Management at the Edge of Situation Awareness during Patient Telemonitoring

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Abstract. The SARS-CoV-2 pandemic has brought unexpected new scenarios in patient-care journeys and has accelerated this innovative process in the healthcare sector, demonstrating the importance of a systemic rethinking of remote care, mostly when patients are discharged from the hospital and continue their therapies at home in autonomy. The possibility to remotely monitor patients at home by means of smart sensors and medical devices has a dramatic impact on the quality of health services. Situation awareness plays an essential role in the decision-making process about the users, patients in this case, and their behaviors. Leveraging an Edge Computing framework, with embedded Artificial Intelligence capabilities to process near real-time data gathered from connected smart devices, would provide automatic decision support, thus improving the physicians' course of action. In this paper we introduce, within an Edge AI framework, a dedicated module, called Clinical Pathway Adherence Checker (CPAC), which identifies the discrepancies between the modeled clinical pathway and the observed one by means of process mining techniques, and hence detecting early clinical deterioration of patient conditions. Also, further analyses are conducted in the anomaly detection at the Edge that may occur during the health data transmission process.

Keywords: Situation Awareness · eHealth · Clinical Pathway · Internet of Medical Things · Ambient Assisted Living · Edge Computing · Process Mining · SARS-CoV-2

1 Introduction

Situation Awareness (SA), already known as Situational Awareness, is an acclaimed decision process to maintain and understand what is happening in a certain situation and leverage this information to avoid or mitigate eventual risks. In the recent years, this trend is gaining strong interest in the eHealth sector [8, 31], since several stakeholders, including domain experts, investors, and researchers, started to leverage awareness and clinical decision-making. One of the objectives of SA in eHealth is to personalize for every patient the therapeutic path, often referred as Clinical Pathway [13, 15], including both the biological characteristics of the pathology, and the aspects of the clinical history, along with the characteristic elements, and the living environment. Despite the advantages given by its applicability, several studies relating to SA in eHealth, and in particular to the Clinical Pathway, offers several lines of research for still unsolved problems. The clinical path, in fact, is manifold and complex [29]:it is not limited only to the moment of the medical consultation or diagnostic examination, but it includes a series of tasks that can be carried out independently by the patient without being monitored by the healthcare staff.

Over the last year, the national health services of different countries have been affected by a substantial and dynamic downsizing of resources and, despite this, they have managed to withstand, albeit with difficulty, the impact of the health emergency related to SARS-CoV-2 [9]. In this scenario, Telemedicine –a particular sub-field of eHealth– arises as a necessary alternative form of care pathways management, allowing remote monitoring of the patient at home. In this perspective, individual patients are encouraged to handle their activities to be managed autonomously, that is, without the medical supervision until a follow-up, in the form of an in-hospital visit or a televisit, which determines an conceptual check-point. Considering the phase of medical-unsupervised clinical pathway management, we envision an autonomous supervision of the patient care to be delegated to an intelligent multi-agent system whose architecture can deal with the specific clinical sub-path for the discharged patient, also verifying its validation by a doctor or nurse, and ensuring compliance with the actual prescriptions. This proposal would bring numerous benefits not only to patients but also especially to caregivers,as telemonitoring-related activities deal with mitigating challenging problems in the Healthcare sector.

This challenging goal recalls the theme known as "domiciliary hospitalization", addressed with Ambient Assisted Living (AAL), a branch of Artificial Intelligence (AI), in which mobile technologies support patients at home with a continuous telemonitoring of their health conditions, addressing the case of clinical worsening which may require the backing of health personnel. Intelligent medical devices and sensors from the world of the Internet of Medical Things (IoMT), along with ambient and interactive devices with limited processing and storage capabilities, make it possible to say that each device connected to a smart home can transmit data that is useful for being aggregated, analyzed and processed. In this way, machine learning (ML) algorithms can be leveraged to provide predictive diagnostics that promote, adapt, and validate to the in-home

