Artificial Intelligence on Edge Computing: a Healthcare Scenario in Ambient Assisted Living

Andrea Pazienza[1[0000−0002−6827−2585]], Giulio Mallardi[1,2], Corrado Fasciano[1,2], and Felice Vitulano[1]

[1] Innovation Lab, Exprivia S.p.A.
Via A. Olivetti 11, Molfetta (I-70056), Italy
{andrea.pazienza, giulio.mallardi, corrado.fasciano, felice.vitulano}@exprivia.com
[2] Polytechnic University of Bari – Via E. Orabona 4, Bari (I-70125), Italy
{giulio.mallardi,corrado.fasciano}@poliba.it

Abstract. The aging population brings many challenges surrounding the quality of life for older people and their carers, as well as impacts on the healthcare market. Several initiatives all over the world have focused on the problem of helping the aging population with Artificial Intelligence (AI) technology, aiming at promoting a healthier society, which constitutes a main social and economic challenge. In this paper, we focus on an Ambient Assisted Living scenario in which a Smart Home Environment is carried out to assist elders at home, performing trustworthy automated complex decisions by means of IoT sensors, smart healthcare devices, and edge nodes. The core idea is to exploit the proximity between computing and information-generation sources. Taking automated complex decisions with the help AI-based techniques directly on the Edge enables a faster, more private, and context-aware Edge Computing empowering, called Edge Intelligence.

Keywords: Edge Computing · Edge Intelligence · Healthcare · Smart Home Environment · Ambient Intelligence · Semantic Web of Things · Argumentation · Decision Support Systems · Explainable AI

1 Introduction

One of the main issues that healthcare is facing is the aging population, which will lead to an ever-increasing rise in the costs associated with prevention, diagnosis, and treatments. In recent years there has been an increasing attention on Ambient Assisted Livng (AAL) topics such as "aging well" or "domiciliary hospitalization". In particular, the latter deals with the situation in which a person is considered or treated as hospitalized even when he/she is at home. In this scenario, Artificial Intelligence (AI) techniques can play a crucial role. The development of new AI-based techniques, supporting older adults and helping them to cope with the changes of aging and healthcare assistance, represents one of the most advanced Information & Communication Technology (ICT) areas.

Thanks to the ever more availability of the Web resources, the Internet of Things (IoT) and mobile technologies, the healthcare system has now the possibility of moving a step forward the path of prevention, diagnosis and care to the patient's home by delegating the use of healthcare facilities, personnel, and machinery only in cases of urgency or specialized expertise.

Due to various challenging issues such as computational complexity and more delay in Cloud Computing, Edge Computing is an emerging paradigm and a promising solution that pushes computing tasks and services from the network core to the network edge. Recently, Edge Computing has overtaken the conventional process by efficiently and fairly allocating the resources i.e., power and battery lifetime in IoT-based industrial applications. In the meantime, considering that AI is functionally necessary for quickly analyzing huge volumes of data and extracting insights, there exists a strong demand to integrate Edge Computing and AI, which gives the birth of Edge Intelligence. Moreover, Big Data has recently gone through a radical shift of data source from the mega-scale cloud datacenters to the increasingly widespread end-devices, e.g., mobile devices and IoT devices. We are then facing an urgent need to push the AI frontiers to the network edge so as to fully unleash the potential of the edge big data.

Therefore, the paper aims are threefold: (i) to introduce a novel Edge Intelligence architecture; (ii) to exploit several interrelated AI techniques that may be involved in an Edge Computing solution; and, (iii) to present a novel full-edge platform, called *eLifeCare*, which is enhanced by the In-Edge computation of AI-based techniques to perform reliable decision-making activities in a high complexity scenario such as the healthcare domiciliary hospitalization in an AAL fashion.

This paper is organized as follows. Section 2 provides an overview of related work and technologies which were investigated as background knowledge. Section 3 describes the architecture of our proposal, taking into account all the requirements coming from different disciplines of AI, and introduces the eLifeCare platform. Section 4 describes the possible scenarios of application specifically designed for our approach, such as Healthcare in AAL. Finally, Section 5 discusses the proposed framework and concludes the paper, outlining future works.

2 Background and Related Work

In this section we will cover all the basics and recent state-of-the-art of Edge Intelligence and AI-based reasoning tasks useful to present the architecture of our proposed platform.

