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Enhancing the Processing of Healthcare Data Streams using Fog Computing

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Abstract— **Healthcare data streams originate from various sensors and Internet of Things (IoT) devices deployed in medical equipment and healthcare facilities as well as worn by patients. These vast volumes of data need to be leveraged to improve patient care, optimize processes, and help health sector stakeholders and applications make faster and more informed decisions. Many healthcare applications use the power of the cloud for data processing. However, time-sensitive healthcare applications cannot tolerate sending data streams to the cloud for processing due to unacceptable high latency and network bandwidth requirements. Healthcare facilities and caregivers need the ability to efficiently stream data and process data streams in real-time at the edge. This paper describes a five-tier architecture that aims to deal with the streaming and processing of data generated by the various devices and equipment of healthcare facilities and systems to enable the creation of smart healthcare applications. The architecture is based on emerging and established technologies, including IoT, edge/fog computing, data integration techniques, cloud computing, and data analytics. The proposed architecture will facilitate the creation of healthcare applications for real-time event detection, notification of alerts, and building monitoring dashboards. Fog node components include an advanced and widely recognized distributed messaging system, Apache Kafka, and the popular stream processing engine, Apache Storm, capable of processing large amounts of data.**

Keywords- edge computing, fog computing, data streams processing, data analytics, IoT, IoT gateway.

I. Introduction

The Internet of Things (IoT) is one of the disruptive technologies of our time that can profoundly transform the health ecosystem. It could potentially change the way healthcare facilities and caregivers collect and use data to improve the delivery of patient care. In modern healthcare facilities, massive amounts of data originate from a variety of sensors and IoT devices, which monitor in real-time the operations of various systems as diverse as medical equipment, buildings, and health conditions of patients. The data streams, in structured and unstructured formats, from these diverse sources, are so broad and complex to manage with conventional data management tools and methods.

By processing health data streams, it will be possible to identify the most significant events and patterns and make appropriate decisions on them in near real-time. It will allow healthcare stakeholders to respond to urgent situations with both speed and precision. The data processing chain may involve operations like filtering, aggregating and ultimately storing resulting data for further processing by data analytics applications. Moreover, the ability to federate and process healthcare sensor data streams will permit to harness the governance of healthcare facilities, reduce costs, and provide better care to patients.

These potential benefits of using IoT solutions in healthcare systems come with challenges with regards to storing, disseminating and processing the vast amounts of sensed data. Many healthcare applications use the power and elasticity of the cloud for data storage and processing [1][2][3]. However, time-sensitive healthcare applications cannot bear transmitting data streams to cloud servers for processing because of unacceptable high latency and high network bandwidth requirements. Instead of conveying data to cloud servers for processing and storage, end devices and sensors should pass the data to an edge computing device to aggregate, process or analyze that data to minimize costs and lower latency while controlling network bandwidth [4]. A substantial benefit of this operation is the reduction of data that must be transmitted and stored in the cloud.

In this paper, we propose an architecture for near real-time processing of healthcare sensor data at the edge of the network where data is generated. The architecture includes several components that are chained to build a data pipeline. Data streams, originating from IoT devices of healthcare facilities and sensors deployed in medical equipment or worn by patients, are conveyed to nearby IoT gateways using a variety of communication protocols (MQTT, CoAP, Zigbee, WiMAX, etc.). These IoT gateways can perform some preliminary data aggregation and then publish aggregated data to a fog node for processing. Fog node components include a publish-subscribe messaging system, a stream processing engine, and a database store. Several technological options are now available for each one of these components. Data that do not require immediate actions and historical data can be conveyed to cloud servers for more profound insights.

The rest of this paper is organized as follows. Section 2 provides background information on healthcare sensor data streams and describes the new emerging paradigms of edge computing and fog computing. Section 3 presents related work on edge/fog computing-based solutions for real-time processing of healthcare IoT data streams. Section 4 describes our proposed architecture that will serve for the real-time processing of IoT data streams. Section 5 describes the fog components for data streams processing. Finally, Section 6 concludes the paper.

