Chapter

On Defining and Deploying Health Services in Fog-Cloud Architectures

Rodrigo da Rosa Righi, Bárbara Canali Locatelli Bellini, Fernanda Fritsch, Vinicius Facco Rodrigues, Madhusudan Singh and Marcelo Pasin

Abstract

Infrastructures based on fog computing are gaining popularity as an alternative to provide low-latency communication on executing distributed services. With cloud resources, it is possible to assemble an architectub re with resources close to data providers and those with more processing capacity, achieved through internet links. In this context, this book chapter presents the first insight regarding fog-cloud architecture for the healthcare area. In particular, we address vital sign monitoring in sensor devices and provide intelligent health services that reside both in the fog and the cloud to benefit the end-users and the public government. The preliminary results show the advantages of combining fog and cloud and critical applications and highlight some points of attention to address system scalability and quality of service.

Keywords: healthcare, architecture, smart services, smart city, fog computing, cloud computing

1. Introduction

Over the last few years, the health sector has understood that the internet can be an essential support instrument in searching for a better quality of life and conditions for patient care [1]. Among other advantages associated with using the internet in the health field, the analysis, and processing of data in real-time through remote servers have been highlighted. A smart model that provides storage and processing of applications over the internet refers to the idea of cloud computing. The cloud can be described as a collection of software and hardware services that are delivered through the network to end-users. The users will have resources (both from hardware and software perspectives) with increasing capacity without requiring significant financial capital investments to acquire, maintain, and manage such resources.

Cloud computing acts as a support to enable the Internet of Things (IoT) applications. IoT environments are composed of hundreds or thousands of devices that constantly generate requests for collected data to be later analyzed. This process naturally generates heavy requests that would be sent to a central processing server, flooding that server's network, and requiring computational power that a single computer would often not be able to supply. Here, cloud computing can be used as a processing medium for IoT scenarios to leverage its scalability and pay-as-you-go business model. However, sending requests from an IoT device to a cloud server adds network latency overhead to the communication that cannot be accepted in some cases. For example, we can cite some e-health scenarios, such as those addressing remote electrocardiogram (ECG), where data collecting and processing times are critical to the correct system functioning. We often cannot wait for a message to be sent, processed in the cloud, and returned, as the time involved in these procedures is prohibitive and can influence essential aspects such as a person's life or death. Furthermore, even with a highly scalable cloud computing environment, scaling it to serve many requests would result in additional power consumption.

To allow better scalability of IoT systems, it is necessary to design new architectures and solutions that simultaneously handle many devices and requests, maintaining the Quality of Service (QoS). Aligned with this sentence, fog computing expands the services the traditional cloud model offers to be closer to the data generators. Also, edge computing enters here to enable some processing and decision support precisely on the network's border, that is, close to the IoT device itself. Computing in fog or edge has as its main characteristics low latency, better support to collect the geographic distribution of data, and mobility over many nodes in the network. Thus, with predominantly wireless access, we have the execution of applications in real-time and more significant support for device heterogeneity. Data read by the sensors is collected, processed, and stored in a temporary database instead of delivered to the cloud, avoiding round-trip delays in network traffic.

A combination of cloud, fog, and the edge is especially pertinent to provide an architecture to answer pandemic research such as the case of COVID-19. More significantly, we are entering a period where long-COVID-19 research is mainstream, where the purpose is to continuously monitor the vital signs of those who were contaminated by the virus beforehand [2]. Most vital sign monitoring systems follow a generalized three-tier architecture composed of sensing devices, a gateway, and a cloud. By analyzing the current initiatives in the literature, they do not address all issues concomitantly as follows: (i) person's traceability, both in terms of historical view of vital signs or places visited in a smart city; (ii) artificial intelligence to execute health services proactively, generating value for end-users, in addition to hospitals and public sector; and (iii) state-of-the-art mechanisms to address QoS, elastic processing capability and an efficient and scalable message notification system.