2.1 Edge Intelligence

Pushing the AI frontier to the edge ecosystem that resides at the last mile of the Internet is highly non-trivial, due to the concerns on performance, cost

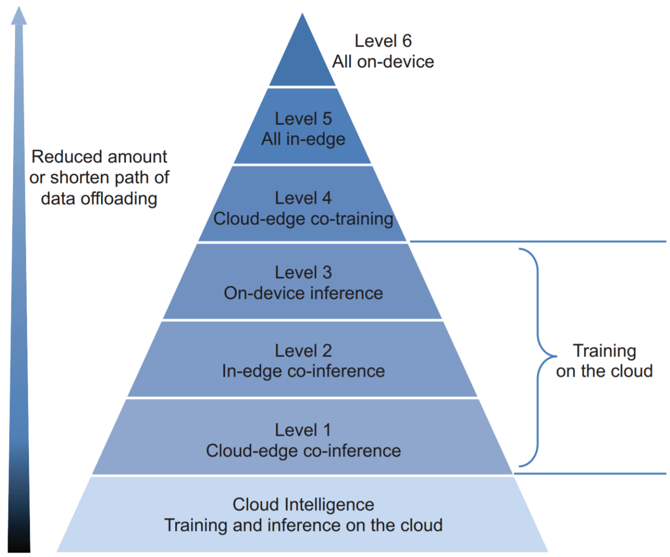

Fig. 1. Six levels of AI on Edge [37]

and privacy. Essentially, the physical proximity between the computing and information-generation sources promises several benefits compared to the traditional cloud-based computing paradigm, including low-latency, energy-efficiency, privacy protection, reduced bandwidth consumption, on-premises and context-awareness [37]. On the one side, Edge Computing aims at coordinating a multitude of collaborative edge devices and servers to process the generated data in proximity; on the other side, AI strives for simulating intelligent human behavior in devices/machines by learning from data. Besides enjoying the general benefits of edge computing, pushing AI to the edge further benefits each other.

Edge Intelligence does not necessarily mean that the AI model is fully trained or inferred at the edge, but can work in a cloud-edge-device coordination manner via data offloading. As shown in Figure 1, as the level of Edge Intelligence goes higher, the amount and path length of data offloading reduce. As a result, the transmission latency of data offloading decreases, the data privacy increases and the WAN bandwidth cost reduces. However, this is achieved at the cost of increased computational latency and energy consumption. The surge of IoT devices makes the Internet of Everything (IoE) a reality [20]. More and more data is created by widespread and geographically distributed mobile and IoT devices, other than the mega-scale cloud datacenters. Edge Computing provides AI also with scenarios and platforms. Many more application scenarios, such as Industry 4.0, Healthcare, and Territorial Control, can leverage data into more useful information and interoperable industrial control networks to put humans in the loop, connecting them in a more relevant, valuable ways [26].

Regarding Edge Intelligence scenarios specifically in the area of AAL, [14] proposed an agent-based system that works in an SHE scenario, which is in charge of handling the different features and capabilities of a situation-aware environment, ensuring suitable contextualized and personalized support to the users actions, adaptivity to the user's status and needs and to changes over time, and automated management of the environment itself. While, focusing on the Healthcare domain, [19] proposed a Telemedicine Platform for the treatment, care, and early prevention of the patient with a strong passage from the hospital to the domestic dimension (called also proximity medicine), through the exploitation of advanced sensors for monitoring and administering patient home-based therapies, including also data analytics. In [27] it is proposed to exploit the concept of Fog Computing in Healthcare IoT systems by forming a geo-distributed intermediary layer of intelligence between sensor nodes and Cloud. Instead, [22] proposed an architecture for IoT based u-healthcare monitoring with the motivation and advantages of Cloud to Fog (C2F) computing which interacts more by serving closer to the edge (end-points) at smart Homes and hospitals. In [16] it is proposed a three layer patient-driven Healthcare architecture for real-time data collection, processing and transmission, giving insights to the end-users for the applicability of fog devices and gateways in Healthcare 4.0 environment. While, [7] proposed the Edge-Cognitive-Computing-based (ECC-based) smart-healthcare system, able to monitor and analyze the physical health of users using cognitive computing, and performing optimal computing resource allocation of the whole edge computing network comprehensively according to the health-risk grade of each user.