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II. Background

A. Healthcare Sensor Data Streams

In recent years, because of the significant decrease in the cost of sensors and the continued miniaturization of electronic devices, various kinds of sensors are proliferating in health facilities. Also, more and more miniature sensors are worn by patients to monitor several vital signs concerning their health. These sensors generate huge volumes of data.

In a healthcare facility, several systems are designed to work with real-time data from sensors, meters, and many other devices used to assure the operations of the facility. In addition, electronic control systems in medical equipment and different probes rely on sensor signals for accurate diagnosis and treatment. These sensors include Temperature Sensors, Pressure Sensors, Position Sensors, Humidity Sensors, Air Bubble Detectors, Force Sensors, Photo Optic Sensors, Piezo Film Sensors, and many more. They collect data used in a variety of medical applications to enhance the manner in which patients are monitored and treated. They are used to provide accurate monitoring, diagnosis and treatment for several healthcare applications. Many healthcare facilities are using advanced IoT solutions to implement smart healthcare applications. Featured applications include Blood Pressure Monitoring, Body Temperature Measurement, Glucose monitoring, Medical Pump Technology, Dialysis Equipment, Medical Wearable Technology, Sleep Monitoring, and Assisted Baby Delivery.

IoT solutions for healthcare deliver the promise of making health organizations smarter and more efficient in what they do. IoT has the potential to redefine in health environments the way devices, technology, and people interact and connect, helping to promote better care and lower costs. Examples of healthcare IoT solutions include:

- Remote monitoring solutions for patient's health
- Remote care for Patients
- Management of hospitals assets and devices using IoT
- Preventative maintenance solutions for medical equipment
- Smart solutions for emergency management in Hospitals
- Prevention of threats and unauthorized entry and departure using video security cameras and electronic ID-enabled security doors
- Smart wearables and mobility solutions for physicians and patients for quicker monitoring patient's health

By converging IoT and data analytics, healthcare organizations will be able to aggregate and analyze data from disparate systems and remote facilities to provide the right information to the right person, anytime and anywhere. Also, the addition of data analytics will help healthcare facilities improve patient satisfaction, operational efficiency and security for all, and provide facility operators with greater insights on how each building or medical equipment is working, enabling decisions based on evidence and predictable patterns.

B. Edge and Fog Computing

Edge computing represents the process of decentralizing computing and storage capabilities by bringing them closer to data sources. This process is designed to reduce application latency and the amount of data that is delivered to cloud servers. Due to the enormous amounts of data generated by sensors and IoT devices, well-established data management systems and practices will no longer be sufficient to take full advantage of IoT. As a result, edge computing places computing resources and storage at the edge of the network, close to data sources [5].

To address the inefficiency of cloud computing in processing data produced at the edge of the network when applications are time-sensitive, some solutions have been designed to be deployed at the edge of the network. They include cloudlets [6], [5], micro-data centers [7] and fog computing solutions [8]. At least 40% of the data generated by the IoT devices would be stored, processed and analyzed at the edge of the network, according to IDC forecasts for 2019 [9].

In healthcare systems where multiple applications are time-sensitive, edge computing will play an important role in implementing smart health applications. For example, for remote patient care to become a reality, physicians need to be able to react in real-time to unexpected situations. Patient monitoring applications do not tolerate sending data to the cloud server and waiting for data analysis results. The system must have the ability to process the sensed data instantly and react accordingly. Healthcare facilities and systems are ideal for the use of edge computing. Indeed, sensors and actuators can receive commands based on decisions made locally, without having to wait for decisions made in another remote location. Health systems can use edge computing to obtain up-to-date information on the conditions of facilities, medical equipment and buildings, and take corrective action before unwanted conditions or accidents occur. The processing of healthcare IoT data streams can be pushed from the cloud to the edge, reducing network traffic congestion and end-to-end latency. Edge Computing can encompass operations such as data collection, parsing, aggregation, and forwarding, as well as rich and advanced analytics involving machine learning and event processing at the edge.