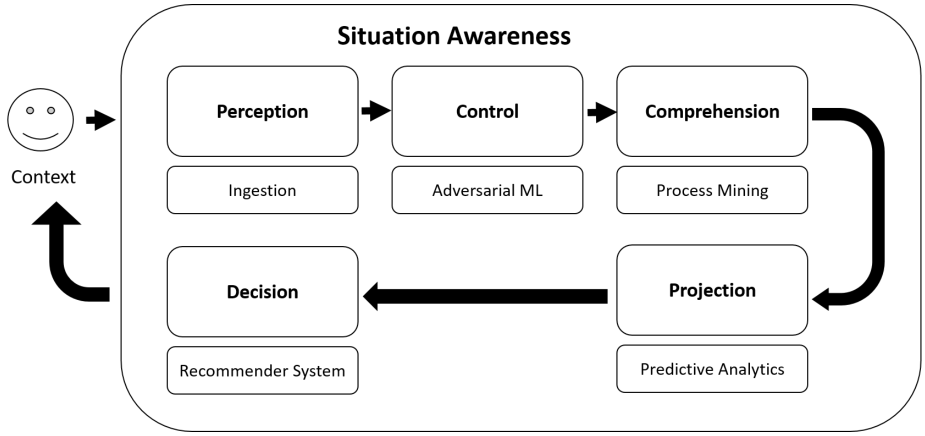

Fig. 1. An Overview of technical model of SA in eHealth.

patient's normal activities. Thus, the patient's tasks would be validated to her attached clinical path, that can be managed as a workflow in an evaluation phase of the Process Mining activity, such as [27]. Faced with this complex task, however, data security must not be overlooked. A reliable SA system in the eHealth and AAL scenario would be able to avoid the processing of false or inconsistent data, which could be life-threatening for a patient.

Therefore, in this paper, starting from the Edge Computing architecture, already proposed in [5], we extend the work presenting a new intelligent software module aimed at checking the adherence to the clinical pathway assigned to a patient at home being remotely monitored, which we call CPAC: Clinical Pathway Adherence Checker.

The remainder of the paper is structured as follows Section 2 provides an overview of related work and technologies which were investigated as background knowledge. Similarities, distinctions, and advancements of our approach in a comparison to them are briefly discussed. Section 3 recalls the Edge architecture which leverages on cloud, edge nodes and medical end-devices to perform AI tasks such as Process Mining and Machine Learning. Section 4 describes a possible scenario of a patient with SARS-CoV-2 symptoms that has to manage her clinical path in her home. Finally, Section 5 concludes the paper, with an outline of future work.

2 Background and Related Work

A desirable condition for providing digital support for strategic decisions during critical situations can be achieved through an SA approach. This is evidenced by the recent health crisis due to the COVID-19 pandemic [14]. Specifically, SA provides a series of techniques and tools to ensure a correct perception, in real time, of what happens in operational scenarios through the punctual analysis of information from a multitude of heterogeneous sources. In Figure 1, we can see the chain of SA. In the clinical setting, the methods of intervention are always conditioned by the following parameters [6]:

1. *Perception* is related to data that comes from the context: in this sense, *Data Ingestion*, as a first step, collects data from all health information systems and standardizes it into a single formalism.
2. *Control* acts on the reliability of perceived data: *Adversarial Machine Learning* is an important area of Machine Learning that can help improve the reliability of systems and protect ingested data from fraudulent attacks in the healthcare sector where disinformation could endanger and compromise the health of patients [11].
3. *Comprehension* is related to the ability to understand the situation: this is why *Process Mining* for healthcare is an appropriate method to extract information from event logs that are scattered throughout the health system and to define (work-)flows to be analyzed.
4. *Projection* is the ability to prevent future events: for this reason *Predictive Analytics*, by means of Supervised Machine Learning techniques, is a good candidate to predict the flow trend in the system in order to monitor the growth likelihood of critical conditions.
5. *Decision* is the reasoned choice of one of the various possibilities of action or behavior in the face of a situation: *Recommender Systems* may help in personalizing the decision according to previous choices or any similar choices made by others, regardless that the choice is made by a human or an agent.