Recently, in [35] an AI-driven mechanism for Edge Computing is proposed as a dynamic approach to adapt the running time of sensing and transmission processes in IoT-based portable devices. Contrariwise, in [25] advances AI mechanism of Computer Vision and Conversational Interfaces are deployed on the devices to improve smart manufacturing processes. Thus, we have to distinguish two different approaches of Edge-AI. On the one hand, *AI for edge* is a research direction focusing on providing a better solution to the constrained optimization problems in Edge Computing with the help of popular and effective AI technologies. Here, AI is used for energizing edge with more intelligence and optimality [18]. On the other hand, *AI on edge* studies how to carry out the entire process of AI models on edge. It is a paradigm of running AI models training and inference with cloud-edge-device synergy, which aims at extracting insights from massive and distributed edge data with the satisfaction of algorithm performance, cost, privacy, reliability, and efficiency [11].

Our research is broadly situated in the latter purpose of Edge Intelligence. Further, our contribution is placed in a scenario where the convergence of multiple AI-technologies allow us to automate complex decision-making activities resulting from a multi-strategic inference approach. In fact, the scope of Edge Intelligence should not be restricted to running AI models, referring exclusively to Machine Learning (ML) or Deep Learning (DL) models [36]. We believe instead that Edge Intelligence should be the paradigm that fully exploits the available data and resources across the hierarchy of end-devices, edge nodes and cloud datacenters to optimize the overall performances of various different AI techniques:

- ML/DL (training & inferring) models;
- Knowledge Representation (KR) and Semantic Web Technologies for IoT;
- Reasoning over uncertain, partial, and conflicting information.

To this end, we can achieve trustable and explainable results, insomuch that an AI distributed at the edge of a multi-IoT network, such as in a Smart Home Environment (SHE), would justify its decisions in a reliable and transparent way.

2.2 Knowledge Representation with Semantic Web of Things

The Semantic Web of Things (SWoT) is an emerging paradigm in ICT, joining the Semantic Web and IoT. On the one side, the Semantic Web initiative aims at allowing software agents to share, reuse and combine information available in the World Wide Web [3]. On the other side, the IoT vision promotes on a global scale the pervasive computing paradigm, which aims at embedding intelligence into ordinary objects and physical locations by means of a large number of heterogeneous micro-devices, each conveying a small amount of information [31]. Consequently, as we can see from Figure 2, the goal of SWoT is to embed semantically rich and easily accessible information into the physical world, by enabling storage and retrieval of annotations from such tiny smart objects [28]. These capabilities enable new classes of smart applications and services by augmenting real-world object, locations and events with semantically rich and machine-understandable information.

SWoT environments are intrinsically dynamic: the availability of hosts, data sources and services can vary frequently and unpredictably, due to device and people mobility, battery limitations and wireless networks unreliability [30]. The SWoT vision has significant impact also on human-computer interaction models, with the goal of reducing the amount of user effort and attention required in order to benefit from computing systems. Such a vision requires an increased flexibility and autonomy of ubiquitous knowledge-based systems in information encoding, management, dissemination and discovery. User agents running on mobile personal devices are designed to be able in dynamically discovering the best available resources according to users profile and preferences, in order to support her current tasks through unobtrusive and context-dependent suggestions [32].

SWoT may enhance also ML classification tasks by merging ontology-based characterizations of data distributions with non-standard reasoning for a fine-grained event detection [29]. In this way, a classification problem of ML can be treated as a resource discovery by exploiting semantic matchmaking. Outputs of classification are endowed with computer-processable descriptions in standard Semantic Web languages, while explanation of matchmaking outcomes motivates confidence on results on a single edge node.

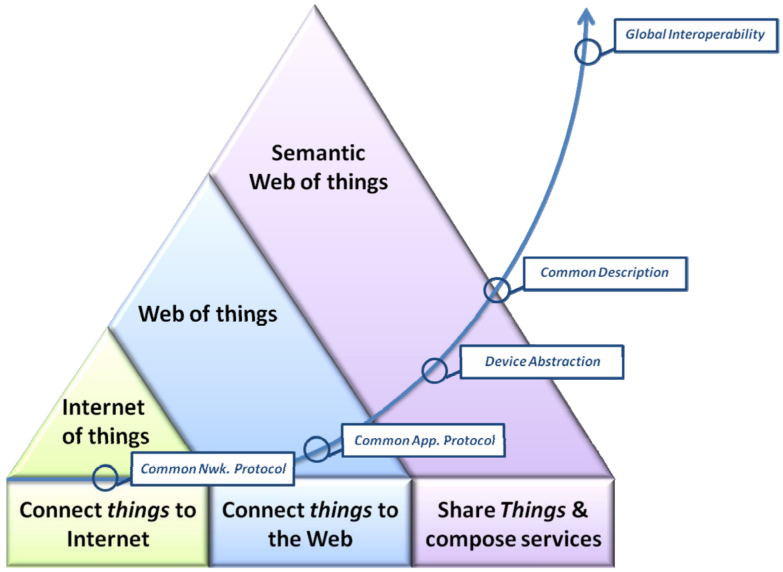

Fig. 2. Evolution from the Internet of Things to the Semantic Web of Things [15]