In this context, this book chapter:

- We introduce an architecture that combines edge, fog, and cloud to address healthcare services.

- We also show how we can deploy health services over this architectural organization.

Our idea is to show details of the proposed architecture, detailing the modules and how multiple edge instances interact with fog nodes. In particular, we will offer vital signs-based services in the fog nodes and the cloud. These services can target a single person, generating personal insights and notifications, and multiple persons. In this last case, we provide health information regarding a community or district of a city [3]. Thus, we capture data from the citizens and process them in the edge and fog nodes, generating appropriate notifications. Finally, we show future directions regarding healthcare services (in particular to monitor long COVID-19 situations), which will execute in a combination of edge and fog resources depending on person priority and service priority (for example, teens and older people, and critical services like ECG or non-critical services like fever detection). We understand the new era of 5G communication will burst and favor scalable IoT data collection, bringing pertinent issues such as reliability, performance, and scalability to the assembly of the proper digital health in intelligent cities.

2. Vital signs remote monitoring

This section details some vital signs and how they are captured from the body. Vital signs monitoring is essential to observe how healthy a person is. Logically, we have lower and upper thresholds for each vital sign, that is, limits that a particular metric should operate. Also, these thresholds variate in accordance with the age of the person, their health status, if they have chronic diseases, and so on. The vital signs discussed here are relevant to give us insights sequels regarding the long COVID-19, which is especially important for patients with chronic diseases. The literature shows us that five health parameters are essential vital signs to detect the evolution of COVID- 19. **Figure 1** depicts them appropriately. They are: (i) heart rate; (ii) heart rate variability; (iii) body temperature; (iv) peripheral oxygen saturation; and (v) respiratory rate.