To achieve greater awareness, it is necessary to monitor the situation rigorously and continuously, through an evaluation process capable of detecting successes and possible bottlenecks of a system. Telemedicine, in this case, allows us to complete this task. On the other hand, data is only useful when analyzed. Therefore, the AI techniques, previously described at a high level, can help to perform an SA of the health system, returning an accurate overview. Process Mining techniques are particularly important in eHealth as they are particularly rich in sequential data, even if unexplored. It would become essential to root process management in the organization, accompanying the health facility towards real and in-depth knowledge of its operating mechanisms, through efficient techniques, with low economic impact, in rapid analysis times and guaranteeing the objectivity of the result. In general, workflows are used to support processes. To understand what it is, some brief notions are provided:

- A *process* is a sequence of elementary activities carried out by agents to achieve a goal.
- A *task* is a piece of work defined to be performed in many cases of the same type.
- An *activity* is the actual execution of tasks.
- A *workflow* (or process model) is therefore a formal specification of how a task sequence can be composed and can end in a valid process.

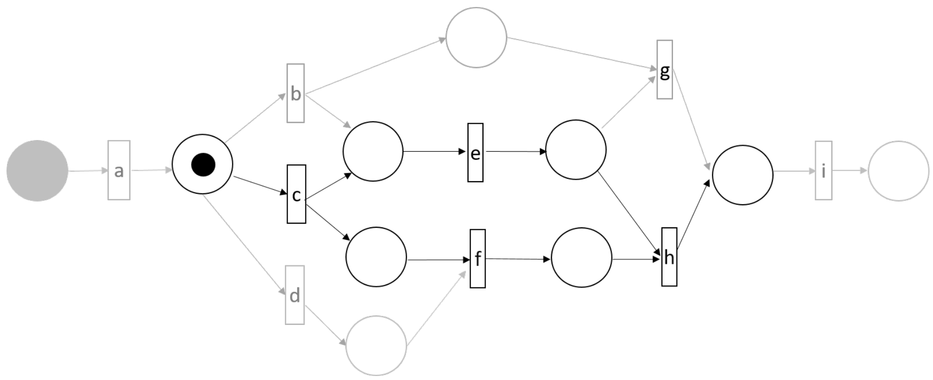

Fig. 2. Petri Net example describing a process that may occur in a Clinical Pathway.

- A *case* is a specific execution of activities in a determined order, as described by a given workflow along an ordered set of steps (time points).
- *Case traces* are lists of events associated to steps.

Health process records can be referred to both patient and healthcare facilities, can be extracted from different sources, and can have different types. For example, the patient's vital parameters, the events associated with her (hospitalizations, rehabilitation, etc.) or even drug therapy, allow to define the treatment processes associated with the individual patient. To this information can be added data from administrative systems, clinical decision support systems, ERP or medical devices, which can be combined in different views: from patient to ward, up to the whole structure.

The term "compliance" is referred, in the medical field, to the behavioral rigor of a patient in following the prescriptions, defining the level at which the patient's actions (drug intake, adherence to diets, physical activity) are in line with the doctor's instructions. Failure to comply with best practice behavior could have repercussions on the quality of care and on the entire health system. For this reason, the Compliance Checking technique used in Process Mining would help discover the similarities and deviations between modeled behavior (the workflow) and detected behavior (the case traces).

In this regard, AAL systems should adapt to user needs and enable activities independently, using information derived from the context. In the operations of modeling human routines, particularly in the case of clinical pathways, it is necessary to understand the sequences of human activities. Therefore, routine depiction can be done using workflows. A workflow can be managed like a Petri net [1], an expressive formalism that can represent activities and their flow, and the competition between them. Workflows are important for describing human behavior, showing the chronological sequences of user activities. In smart contexts or intelligent environments, this allows us to understand events and build a series of services capable of responding to situations. Therefore, having identified the analogy between the workflow and the clinical path as the succession of events that are performed by a patient, this can be evaluated with process mining techniques to ensure adherence to the doctor's prescriptions and compliance with the clinical guidelines. To improve system performance, at this stage, the evaluation component of the process must be brought on board the Edge module.

The paper [18] discusses an example of eHealth process analysis. A solid basis for the management and improvement of processes within hospitals is provided. By combining event data and process mining techniques, it is possible to analyse fact-based processes within a hospital. In the paper [12], an ontological model is presented for auditing the clinical process to improve the quality of services and reduce hospital costs. Binti *et al.* [22] provide a methodology for the development of a clinical treatment pathway to facilitate the diagnosis and treatment of patients. This work is particularly contextualised in the treatment of patients with heart failure and makes use of machine learning techniques. Interestingly, the work in [20] is more focused on a well define condition like suffering from aftereffects of a stroke event, however, it does not account for monitoring the patient at home.