Cisco Systems defined Fog computing as: "*Fog Computing is a highly virtualized platform that provides compute, storage, and networking services between end devices and traditional Cloud Computing Data Centers, typically, but not exclusively located at the edge of the network.*" [8]. Much of the earlier literature has treated "fog" and "edge computing" as synonymous and used the terms fog and edge interchangeably. Fog Computing and Edge Computing are both concerned with processing and filtering IoT data before it arrives in a data center or cloud server. Edge computing is a subdivision of fog computing. The main difference between them lies in the place where the data processing takes place. With Fog Computing, data processing usually takes place in a fog node located near the local network. Edge Computing processes data in edge devices and uses the communication capabilities of edge gateways to send data to the data center or cloud.

Edge devices run full operating systems such as Linux and Android and are often battery powered. They process the raw data they receive from IoT sensors and devices and send commands to the actuators. Edge gateways also run full operating systems, but have relatively more power, processor resources, memory, and storage. They act as intermediaries between the fog node and the edge devices. They transmit raw or aggregated data sets to the fog node and receive commands such as data configurations or queries. The fog nodes components store and analyze data using machine learning algorithms and analytics. Its openness mostly characterizes fog computing as opposed to edge computing, which typically relies on proprietary solutions.

III. Related Work

Over the last few years, there have been several research efforts that investigated the implementation of real-time processing of IoT data streams at the edge of the network. Furthermore, a growing number of works have studied how to harness IoT and fog computing for healthcare systems. In the following, we highlight some recent works on the subject.

Singh S. et al. [10] proposed a fog-based framework to classify dengue patients as uninfected, infected and severely infected using a data set constructed by Beatty et al. [11]. Dengue fever is one of the most frequent viral diseases transmitted by mosquitoes. The framework consists of three layers, namely IoT layer, fog computing layer, and cloud computing layer. The fog computing layer provides storage capacity for large amounts of dengue data after pre-processing and allows efficient connectivity between IoT sensors and the cloud. They concluded that the use of network devices in the fog infrastructure reduced system latency and that the fog computing usage resulted in improved response and execution times for the classification application without affecting its accuracy.

Mutlag A.A. et al. reviewed several works on fog computing for IoT healthcare [4]. They classified them into three classes, namely, methods and approaches, system development, and reviews and surveys on fog computing in the healthcare applications. By studying different review papers, they identified the problems, difficulties, and challenges of using fog computing in health applications and made recommendations to overcome them by adopting computation offloading, load balancing and interoperability.

Kumari A. et al. proposed a fog-based three-layer eHealth architecture that can help hospitals, clinics and caregivers deliver exceptional health services to patients [12]. This architecture consists of three main layers: Medical Device Layer (MDL), Fog Layer (FL), and Cloud Layer (CL). It allows managing data pipeline activities from data acquisition, data processing, and big data analytics on the cloud.

Kraemer F.A. et al. investigated several health care applications, categorized by deployment scenario and use case class, and provided an inventory of computing tasks suitable for fog computing [13]. They concluded that a large number of computing tasks, in different deployment scenarios and application use cases, could benefit from fog computing. Since computing is needed for most ubiquitous healthcare applications, it often has to be run somewhere between sensors and the cloud. They provided an inventory of computing tasks and described where they could be performed in a network.

This work shares with these efforts the common goal of processing healthcare data streams at the edge to cope with the issues of network bandwidth and latency that are vital for time-sensitive healthcare applications. As different technological solutions could be used at the fog nodes to process data streams, we opted to use the most popular messaging system, Kafka, the Apache Storm stream processing engine, and the MongoDB NoSQL database. Published data is stored in Kafka topics and made available to an Apache Storm topology, which helps find valuable information in an impressive amount of data.

IV. A Framework for Healthcare Sensor Data Processing

A. Healthcare Data Pipeline

Building a healthcare data pipeline is a five-phase process, which includes data acquisition, data pre-processing, data streams processing, presentation and visualization, and decision-making (see Fig. 1).

Data acquisition. This phase includes obtaining relevant healthcare sensor data streams from different sensors and devices deployed in a healthcare facility. These data streams can be received and sent in various data formats such as XML, JSON, and Text. Data can be written into data repositories such as RDBMS or NoSQL databases like Apache Cassandra. Transport protocols such as MQTT and publish-subscribe messaging systems like Apache Kafka need to be supported to enable persistence of data and its consumption by several applications.