2.3 Explainable and Reliable Decision-making with Argumentation

In AI, Abstract Argumentation is a very simple but also very powerful formalism to reason over conflicting knowledge. It studies the acceptability of arguments based purely on their relationships and abstracted from their content. An argument is a set of assumptions (i.e., information from which conclusions can be drawn), together with a conclusion that can be obtained by one or more reasoning steps. Given a problem to solve (making decision, reasoning with uncertain information, classifying an object), arguments are different from proofs in that they are *defeasible*, that is, a type of non-monotonic reasoning in which the validity of their conclusions can be disputed by other arguments in the light of new evidence. Then, *Argumentation* is the process by which arguments and counterarguments are constructed and handled. Handling arguments may involve comparing arguments, evaluating them in some respects, and judging a constellation of arguments and counterarguments to consider whether any of them are warranted according to some principled criterion [4].

Basically, *Abstract Argumentation*, introduced by Dung [12], is a graph-based formalism to reason over conflicting knowledge without considering the internal structure of the arguments but only on their relations of attack, denoting the conflicts between the arguments, and a semantics for evaluating them, i.e. assessing to what extent each argument is acceptable.

Building appropriate argumentation formalism can cause much more concern than expected. Attention must be paid to avoid the risk of violating some natural rationality postulates [5] in the overall instantiation-based argumentation

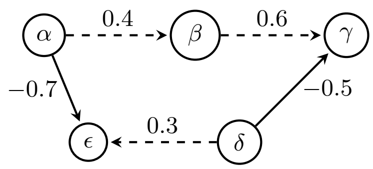

Fig. 3. Example graph to illustrate a BWAF

process. Here, generating proper argumentation structures is the key to obtaining reasonable and consistent output. Dung's original formalism for abstract argumentation has been extended along many lines giving rise to a large and thriving literature in AI (see [34, 1] for an overview). Most relevant frameworks may consider a *support* relation alongside the attack relation [6] (leading to a notion of bipolar frameworks), or may add quantitative information to empower the strength of (attack) relations [13, 10], others assign a preference between arguments [21, 2].

A Bipolar Weighted AF (*BWAF*) [24, 23] incorporates two of most important generalizations of Dung-style AFs: the bipolar AF (BAF), and weighted AF (WAF). The idea behind it is to allow not only weighted attack relations between abstract arguments, but also weighted support relations. This is achieved by assigning to each relation a weight which can be positive or negative. As depicted in Figure 3, a BWAF can be represented as a directed graph whose nodes represent arguments, relations represent attacks (with normal arcs) and supports (with dashed arcs), and weights represent the relative strength of relations.

This representation has been chosen as the most convenient and suitable to reason over partial and/or inconsistent knowledge conveyed by devices in an Edge Intelligence system. In fact, giving the sensors, actuators, and other edge devices the faculty of arguing about the information they are conveying, it follows that the whole IoT network and Edge infrastructure would become smarter and more reliable. Devices would become able to perform operations such as processing data on Edge so as to produce higher-level information and autonomously deciding their own course of actions toward the achievement of their (individual or collectively shared) goals [17]. With argumentation, smart devices will be capable of explaining their behavior and motivating their choices and decisions, also improving their capability of interaction with humans-in-the-loop.

3 Exprivia's AI on Edge

In this section we firstly present a generic Edge Computing architecture that exploits several AI techniques to optimize healthcare in a SHE autonomous setting, and then we focus on eLifeCare, that is our platform in which AI on Edge is actually performed.