Aspland *et al.* [7] propose a literature review on taxonomies of problems related to clinical pathways. The authors explored the combination of this with Information Systems (IS), Operations Research (OR), and industrial engineering. The work [28] highlights in an AAL scenario, the context-awareness, and adaptability of a care pathway in the daily life of the patient. A review of process mining techniques used to manage clinical pathways is carried out in the papers [21, 30]. Ardito *et al.* [2] provide a formalisation of the Clinical Pathway management method. Through the application of this, it is evident how patient monitoring is increasingly improved. Edge Computing is an architectural solution whereby the processing and storage of resource data are moved to the edge of the network. Thanks to the use of AI in the Edge, it is also possible to make a significant contribution to telemonitoring solutions in eHealth. Thanks to this combination, medical devices connected to the remote hospital information system (HIS) can be exploited even more efficiently. The combination of these has led to a massive deployment of smart and wearable devices and Internet of Things (IoT) communication technologies in the healthcare sector. The authors of the papers [26, 24] highlight the potential of the IoT in integrating and harmonising the data produced by Cyber-Physical Systems (CPS) with those already present and generated by classical information systems. In this way, it is possible to unite people, processes, data, and things. The clinical domain is addressed in the work [25, 23] in which the development of integrated solutions for seamless care is contextualised. AI and IoMT techniques at the Edge are used. The work emphasises a people-centered approach, which continuously adapts to the needs of caregivers and is embedded in their workflows.

Finally, Ardito *et al.* in [3] present an approach to bring together IoT technologies with End-User Development (EUD) tools and paradigms. This integration is aimed at identifying innovative scenarios in which end-users are directly involved in the creation and customisation of the AAL systems they use.

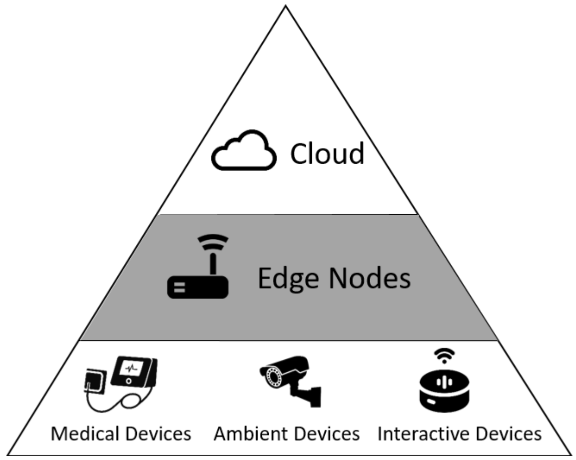

Fig. 3. Edge Computing Cognitive Architecture.

3 Edge Computing Cognitive Architecture

In this section we firstly present the Edge Computing architecture that permits to process data on devices (i.e. end-nodes) or gateways (i.e. Edge nodes). This would reduce unnecessary processing latency and data traffic, which is a valuable benefit for applications like analyzing and monitoring critically ill patients. Afterwards, we show two intelligent modules that leverage data collected from sensors and devices connected to Edge nodes, and perform predictive analyzes preventing the worsening of the patient's clinical condition. In particular, the Clinical Pathway Adherence Checker (CPAC) module is introduced, aimed at verifying that the patient follows her therapeutic path correctly.

3.1 System Architecture

The system architecture is depicted in Figure 3. The Edge architecture results quite general to be configured in an AAL typical scenario, specifically in the case of a Smart Home Environment. Here, we deal with an high number of heterogeneous devices which differ from one another in storage, computational, and communication capabilities. Therefore, the architecture, at the bottom of its pyramidal topology, presents three types of end-devices:

1. *Medical Devices*: any device adopted for medical purposes, such as the treatment, prevention, diagnosis, monitoring, alleviation or compensation of an illness.
2. *Ambient Devices*: any kind of consumer electronics that brings smartness to living environments, such as cameras, motion sensors, smoke sensors, smart appliances, etc.