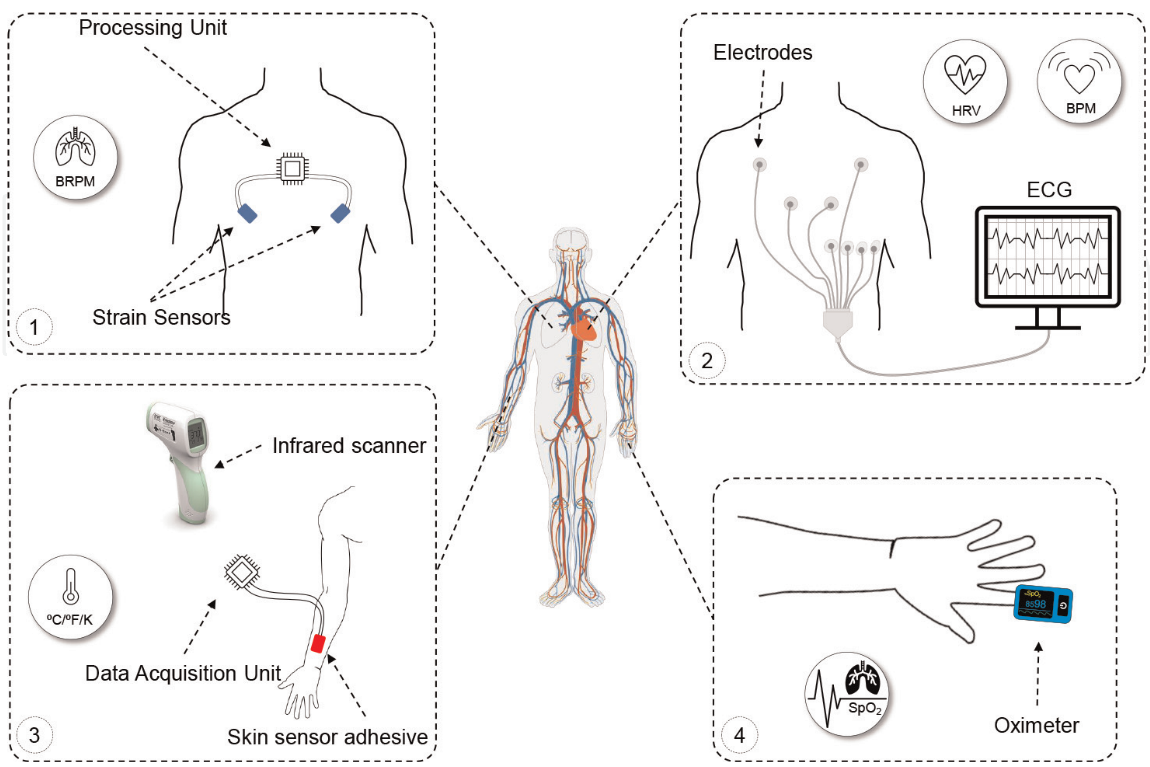


Figure 1.
Five vital signs are captured: (1) respiratory rate; (2) heart rate and heart rate variability; (3) body temperature; and (4) peripheral oxygen saturation.

2.1 Vital sign 1: respiratory rate

This vital sign analyzes the breathing rate per minute (BRPM). The literature states that an expected respiratory rate is between 12 and 20 BRPM. Regarding the idea of reducing the BRPM, there is a more significant change that a particular person has COVID-19. This occurs because COVID-19 attacks the lungs, turning challenging to breathe well and regularly. A wearable device collection can monitor BRPM through piezoresistive and inertial sensors [4]. Moreover, when analyzing the literature, we observe that most approaches require sensors in the patient's chest, abdomen, neck, or nose. We also observe the growth of new solutions that explore algorithms to derive the respiratory rate from optic sensors embedded in smartwatches and wristbands.

2.2 Vital sign 2: temperature

Body temperature is one of the most used signals to understand a person's health. The temperature is primarily used to observe that a person has an inflammation process, the starting of a disease, or particle reactions against viruses or bacteria [5]. Thus, fever is the second most common symptom of a COVID-19 infection. Usually, a body temperature over 37.3°C characterizes fever. As said, this could indicate that the body is trying to fight an illness or infection. Body temperature is captured in different ways: axillary, orally, and rectally using traditional thermometers.

Recent solutions use technologies that can measure skin temperature too. The skin temperature frequently varies to regulate and stabilize the core temperature. The use of imaging and infrared devices became common to fastly check the body temperature of individuals in a touchless manner. Other strategies apply skin carbon nanotube (CNT) printed adhesives that provide more precise temperature detection. However, CNT-based sensors require a computing unit to acquire data from them to make them available for processing.

2.3 Vital sign 3: heart rate

Heart rate measures the beats per minute (BPM) of an individual's cardiac cycle [6]. It varies throughout the day physiologically in a healthy individual, according to physical activity, consumption of caffeinated foods, and emotions, for example. However, the appropriate heart rate range for an individual at rest is from 50 to 90 BPM, which may be lower in people who practice physical activities [7]. Segundo [8] with a 1°C rise in body temperature, there is approximately the same amount as an 8.5 BPM increase in heart rate. For example, traditional methods for measuring heart rate include the electrocardiogram (ECG) and radial pulse palpation. However, such methods, in addition to depending on a professional to be measured, also have little mobility for access and difficulty monitoring daily activities. The ECG is an accurate method, but it needs to be in a specific place to perform it since the measurement through the radial pulse can be imprecise. Thus, current initiatives seek to explore different strategies of bioelectric sources to measure heart rate accurately. Smart bands often use photoplethysmography (PPG) to measure heart rate [9]. When the heart beats, capillaries expand and contract based on changes in blood volume. PPG is a non-invasive optical technique capable of measuring blood volume variations in the capillary structure [10]. Thus, continuous monitoring can predict some pathologies, such as arrhythmias, anemia, and hyperthyroidism. In the context of COVID-19, the heart is one of the organs affected by the virus. It can attack the organ of someone who already has a previous cardiac pathology or even an acute form of a healthy heart [11]. Thus, some pathologies such as myocarditis, arrhythmias, and cardiac arrest may be present in infected patients [12]. Thus, early detection of heart rate can help in the perception of a sign of severity in patients with the disease, in addition to facilitating the early detection of symptoms at home and in hospitals.

