pp. 53 – 69, 2015, special Issue on Networking and Communications for Smart Cities. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0140366414002989
27. M. S. Mahdavinejad, M. Rezvan, M. Barekatain, P. Adibi, P. Barnaghi, and A. P. Sheth, "Machine learning for internet of things data analysis: a survey," *Digital Communications and Networks*, vol. 4, no. 3, pp. 161 – 175, 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S235286481730247X
28. F. Chen, P. Deng, J. Wan, D. Zhang, A. V. Vasilakos, and X. Rong, "Data mining for the internet of things: Literature review and challenges," *International Journal of Distributed Sensor Networks*, vol. 11, no. 8, p. 431047, 2015. [Online]. Available: https://doi.org/10.1155/2015/431047
29. J. Dean and S. Ghemawat, "Mapreduce: Simplified data processing on large clusters," in *OSDI'04: Sixth Symposium on Operating System Design and Implementation*, San Francisco, CA, 2004, pp. 137–150.
30. J. Deogirikar and A. Vidhate, "Security attacks in iot: A survey," in *2017 International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)*

(I-SMAC), Feb 2017, pp. 32–37.

31. C. Wang and Z. Ma, "Design of wireless power transfer device for uav," in *2016 IEEE International Conference on Mechatronics and Automation*, Aug 2016, pp. 2449–2454.
32. D. Zhang, Z. Zhou, S. Mumtaz, J. Rodriguez, and T. Sato, "One integrated energy efficiency proposal for 5g iot communications," *IEEE Internet of Things Journal*, vol. 3, no. 6, pp. 1346–1354, Dec 2016.
33. X. Ge, S. Tu, G. Mao, C. Wang, and T. Han, "5g ultra-dense cellular networks," *IEEE Wireless Communications*, vol. 23, no. 1, pp. 72–79, February 2016.
34. A. Dionysiou, M. Agathocleous, C. Christodoulou, and V. Promponas, "Convolutional neural networks in combination with support vector machines for complex sequential data classification," in *Artificial Neural Networks and Machine Learning – ICANN 2018*, V. Kůrková, Y. Manolopoulos, B. Hammer, L. Iliadis, and I. Maglogiannis, Eds. Cham: Springer International Publishing, 2018, pp. 444–455.
35. W. Rawat and Z. Wang, "Deep convolutional neural networks for image classification: A comprehensive review," *Neural Computation*, vol. 29, pp. 1–98, 06 2017.
36. A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume 1*, ser. NIPS'12. USA: Curran Associates Inc., 2012, pp. 1097–1105. [Online]. Available: http://dl.acm.org/citation.cfm?id=2999134.2999257
37. S. Srinivas, R. K. Sarvadevabhatla, K. R. Mopuri, N. Prabhu, S. S. Kruthiventi, and R. V. Babu, "A taxonomy of deep convolutional neural nets for computer vision," *Frontiers in Robotics and AI*, vol. 2, p. 36, 2016.
38. K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.
39. C. Cortes and V. Vapnik, "Support-vector networks," *Machine learning*, vol. 20, no. 3, pp. 273–297, 1995.
40. R. Caruana and A. Niculescu-Mizil, "An empirical comparison of supervised learning algorithms," in *Proceedings of the 23rd international conference on Machine learning.*

ACM, 2006, pp. 161–168.