3. *Interactive Devices*: any mobile or fixed hardware component which favors interaction between human users and an interactive application, such as wearable devices, smartphones, speech recognition devices, etc.

Above the end-devices, there is the Edge Layer, which is composed of one or more Edge nodes which can be an adjacent connectable device through a device-to-device (D2D) communication [10], a server attached to an access point (e.g. router, WiFi, base station), a network gateway or even a micro-datacenter available for neighboring devices. As shown in Figure 3, Edge nodes can communicate with each other and exchange the results of a preliminary Edge processing phase. A typical Edge node adopted by the proposed architecture is a *Raspberry Pi 3 Model B* (RPi for short) with a 1.2 GHz quad-core 64-bit ARMv8 CPU and 1 GB of RAM. In order to implement a scalable, adaptable and general-purpose architecture, the maximum number of devices that can interact via Bluetooth Low Energy (BLE) connectivity simultaneously with RPi and the width of the time window in which the vital signs are collected have been set in a configuration file, parameterized as desired by the user. If, during the time window, the same information is updated several times, at the time of the final acquisition, the system considers the most updated value.

Lastly, the architecture presents a Cloud Layer in which collected raw data and processed data at the Edge are transmitted to enhance the general performances and supply a refinement of the clinical pathway just in case of patient's condition degradation. Consequently, the Cloud Layer would act as an intermediary, by receiving any alert and/or request sent by the Edge Layer after the collection of specific vital parameters, and by activating specific operating protocol with the hospital or the health personnel, hence supporting a remote adaptive and complex decision making process.

In this architecture, an Edge node can gather useful information from, ambient, interactive, and medical end-devices, and process them for a specific purpose. As shown in Figure 4, a node in the Edge Layer is designed to run *Conformance Checking* on a predefined sub-process of the Clinical Pathway, another node would be exploited to be an *Anomaly Detection Module* which is able to address the security risks that may occur during the transmission process for the gathered data. Eventually, as already addressed in [23], a further node may be adopted as *Adaptive ML Module* for predicting the clinical risk of a patient, constantly monitored even where a limited number of vital parameters is readily measurable. Hence, introducing an Edge architecture to Healthcare would be beneficial to physician's workload by removing less critical tasks, such as collecting and managing patient data. Moreover, a major benefit would make healthcare more affordable and accessible, especially for remote areas where medical care is limited.

3.2 CPAC: The Clinical Pathway Adherence Checker Module

In this section, we introduce our approach to performing process mining tasks in eHealth domain. This would foster the intelligent software modules characterizing the Edge nodes in applying AI techniques to perform an automatic decision,

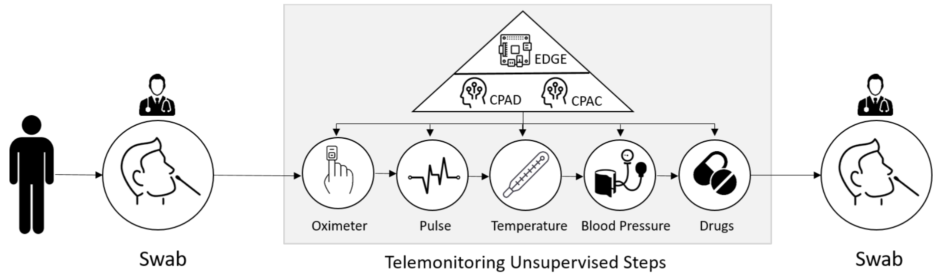

Fig. 4. Steps of a Clinical Pathway.

and proactively support the patient at home. Within the clinical course, we can distinguish between the intervention made by health personnel, and the ones made by medical instruments. Considering the clinical pathway as a workflow, each activity is therefore represented as a node in the Petri Net. These nodes can, in turn, be sub-processes. Giving a formal notation, the following definition is formulated.