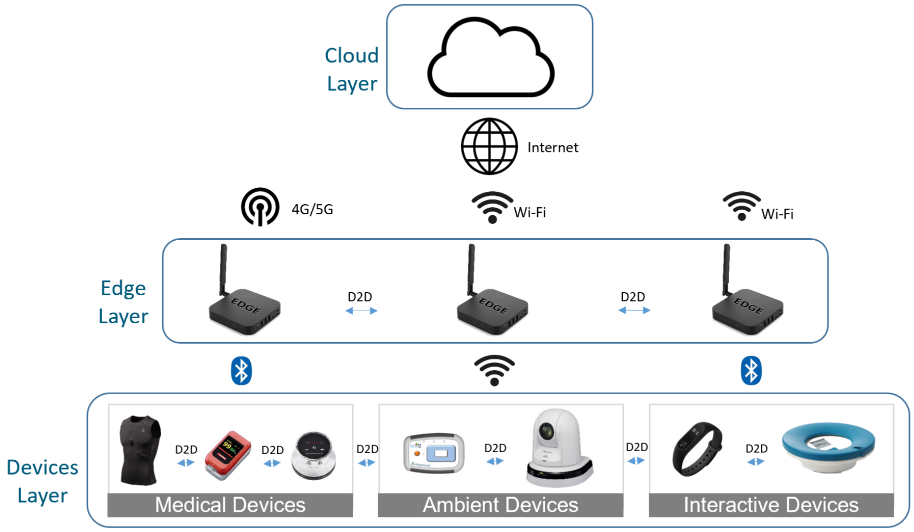

Fig. 4. AI on Edge Architecture for Healthcare

3.1 AI on Edge Architecture for Healthcare in AAL

We have to deal with and Edge Computing architecture so that processing can be done at the devices (i.e., end-nodes), or at the gateways (i.e., edge nodes). This will reduce unnecessary data traffic and processing latency, and is important for applications such as critical patient monitoring and analysis. Focus is placed on designing and developing edge nodes, with associated end-nodes for various patient monitoring applications. In this complex scenario, we deal with a large scale of heterogeneous devices as edge nodes in an IoT environment, which, at different levels of abstractions and different roles, communicate and convey different kinds of information:

1. End-nodes / Device Layer:
   – Simple, Complex sensor;
   – Mobile, Wearable, Embedded devices;
   – Actuators.
2. Edge nodes / Edge Layer:
   – Gateway, Sink devices;
   – Fog, Decider nodes.
3. Cloud Datacenter / Cloud Layer.

In an healthcare scenario, end-nodes can be distinguished in a further taxonomy, as shown in Figure 4:

1. *Medical Devices*: any device intended to be used for medical purposes, such as the diagnosis, prevention, monitoring, treatment, alleviation or compensation of a disease or an injury.

2. *Ambient Devices*: any type of consumer electronics, characterized by their ability to be perceived at-a-glance, such as motion sensors, cameras, smoke sensors, smart appliances, etc.
3. *Interactive Devices*: any mobile or stationary hardware component which enables the interaction between the human user and an application or the environment of the user, such as smartphones, speech recognition devices, wearable devices, etc.

Here an edge node can be nearby end-device connectable by device-to-device (D2D) communications [8], a server attached to an access point (e.g., WiFi, router, base station), a network gateway, or even a micro-datacenter available for use by nearby devices.

Focusing on AI, we envision a Edge Computing network capable of performing not only data analysis, classification, regression and/or clustering via ML/DL online training and inference, but also a wider range of AI techniques, adding a context-awareness and explainability/reliability of results. In this vision, ML/DL models are deployed in a hybrid mode which combines the decentralized training/inferring mode with a centralized revised/refined mode.

As shown in Figure 5, the edge servers may train the ML/DL model by either decentralized updates with each other or centralized training with the cloud datacenter. The hybrid architecture is also called as Cloud-Edge-Device training due to the involved roles. As the hub of the ML/DL architecture is placed as close as possible to end-nodes and edge nodes, there is an improvement of performances regarding the training loss, convergence, privacy, communication cost, latency, and energy efficiency.

The structure of such a complex heterogeneous network of edge nodes may have a *pyramidal topology*, as in Figure 4. In this configuration, the nodes at the upper level are intended to have a different role since at a higher level of "abstraction" of the heterogeneous network, and may, therefore, have different tasks from the end-nodes, not excluding that they may include an exclusive partial knowledge over the entire network. Therefore, they can act as simple collectors of information deriving from groups of sensors, or from aggregators of such information, or they can make further processing steps on the edge network. A key issue in this complex scenario is that of the truthfulness and reliability of information gathered by groups of heterogeneous sensors that can:

– detect conflicting information within a end-nodes and/or edge nodes;
– group information at different levels of abstraction;
– perform partial processing at the Edge Layer.