2.4 Vital sign 4: heart rate variability

Heart rate variation (HRV) is the variation between the time interval between two beats in the cardiac cycle and is one of the main ways to assess the proper functioning of the heart and the regulation of the autonomic nervous system [13], so it is a relevant measure to identify and assist in the prognosis of various pathologies. It has a large interpersonal variation, and a high value represents a more significant resistance to stress, while a low value may indicate illness, stress, depression, or anxiety, and low values may provide an early indication that the individual is suffering from infection [14]. In the context of COVID-19 infection, it is a relevant parameter to indicate how the patient's prognosis will be. Recent studies carried out with patients over 70 years old showed that those with high HRV had greater survival and low HRV showed greater survival. Intensive care unit admission rate [15]. The main way to detect HRV is through continuous monitoring in the hospital or the ward through the electrocardiogram. Hence, the lack of mobility is the main difficulty in continuous monitoring. In this way, wearable smart bands that rely on heart rate measurements, calculating the root mean square of successive differences between normal heartbeats (RMSSD), it is possible to determine and measure HRV using heart rate measurements, and thus help to monitor patients both in hospital and domestic environments, mitigating the problem of mobility [16].

2.5 Vital sign 5: oxygen saturation

Blood oxygen saturation (SpO_2) level measures the percentage of oxygen carried by hemoglobin molecules in an individual's peripheral blood. It may be decreased when an infection occurs, such as COVID-19, in which inflammatory cytokines prevent the efficient gas exchange from occurring in the respiratory membranes. Rates below 95% of oxygenated blood indicate a warning that the individual may be starting to become short of breath. Oxygen levels commonly remain at the same rate during all daily activities. Standard approaches to compute SpO_2 use PPG signals composed of red and infrared light sensors applied to the extremities of the body [17].

3. Fog-cloud architecture to monitor vital signs in smart cities

Employing several sensor devices to monitor the health parameter of people daily is crucial to track and monitor the spread of new diseases. We developed a monitoring infrastructure for intelligent cities to enhance public health topics. **Figure 2** depicts our vision of an innovative city architecture, where we focus on mobile health, vital signs collection, and artificial intelligence services. In the considered architecture, citizens use wearable devices (such as smart bands or standalone sensors) to send their vital sign parameters into the public health data center in real time. By combining fog and cloud computing, we offer a collection of health services to patients/users in a