Definition 1. *The execution of a process σ is described as a sequence of actions $\sigma = \langle a_1, \ldots, a_n \rangle$, where $a_1, \ldots, a_n$ is the sequence of the single activities carried out by the user in a specific and strict order. We denote with $l_\sigma = n$ the length of σ.*

When the patient is discharged from the hospital and returned at home, she has the task of following the doctor's prescription, to maintain stable or improve the clinical situation. The prescription can be processed in a series of steps that make up the patient's clinical journey and must be performed by the patient at home without supervision. To manage this home monitoring, we introduce a new level of control that can replace medical personnel, as shown in the Figure 4. Patients are endowed with one or more Edge devices that can process their activities at home aware of being constantly monitored. The part of the clinical pathway that has to be managed at home can be thought of as a specified subset of activities that the Edge node will be responsible for validation. In a formal way:

Definition 2. *Given an execution process σ, an execution of a sub-process τ, managed without supervision, is described as a sequence of actions $\tau = \langle b_1, \ldots, b_m \rangle$, with $l_\tau = m$, $\tau \subseteq \sigma$ and $l_\tau \leq l_\sigma$, and where $b_1, \ldots, b_m$ is the sequence of single activities, arbitrarily carried out by the user.*

A translation of these steps becomes a prescription to follow that cannot be verified except in the patient's level of rigor. Our idea is to introduce a control level, based on Edge computing, which can supervise and manage the phases of the Clinical Pathway that the patient must carry out independently at home to avert the worsening of the clinical picture and guide her towards a prompt healing.

As a first step, we have to perform a process model, to which an instance of patient activities must adhere. In this context, logs of general patient enrollment are fed into the process mining task to generate the process model. Once the reference model has been defined, the Edge component will be able to verify in real-time the correctness of the operations performed by the patient in the home concerning the clinical pathway. Thus, the Edge architecture will receive from the Cloud layer the process model to be stored. In particular, the Edge framework identifies the most suitable clinical path model for the type of patient by connecting to the cloud and downloading the portion of the clinical pathway as a validated process model. The development of the monitoring phase involves the activation of a series of medical devices that allow the collection of clinical data. These are collected by the Edge module which pre-processes them in log in a standard format (for example, eXtensible Event Stream, XES), with which the process model stored in our Edge node is represented. Logs analysis can be performed immediately for each individual step run (e.g. blood pressure measurement, medication intake, etc.) to verify model compliance. As a matter of choice, in less severe clinical pathways, it can be generated at the end of the period (e.g., a day), in order to appraise the discrepancy on individual activities or on the full pathway. Translating activities into formal notation is a first step to enable the use of algorithms that verify compliance and detect gaps from the process model.

Based on the deviation, it is possible to evaluate the discrepancy (e.g., missing to take pills) and also to define the corrective actions to bring back the executions towards the correct pathway model. In order to accomplish this task, we introduce a new module called Clinical Pathway Adherence Checker (CPAC). The strategy exploited in this module involves a Deep Learning approach. A Recurrent Neural Network would be able to suitably process sequences of observations to predict a probability of variation of the pathway. Therefore, a Long Short-Term Memory (LSTM) is the candidate deep architecture to perform the Conformance Checking task. The idea behind the approach is to consider the sequences of actions performed by a patient (stored in the logs) and analyze them as characterizing elements of a pattern. Each pattern can be compared with the ideal process model defined by the clinical staff and, through the use of the LSTM, it will be classified according to the level of compliance. Starting from event logs collected by the Edge node, we can give in input and infer the discrepancy from two different models: the first one for clinical pathway step prediction, and the second one for time prediction. A representation of this conceptual strategy is depicted in Figure 5. At a later stage, in the event of non-compliance between the current execution and the model, the CPAC module autonomously discloses the specific incident to the medical personnel, sending reports to the Cloud layer of our Edge infrastructure.

3.3 CPAD: The Clinical Pathway Anomaly Detection Module

Supervised Machine Learning techniques can be used to predict when a clinical deterioration of vital parameters will occur. These techniques, which are also