In particular, an Edge Intelligence task could be performed either with partial ML/DL model training or with specific inference and reasoning tasks on the data collected through semantic descriptions and ontological dictionaries. A certain degree of uncertainty or inconsistency is likely to arise from all the partial small amount of processed data by any type of device in the heterogeneous network.

Therefore, a key problem regards to evaluate the reliability (or justifiability) and explainability of the partial results from the entire network. Moreover,

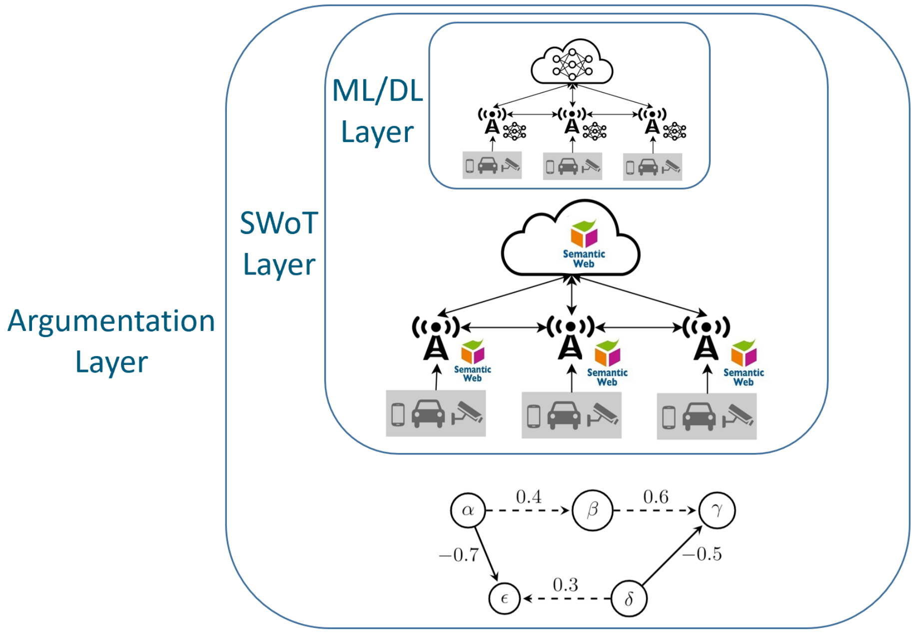

Fig. 5. AI Fundamental Techniques involved in AI on Edge Processing

such information may be conflicting, yielding the system unable to take autonomous trustable decisions. A computational model of argumentation, such as the BWAF, could solve two types of inconsistencies between conflicting information:

1. in a "horizontal" way, it can resolve the conflicts created by the end-nodes that transmit similar but conflicting information;
2. in a "vertical" way, it can solve problems of conflicting knowledge between the information (possibly aggregated) sent by the lower levels of the pyramid towards the higher levels, in which an inconsistency is found between partially disjointed knowledge between the end-nodes and edge-nodes.

The automatic building of an argumentation framework like the BWAF and its subsequent evaluation through argumentative semantics for the selection of acceptable arguments is a perfect solution in this context. Specifically, endowing the information coming from end-nodes and edge nodes with semantic annotations allows a machine-understandable representation of information that can be exploited to automatically build the BWAF, which can give a representation of conflicting and/or supporting arguments of the entire network. In particular, the non-standard inference method of semantic matchmaking between pairs of arguments is employed to define a weighted notion of relation between arguments (i.e., attack or support).