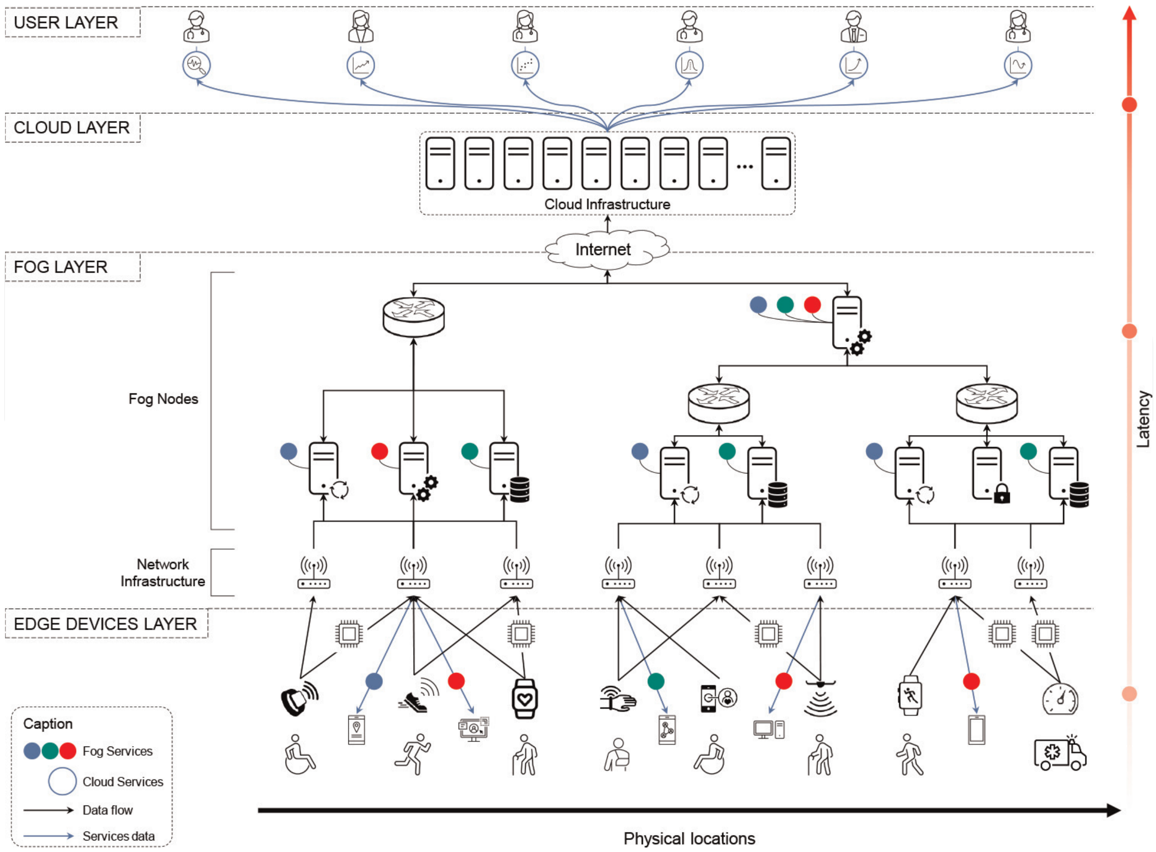
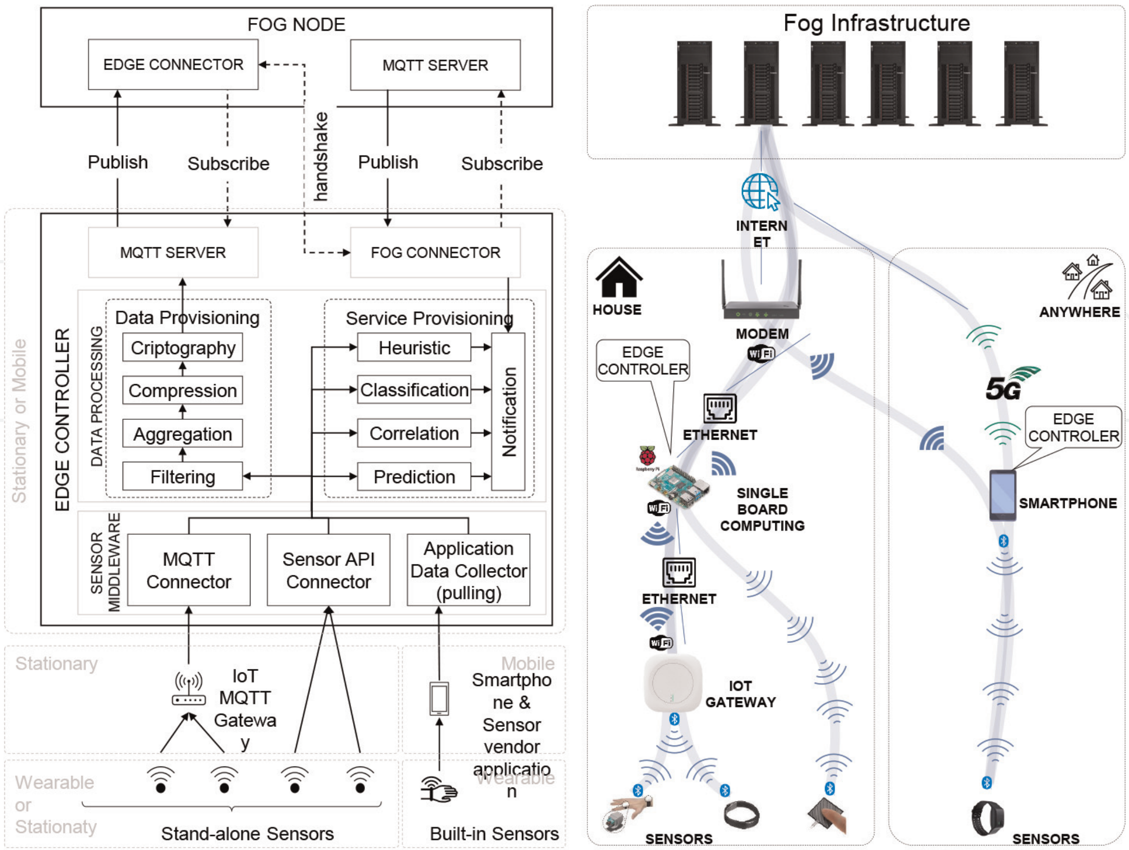