Data pre-processing at the edge. This phase can rely on one or several techniques for data integration including data consolidation, data federation, data propagation, and semantic integration to be able to fuse data generated by diverse devices and sensors systems [14]. Data integration will enable healthcare stakeholders and care givers to get, for example, the full picture of what is happening in facility or sub-system, or to have a preliminary evaluation of the current health condition of a patient. Data propagation refers to the movement of data from one or more data sources to target locations. Data consolidation refers to collecting data from multiple sources and integrating them into a single persistent data store. Data federation refers to software resources that provide users with a single logical view for presenting and accessing data stored in one or more data sources. Controlled vocabularies represent a form of semantic data integration by imposing standardized terminology for data elements that appear in databases. Example of controlled vocabularies are the various ontologies developed for healthcare. An ontology typically acts as a mediator for the separate schemas of different data sources and as a reference schema for federated data queries.

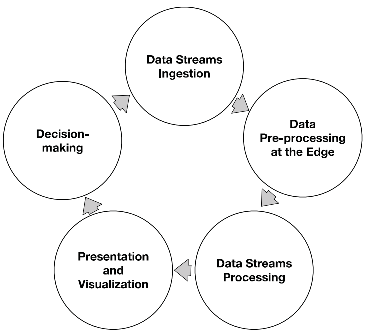

Fig. 1. Phases of a healthcare data pipeline

Data streams processing. The results of this phase will have a significant effect on the information and metrics in the presentation stage, thus the success of future decisions or actions a healthcare professional might take. Data streams processing typically rely on a streaming processing engine such as Apache Storm, Apache Flink, SensorBee, WSO2 CEP, or Spark Streaming. The extraction of useful information from unstructured data often requires the use of machine learning techniques. These engines typically support various machine learning toolkits, such as Jubatus and Scikit-learn.

Presentation and visualization. In this phase, the results from different processing approaches and analytics are summarized, evaluated, and shown to users in an easy-to-understand format. Visualization techniques may be used to present useful information; one commonly used interface design is the visual dashboard, which aggregates and displays information from multiple sources. Visualization will rely on open source tools, such as Pentaho and Helical Insight, or public or community editions of commercial tools such as Tableau public and Qlik Sense Desktop.

B. *Architecture Overview*

To design our proposed architecture, we assume that IoT devices publish data to a nearby IoT gateway able to aggregate and summarize data to reduce the amount of data conveyed to a fog node having more computing power and storage. Given that several processing tools and applications might be used in the fog node, it is essential to have a messaging system capable of persisting received data and implementing a publish/subscribe model as well as a pull model that processing tools and applications can use to access the data streams. The messaging system, as well as the processing platform, need to be able to scale up with the vast amount of data transmitted by the IoT gateways. This section gives an overview of our proposed architecture, depicted in Fig. 2, and describes its components.

Our proposed architecture consists of five tiers. The first tier comprises networked devices typically sensors while the second one includes IoT gateways responsible of analog-to-digital conversion and aggregation of sensed data. The third tier includes fog nodes responsible for processing data received from the second tier before it moves to the cloud for more profound insights. Data processing in this tier is more appropriate for time-sensitive healthcare applications, which require near real-time information to make decisions that can save patient's life. The cloud computing tier is in charge of processing, analyzing, and storing non-time-sensitive data on cloud servers. Finally, the application tier provides monitoring and alerting dashboards. The fifth tier includes applications such as monitoring alerting, and queries.

1) *IoT Healthcare Infrastructure Tier*

This tier consists of sensors and smart IoT devices. Smart devices permit to automate the operations of a healthcare facility by collecting data on its physical assets (buildings, facilities, equipment, etc.). Collected data allows monitoring the behavior and status of these assets and optimizing the resources and processes of the healthcare facilities. Also, smart devices and sensors are deployed to monitor vital signs of patients, especially those with chronic diseases. A device detects some input, like temperature, motion, vibration, pressure, water level, heat, or any other phenomenon, from its surrounding environment and responds to it. The device reading, which is then converted into a human-readable form, is sent over a network to a gateway at the edge for further processing. Devices, without a direct connection to the Internet, forward the gathered data to edge devices or edge gateways using Ethernet or WiFi connections of a Local Area Network or using other protocols such as Bluetooth and ZigBee.