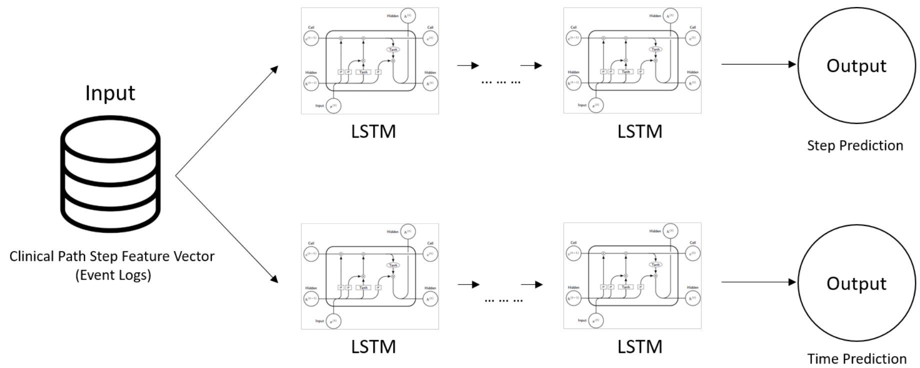

Fig. 5. Logs processing towards Conformance Checking predictions.

used in AAL scenarios, are able to understand whether the communication between the patient's devices in the care state is correct or compromised. Such methods, used to detect intrusions in the communication between devices (and the related data exchange between these and the Edge node) have traditionally been developed under the assumption that the environment is not harmful.

In a hospital or home care context, it is reasonable to assume that there are no attackers who want to circumvent data monitoring systems. To avoid this issue, it is useful to equip the system with an anomaly detection module. We intend to define a system that is able to monitor several vital parameters of the patient (e.g. blood pressure, heart rate, and respiratory rate). Compromising the data collected by a sensor worn by the patient would risk compromising the clinical course, the doctor's diagnosis, and the patient's health. In order to verify the correct transmission of data and prevent the system from intrusions, the system is equipped with a module called Clinical Path Anomaly Detection (CPAD) [4].

Using Machine Learning techniques, the CPAD manages the security problems that may occur during the data transmission process, analysing them and, if necessary, notifying the anomalies detected. Using a Cognitive Security approach, thanks to advanced AI techniques, the system will be able to learn and analyse at each interaction any threats that are detected. By doing so, it will be able to provide the healthcare provider with an explanation of the intrusion, and thanks to this we will be able to correct the patient's clinical course immediately. In design terms, the data collected in the node can be viewed as a queue and organized into several sub-processes. Each sub-process represents the phase of detecting a vital parameter from a single device worn by the patient. Using a recurrent sequential autoencoder Long Short Term Memory (LSTM), the CPAD module analyzes the various sub-processes of the chain to perform anomaly detection on the steps of the chain [16, 19]. In fact, the advantage of using sequential LSTM autoencoders is twofold: firstly, it takes advantage of the reduced dimensionality and extraction capabilities of the autoencoder to efficiently perform the data reconstruction process and then detect the anomaly, and secondly, it uses the networks to handle the sequential nature of the data detected by the sensors.

The anomaly could also result in an attack on the monitoring of the patient's clinical parameters. In doing so, it causes a dysfunction in the Clinical Pathway which in turn has a direct impact on the patient's health. The anomaly may represent a direct attack on the monitoring of vital parameters in order to modify the expected behaviour of the detection or to compromise it completely, with related tampering of the clinical pathway. Using intrusion detection techniques, the system is able to prevent attacks at various stages of the clinical pathway. It also provides intelligent information to the treating physician and allows domain experts (system IT administrators) to isolate the security breach and reschedule the clinical path together with the physician.

4 SARS-CoV-2 Patient Monitoring Scenario

We propose in this section a usage scenario for clinical pathway handling on Edge related to SARS-CoV-2 patients management. With the help of telemedicine, the traditional treatment scenarios have changed profoundly during the pandemic, bringing beyond its physical boundaries. Thanks to telemedicine, even patients who are distant and isolated can be reached, such as the ones undergoing quarantine measures as they test positive for SARS-CoV-2. In this context, the control setting provides the use of a monitoring and control kit, based on a telemedicine platform [17]. The patient's clinical pathway is downloaded on the Edge node from the aforementioned telemedicine platform, which acts as our Cloud layer, and enables the steps that must be activated at patient's home. The most suitable medical devices are involved, on the basis of the types of the activities to be performed by the patient, in order to detect and monitor the relevant vital parameters.