Figure 2.
Smart city architecture focuses on monitoring patients' health parameters. People wear sensors that transmit health parameters to a fog-cloud infrastructure that provides health services.

new paradigm. Here, the public health system provides intelligent services in proactive and on-demand services.

We envisage the functioning of the services by using both artificial intelligence and inferential statistics. The main idea is to enable a set of capabilities for end-users. The most used functionality is event prediction, which analyzes a collection of data in the past (where each element represents a vital sign data and a timestamp), employs a prediction engine, and presents as output a forecast of an event for the future. We can implement event prediction using logistic and linear regression, ARMA, ARIMA, random forest, or neural networks. The second type of event refers to correlations. For example, they can be implemented using confusion matrices, cosine's rule, and Pearson's coefficient. The third type of service uses data classification. Here, we have a learning process that helps build a learning model, enabling us to classify health situations. Classification is commonly deployed with Support Vector Machine and k-nearest neighbors.

Yet, pattern recognition is another type offered in the proposed architecture of health services. The main idea is to analyze raw data to perceive clusters with standard features. To implement pattern recognition, at this moment, we plan to use Neural Networks and K-means clustering. For example, a health surveillance system can forecast the health disorders of a person wearing smart bands. Thus, the system can proactively call an ambulance and schedule appropriate human resources in hospitals to support a patient. Using pattern recognition, we can identify sections of a city with a more considerable risk of a particular disease. Moreover, by blending vital signs and a geolocation system, we architecture can analyze the efficiency of lockdown policies.



(a) Edge Controller (b) Local deployment

Figure 3.
Edge architecture and deployment proposal.

In addition, in the case of a pandemic scenario, we can generate cost-efficient procedures to reopen cities in a secure and timely way.

Our architecture can support different wearable devices, each functioning with a particular IoT protocol. In this way, we present in the Edge Controller a middleware to support device heterogeneity. It acts as a gateway, receiving different types of inputs and outputting a uniform protocol for the upper layers. We can consider a collection of factors that need to be considered when deploying health monitoring devices for remote patients. For example, some topics that should be considered are user authentication, data regulations, data privacy, API availability, data extraction mechanism, data processing system, and information transmission (including direct and indirect communication directives and intermediary brokers).

In our architecture, an Edge Controller is placed near the patient to collect, process, and transmit data to the Fog infrastructure. Also, the architecture envisages a mobile Edge Controller, enabling a user to change effortlessly from one Fog Node to another. **Figure 3a** illustrates the Edge Controller architecture and possible deployments at the patient's site. **Figure 3a** presents a collection of components and their communication to process sensor data. In addition, a viable deployment is depicted in **Figure 3b**.