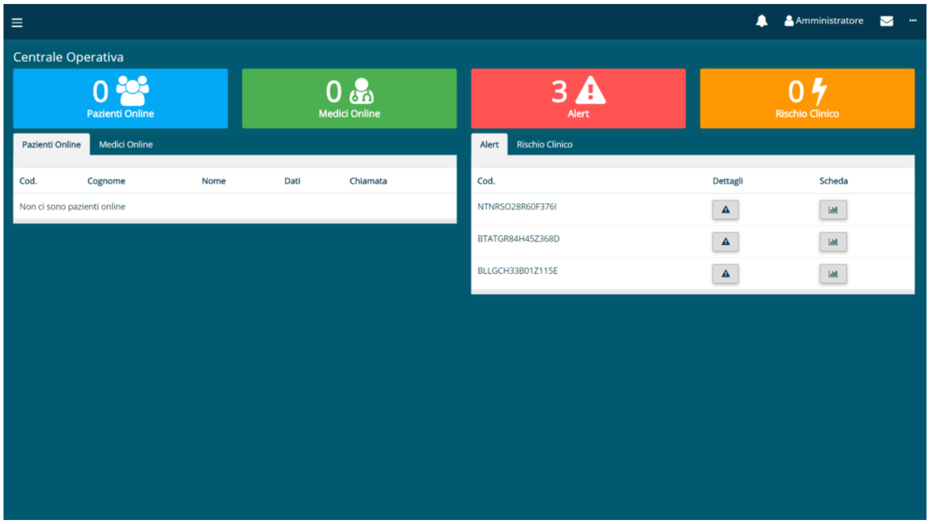

Fig. 6. The eLifeCare Platform dashboard

From the result obtained it will therefore be possible to be certain of the truthfulness and reliability of the information detected and processed at the Edge, in a heterogeneous and complex multi-IoT network, which can be crucial when a complex decision is automatically taken.

3.2 The eLifeCare Platform

The eLifeCare platform is the Telemedicine system that contains the set of solutions and services provided by Exprivia for Teleconsulting, Telereporting, Telepresence and Telemonitoring to support all operators involved in the care and monitoring of the patient at home (see Figure 6).

The eLifeCare platform revolutionizes the approach to home patient care in that it provides the technological Edge Computing infrastructure and all the services necessary for the full, integrated management of all the care-giving processes and services, accessible and usable from any kind of IoT device:

- Remote monitoring;
- Telemedicine and Teleconsulting;
- Medicinal product procurement monitoring;
- Reporting and filing systems;
- Patient's medical history in electronic folders.

The eLifeCare platform deals with the new Digital Health challenge that puts the patient at the centre and guarantees continuous services that improve quality

https://www.exprivia.it/exprivia-resources/images/File/flyer-healthcare-05-2018/italiano/20180522_004-0_EXPITL_H_FS_eLifeCare_ITA.pdf of life and, at the same time, help to limit the costs of the local health authorities and hospitals by removing the patient from hospital. The platform is based on a WebApplication used to monitor and manage all patients in real time, acting as an operating intermediary between the patient and the medical team or specialist that is following the patient. The full-Edge architecture of the platform allows the medical team to perform AI-driven autonomous decisions for a single patient at home, according to his clinical record data on the treatment, vital parameters, diagnosis, etc. If necessary, it decides to modify the treatments, sharing specific treatment protocols and consulting any reports in support of the treatment. The AI on Edge component of eLifeCare gathers data from devices and performs ML classification tasks to monitor the treatment process, endowing data with small pieces of semantic annotations inferred from healthcare ontologies on the edge nodes, and finally performing argumentation to discard the unjustified possible treatments in case of therapy modification.

The eLifeCare platform has specific mobile applications for use by the patient that support active participation of the patient himself, the care giver, and the medical team allowing them the remote management of:

- Care giving at the patient's home on the basis of the programme indicated in the Care Plans;
- Measurement of vital parameters;
- Videoconsulting sessions;
- Patient geolocation;
- Administration of pharmacological treatment;
- Medicinal product procurement requests.

4 A Healthcare Scenario in AAL

As a sample scenario, consider a SHE in which the patient at home has monitoring instruments and wearable technology, and is constantly monitored from the Edge Computing infrastructure of heterogeneous multi-IoT network devices. The Edge Layer coordinates and monitors the patient's care at home through active interaction designed to detect the care needs and critical factors involved in the care. The platform provides the operators involved with the information about the patient by opening a clinical record (medical history, clinical diary, treatment, vital parameters, etc.). The Cloud Layer acts as an intermediary: it receives any requests and/or alerts sent by the Edge Layer after the measurement of specific vital parameters, and activates specific operating protocols. If the Cloud-Edge-Device coordination of AI/ML models with SWoT annotation and inference and argumentation autonomously decides to make a change in the patient's treatment, the platform starts Teleconsulting or Videoconsulting session with the specialists that are following the patient to communicate the therapy variation and send a confirmation request. Using the platform, the specialist views the patient's clinical documentation and manages the care pathway.