41. T. Kohonen, “The self-organizing map,” *Proceedings of the IEEE*, vol. 78, no. 9, pp. 1464–1480, Sep. 1990.
42. P. Jiang, M. Maghrebi, A. Crosky, and S. Saydam, “Chapter 23 - unsupervised deep learning for data-driven reliability and risk analysis of engineered systems,” in *Handbook of Neural Computation*, P. Samui, S. Sekhar, and V. E. Balas, Eds. Academic Press, 2017, pp. 417 – 431. [Online]. Available: http://www.sciencedirect.com/science/article/pii/B9780128113189000235
43. L. P. Kaelbling, M. L. Littman, and A. P. Moore, “Reinforcement learning: A survey,” *Journal of Artificial Intelligence Research*, vol. 4, pp. 237–285, 1996. [Online]. Available: http://people.csail.mit.edu/lpk/papers/rl-survey.ps
44. R. A. Howard, “Dynamic programming and markov processes.” 1960.
45. R. Bellman, “Dynamic programming,” *Science*, vol. 153, no. 3731, pp. 34–37, 1966. [Online]. Available: http://science.sciencemag.org/content/153/3731/34
46. S. Haykin, *Neural Networks: A Comprehensive Foundation*, 1st ed. Upper Saddle River, NJ, USA: Prentice Hall PTR, 1994.
47. C. J. Woolf and M. W. Salter, “Neuronal plasticity: Increasing the gain in pain,” *Science*, vol. 288, no. 5472, pp. 1765–1768, 2000. [Online]. Available: http://science.sciencemag.org/content/288/5472/1765
48. V. M. Suresh, R. Sidhu, P. Karkare, A. Patil, Z. Lei, and A. Basu, “Powering the iot through embedded machine learning and lora,” in *2018 IEEE 4th World Forum on Internet of Things (WF-IoT)*. IEEE, 2018, pp. 349–354.
49. Y. Yuehong, Y. Zeng, X. Chen, and Y. Fan, “The internet of things in healthcare: An overview,” *Journal of Industrial Information Integration*, vol. 1, pp. 3–13, 2016.
50. N. Zhu, T. Diethe, M. Camplani, L. Tao, A. Burrows, N. Twomey, D. Kaleshi, M. Mirmehdi, P. Flach, and I. Craddock, “Bridging e-health and the internet of things: The sphere project,” *IEEE Intelligent Systems*, vol. 30, no. 4, pp. 39–46, 2015.
51. L. M. R. Tarouco, L. M. Bertholdo, L. Z. Granville, L. M. R. Arbiza, F. Carbone, M. Marotta, and J. J. C. De Santanna, “Internet of things in healthcare:

Interoperatibility and security issues," in *2012 IEEE international conference on communications (ICC)*. IEEE, 2012, pp. 6121–6125.

52. D. He and S. Zeadally, "An analysis of rfid authentication schemes for internet of things in healthcare environment using elliptic curve cryptography," *IEEE internet of things journal*, vol. 2, no. 1, pp. 72–83, 2015.
53. A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, "Internet of things for smart cities," *IEEE Internet of Things journal*, vol. 1, no. 1, pp. 22–32, 2014.
54. C. Perera, A. Zaslavsky, P. Christen, and D. Georgakopoulos, "Sensing as a service model for smart cities supported by internet of things," *Transactions on Emerging Telecommunications Technologies*, vol. 25, no. 1, pp. 81–93, 2014.
55. J. Jin, J. Gubbi, S. Marusic, and M. Palaniswami, "An information framework for creating a smart city through internet of things," *IEEE Internet of Things journal*, vol. 1, no. 2, pp. 112–121, 2014.
56. C. Tsai, C. Lai, M. Chiang, and L. T. Yang, "Data mining for internet of things: A survey," *IEEE Communications Surveys Tutorials*, vol. 16, no. 1, pp. 77–97, First 2014.
57. S. Bin, L. Yuan, and W. Xiaoyi, "Research on data mining models for the internet of things," in *2010 International Conference on Image Analysis and Signal Processing*. IEEE, 2010, pp. 127–132.
58. F. Chen, P. Deng, J. Wan, D. Zhang, A. V. Vasilakos, and X. Rong, "Data mining for the internet of things: Literature review and challenges," *International Journal of Distributed Sensor Networks*, vol. 11, no. 8, p. 431047, 2015. [Online]. Available: https://doi.org/10.1155/2015/431047
59. P. Wlodarczak, M. Ally, and J. Soar, "Data mining in iot: Data analysis for a new paradigm on the internet," in *Proceedings of the International Conference on Web Intelligence*, ser. WI '17. New York, NY, USA: ACM, 2017, pp. 1100–1103. [Online]. Available: http://doi.acm.org/10.1145/3106426.3115866
60. J. Cooper and A. James, "Challenges for database management in the internet of things," *IETE Technical Review*, vol. 26, 09 2009.
61. A. Munoz and J. Muruzábal, "Self-organizing maps for outlier detection," *Neurocomputing*, vol. 18, no. 1-3, pp. 33–60, 1998.

62. Y.-K. Chen, “Challenges and opportunities of internet of things,” in *17th Asia and South Pacific design automation conference.* IEEE, 2012, pp. 383–388.