4. Data processing in fog and cloud instances

To execute the health services, we plan to use two functionalities: (i) serverless computing; and (ii) vertical elasticity. In serverless computing, the user is in charge of submitting a collection of functions to the cloud using the HTTP protocol. Thus, the cloud, in its turn, is responsible for allocating an adequate number of virtual instances (containers or virtual machines) to execute the functions correctly. The name "Serverless," therefore, refers to the ability of the user does not take care of the number and configuration of resources to execute their demands. Vertical elasticity is used to reconfigure the resources with resizing. Taking as a starting point the physical resources, we can slice them into virtual parts (vCPU, vDisk, vMem, for example). The main with vertical elasticity is to adapt this virtual slice at runtime, allocating more or fewer resources by the demand. This strategy is pertinent to use the resources better, enabling us to pass resources from one health service to another (for example, from one that does not require so much processing power to another that is CPU hungry).

In addition to serverless computing and vertical elasticity, our architecture also uses data compression. Here, we employ two types of compression. First, we perform the following tasks: dynamic tune the interval for data collection for each person and each observed vital sign; adapt the changes on captured values to postpone data acquiring, so saving network latency. For example, the times to take data from an older adult could be different from a mid-age one. Also, if a person has a particular chronic disease or is passing through a health treatment, the time interval to analyze their vital signs should be reduced compared to that of healthy people. In addition to this first type of compression, we employ traditional lossless data compression. This compression is taken at the border to the Edge Controller. Considering that we are encapsulating vital sign data in JSON format, which is ASCII-based clear text, it is possible to use either LWW or Huffman Code algorithm to reduce the number of bytes transmitted through the network. These last two examples are known in the literature as being very efficient in dealing with text messages.

Privacy is another concern handled in the project. Our architecture deals with privacy by using federated learning and homomorphic cryptography concepts. With federated learning, data always stays close to the users. The user is in charge of training the ML algorithm, and only the gradients (the result of the ML model) are passed through the network. We can tune and update a global machine-learning model by collecting all user gradients. Homomorphic cryptography, in its turn, helps perform some action with a vector of data without exposing names or character data inside the vector. Homomorphic encryption can only be used over integer data by performing a particular arithmetic formula (for example, mean, maximum, and minimum, standard deviation). Thus, we can create insights into a specific district of a city. For instance, we can verify the number of people with fever, the mean temperature of a collection of people, and if they have heart disorders.

Our organization for information data flow is presented in **Figure 3b**. We can use a single board computer (such as Arduino or Raspberry Pi) to collect data from a family or people that work in a company. Also, the own smartphone can act as a gateway since it is commonly employed to collect that from smart bands. Employing an SBC or a smartphone depends on the use case. An SBC sends data to the internet via connectivity or an ISP provider and can interact with as many sensors as available at the patient's house. The smartphone has the advantage of online monitoring no matter where the patient is. At any moment, the user can receive notifications regarding their health status. The main idea here is to enable a proactive architecture, where we can alert the users about an eventual problem in the future, allowing them to seek timely treatment.

5. Proposal of health services

A health service can be understood as a computing service that inputs one or more vital signs from one or more persons. The output of a health service refers to insights regarding a particular person or a collection of persons (common health conditions of citizens of a city district or community). Thus, the heart rate sensors can detect and predict whether this rate is increasing or decreasing and whether it is falling to the point of causing heart failure [18, 19]. Under normal conditions, a person's heart rate varies between 60 and 100 bpm. Critical situations are considered when the heart rate is less than 40 bpm or greater than 150. In this case, the sensors can be used on patients in the hospital emergency room and patients with chronic cardiorespiratory diseases who want to monitor at home, using historical data from a single user over time. It is possible to trigger an alarm warning that the heart rate is decreasing so that doctors can verify the cause and possibly prevent a cardiac arrest. Not only that but an alert can be sent to the nearest emergency station, automatically triggering an ambulance to where the person is. Moreover, the same system can perform an alert network in the hospital environment, whether during observation, hospitalization, or in the ICU, generating a specific signal to the nearest infirmary, alerting that the patient is in cardiorespiratory arrest.