As briefly depicted in Figure 7, the eLifeCare platform exploits AI on the Edge level to perform different kinds of reasoning an take complex autonomous

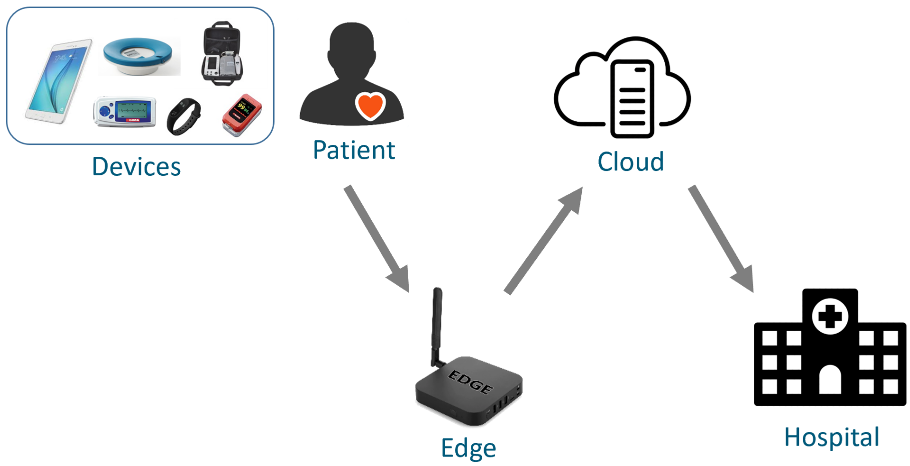

Fig. 7. Healthcare Scenario in AAL

decisions at different layers of the Edge network. This is helpful in recognizing the severity, timeliness, and appropriateness of intervention among the factors determining the clinical outcome. Moreover, the platform acts as an alert systems, such as Early Warning Scores (EWS), which help in identifying specific phases of illness and provide appropriate care.

5 Concluding Remarks and Future Work

Edge Intelligence, although still in its primary stage, has attracted more and more researchers and companies to get involved in studying and using it. This paper attempts to provide possible research opportunities about AI on Edge. Concretely, we first discuss the relation between Edge Computing and AI. We believe that the synergy of multiple AI-technologies allow us to automate complex decision-making activities resulting from a multi-strategic inference approach. In fact, we state that Edge Intelligence should be the paradigm that fully exploits the available data and resources to optimize the overall performances of not only Machine Learning models, but also other inference and reasoning tasks, including Semantic Web of Things and Argumentation.

In particular, semantic-enhanced ML on heterogeneous data streams in the IoT allows a mapping of raw data to ontology-based concept labels, providing a low-level semantic interpretation of the statistical distribution of information, while the conjunctive aggregation of concept components allows building automatically a rich and meaningful representation of events during the model training phase. Specifically, the exploitation of non-standard inferences for matchmaking enables a fine-grained event detection by treating the ML classification problem as a resource discovery. In particular, Mini-ME [33] is an extremely lightweight reasoning engine, conceived especially for SWoT applications, which, thanks to its non-standard Semantic Web services [9], is the candidate reasoning tool to perform KR tasks on Edge in ubiquitous scenarios, where mobile agents must provide quick decision support and/or on-the-fly organization in intrinsically unpredictable environments. While, exploiting argumentation within this domain potentially presents several advantages:

– *explainability*: decision making based on argumentation, leveraging declarative approaches, make decisions amenable of interpretation, so that any action may be easily explained and justified by a chain of arguments both to human users or supervisor systems.
– *security*: it is naturally supported, despite uncertainty of perceptions and system openness. Argumentation in fact, on the one hand enables reaching consensus despite discrepancies in measured metrics by guaranteeing that only well-backed claims win a debate, on the other hand may be used to spot malicious behaviors by proof-checking false claims.
– *reliability*: if users can get justifications about why a system is pursuing a given course of actions, and how it came up with a precise conclusion about the state of the world, they are likely to increase their confidence in relying on the autonomous capabilities of the system.

We also showed how all these AI techniques promote and reinforce each other by presenting a novel Edge Computing architecture and the eLifeCare platform, specifically designed for healthcare, outlining also a use case scenario in SHE.

Looking at future work, the progressive deployment of 5G networks will make available a backbone with significantly enhanced spectral efficiency, improved signal efficiency and significantly reduced latency, all factors that will facilitate new services in the healthcare domain. There will be a change of paradigm from "hospital based" to "distributed patient care".

This approach can then be refined if dynamic networks are also taken into account, in which the Edge nodes change over time, introducing or eliminating information in the Edge network.

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