For example, a pill dispenser can be used to provide information on taking medications to follow the therapy, while the use of the blood pressure monitor can provide the clinical status of the patient. In the specific case of SARS-CoV-2, a subset of relevant vital parameters, such as heart rate, body temperature, and oxygen saturation, must be gathered several times in a day. With the interaction with the medical devices, Edge nodes can monitor the status related to Adherence and Anomalies with the CPAC and CPAD modules. If dangerous situations are detected, alerts can be sent in real-time to an operations center. Detecting simple vital signs can transform radically the lives of many people during a pandemic, while allowing them to monitor and contain the contagion. The crucial role of the health personnel was highlighted during the pandemic emergency. They need to perform their work in safety conditions. The usage of intelligent techniques at the Edge would help to ensure the required safety, thus making digitally viable the relationship between the hospital and the patients, and hence placing the whole monitoring process in a safer place. Providing continuously monitoring and information about the disease, possible complications, and the activities to be carried out can make patients feel more protected.

The health personnel of the Medical Control Room, receive the monitoring data through the monitoring system, check the progress of the clinical path and evaluate any anomalies in the state of health that could require a change of therapy or a possible hospitalization. The Edge infrastructure ensure a high level of continuous surveillance and proactive collaboration, making the patient and his relatives more relaxed and making the experience discharge from the hospital more peacefully.

5 Concluding Remarks

The need for more healthcare choices for SA technologies is reflected in the pursue of established practices related to Telemedicine, allowing teleconsultations with specialists and a more flexible monitoring of the patients at home. In fact, SARS-CoV-2 has accelerated this innovative process in the healthcare sector, demonstrating the importance of a systemic rethinking of remote care.

Based on Edge Computing and AI techniques, this work presented a level of unmanned supervision which can somehow control the steps of the Clinical Pathway that the patient should follow autonomously in his/her living environment to deflect worsening of clinical conditions. The paper shed light on formal aspects of executing process mining tasks in an Edge infrastructure, in which activity logs are collected by data coming from medical, mobile, and interactive devices, in the spirit of IoMT perspective. The core proposal presented an intelligent module which is applied to check patient behavior by means of their adherence to their clinical pathway. This module, called CPAC (Clinical Pathway Adherence Checker) helps patients to follow medical prescriptions (i.e. therapies) and provides physicians actions to induce them to exclude a clinical deterioration. The present paper adds further conceptualization to the aim of designing and developing a full-Edge platform architecture, in which several AI modules cooperates towards a big conjunct goal or more little objectives related to the world of healthcare. The benefits are various: firstly by lightening the physician's workload by removing less critical tasks, secondly by making telemonitoring more affordable and accessible, especially for remote areas where medical care is limited, and lastly by stimulating the advancement of medical technology through Big Data. Definitively, Edge computing will make it easier to manage and classify data in a uniform, efficient, and secure way.

Aware of the intrinsic vulnerability of AI techniques, we detailed also the anomaly detection module, called CPAD (Clinical Pathway Anomaly Detection). Interestingly, the detection system may act as an Explainable Security module, which allows receiving an exhaustive explanation of the attack reports that can be easily interpreted even by non Machine Learning experts and therefore in this case by the physician and the user who is undergoing treatment. In fact, the Explainability of AI, which aims to make people understand how ML models work, is essential to promote trust and reliability in AI systems. It will also allow the patient in care to have an overview of the decision-making process of the system. Another scenario will involve this technology to explain other types of alarms that can emerge from the analysis of sensor data, providing explanations both to patients and, remotely, to physicians. Interestingly, one would think about the Petri Net representation to be exploited as an explanatory tool of the clinical pathway executed by the patients.

Future works will concern the many opportunities the Edge module could offer in healthcare. The research will continue in Robotic Process Automation (RPA) to automate the activities performed by physicians in interacting with patients (e.g. notification of therapy changes and acknowledgment). Also, we will investigate recommender systems to support physicians more directly in guiding the treatment path. In particular, we will focus on the fundamental aspects of data security at the Edge level: by combining the strengths of AI and human intelligence, it is possible to ensure a reliable level of privacy. Finally, while providing efficient and cost-effective monitoring action to gain situational awareness, the proposed study has laid the groundwork for improving the quality of action that can be taken by stakeholders with decision support systems. Equipping humans with the ability to make better decisions thanks to AI, and in particular AI on Edge, defines a process in which AI can be seen as a tool capable of strengthening and increasing human capabilities, thus approaching a Digital Twin model of the physician.

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