Besides, the sepsis prediction could be made too. It is characterized by a dysregulation of the inflammatory and their stems in response to a microbial invasion that produces body injury. During sepsis, tachypnea, tachycardia, and the high temperature usually occur. According to [20], two or more of these signs indicate sepsis temperature >38°C, heart rate >90/min, and respiratory rate >20/min. From the detection by the sensors, it can be predicted whether the patient is experiencing a worsening of his condition and getting septic. So, historical data from a single user to monitor over time can be used. This way, the hospital staff can be notified, and the patient should receive proper care.

In addition, from the measurement of individuals' vital signs, it is possible to follow the progression or regression of the chronicity of disease through the analysis of baseline reference values of the analyzed vital signs [21]. In chronic diseases such as cardiac diseases, chronic obstructive pulmonary diseases (asthma, emphysema, bronchitis), and renal diseases, all vital signs are usually monitored, as any of them can worsen and lead to decompensation of the disease. Data from the elderly would be monitored in a home for the elderly with chronic diseases or homes of an older population. This data could be saved for them or their caregivers to follow up. In this case, historical data from a single elderly user is used to monitor over time, and the underlying disease of the elderly can be followed over time.

Monitoring oxygen saturation in patients with Chronic Obstructive Pulmonary Disease (COPD) to help decrease respiratory function can be done. Patients with COPD are more likely to experience a drop in peripheral blood oxygen saturation (hypoxia) because oxygen entry into the lungs is impaired [22]. This way, neighborhoods, and cities could be monitored to predict a worsening clinical picture. Analysis of this vital sign can be sent to the hospital caring for that patient. It may indicate the need for mechanical ventilation or oxygen for the patient or additional treatment.

By measuring oxygen saturation, hypoxemia can be identified. It is characterized by a decrease in partial pressure of oxygen in the blood, leading to impaired blood perfusion and cyanosis in more critical cases [23, 24]. It can be measured through arterial oxygen saturation, characterized by the percentage of hemoglobin saturated with oxygen. Oxygen levels below 90% describe severe hypoxemia in peripheral blood

[25]. Some causes of hypoxemia are asthma, chronic obstructive pulmonary disease, idiopathic pulmonary fibrosis, pulmonary embolism, and COVID-19. Thus, measuring the arterial oxygen saturation becomes helpful in the hospital environment because once the oxygen saturation level of a patient who has entered the hospital or even who is already hospitalized is detected as low, it can be predicted whether the patient should be in an alert or critical state, and should or should not be intubated due to the need for interventions for mechanical ventilation.

Preeclampsia is a gestational disorder characterized by increased blood pressure and proteinuria during the third trimester of pregnancy. It is one of the leading causes of maternal and infant mortality. The diagnosis is based on the presence of hypertension, with measurements performed at two different times, with systolic blood pressure >140 mmHg and diastolic blood pressure at >90 mmHg, in previously normotensive patients and proteinuria at >300 mg. Thus, the measurement of blood pressure in gestational patients through a device can help diagnose the pathology in pregnant women, with measurement both in the residential and in the hospital or clinic. The device can send an alert to the hospital or pregnant patient, warning that the blood pressure is increasing. With this, the doctor who takes care of the patient can provide adequate treatment to avoid eventual problems.

6. Conclusion

We have presented an idea of a smart city organized in edge and fog nodes to manage vital signs-based healthcare services. In the future, each citizen will wear a smart band or smartwatch, which will help monitor vital signs, and input data into the architecture. With data from the whole city, public sectors can proactively address healthcare problems in particular districts or develop public strategies destinated to a particular aging interval. We are confident that the future will combine edge, fog, and cloud resources with supporting critical and non-critical services. The term critical here can be understood that services must be executed with high priority, for example, when involving older people with diseases or chronic problems or when addressing health services where the latency time is crucial, like ECG.

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