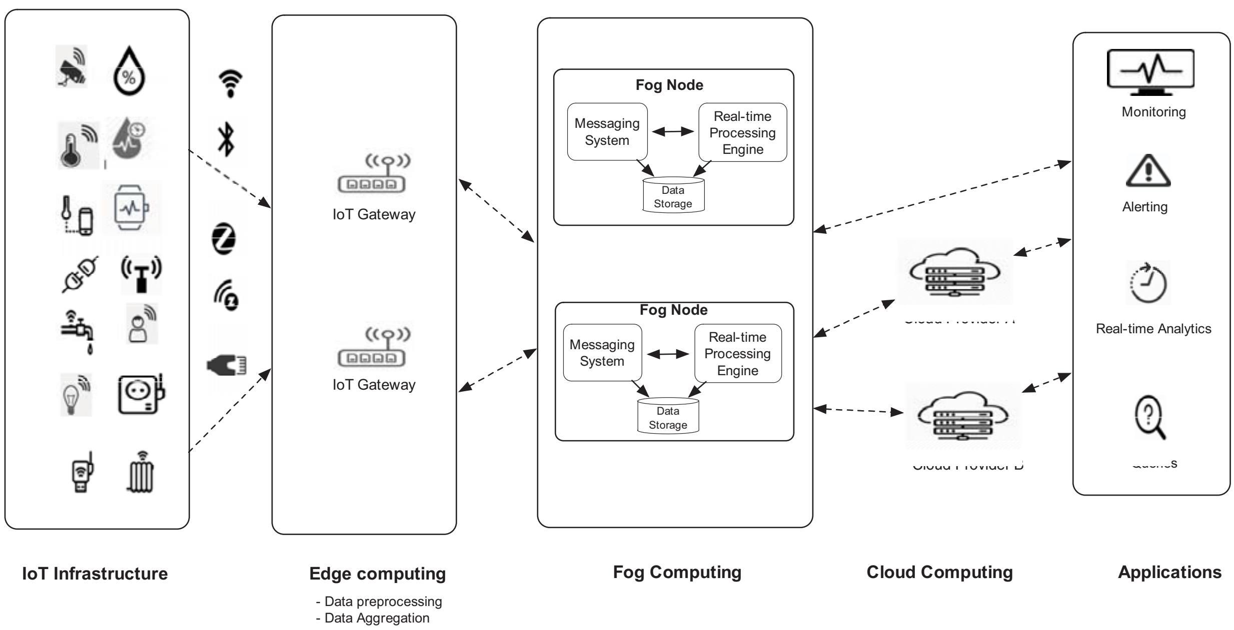

Fig. 2. Architecture for healthcare IoT data streams processing at the edge

2) Edge Computing Tier

Edge (or IoT) gateways are a critical component in any IoT implementation. This component is in charge of aggregating data, translating sensor protocols, and preprocessing data before conveying it to other tiers (fog/cloud) for more processing. Aggregation and preprocessing of sensed data are required to cope with the high volume of data coming from sensors and devices. In contrast with traditional network gateways, which typically perform protocols translations, today's IoT gateways are full-fledged computing systems capable of performing advanced tasks such as protocol and data bridge between devices using heterogeneous communication protocols and data formats, malware protection, and storage and analytics.

3) Fog Computing Tier

Digitized and aggregated data, by IoT gateways, for which immediate feedback is not expected may require further processing before moving to the cloud. Such processing is performed in fog nodes located at the network edge closer to the sensors. These fog nodes, which can perform analytics at the edge, permit to lessen the burden on core IT infrastructures because the massive amounts of IoT data can easily swamp data center resources and eat up network bandwidth. The next subsection describes the components and technologies that could be used to process data streams in a fog node.

4) Cloud Computing Tier

Data that does not require immediate feedback but requires further processing is transferred to physical data centers or cloud systems, where more powerful computer systems can securely store, analyze, and manage data. Data processing at the cloud allows for more in-depth analysis and allows to combine sensor data with data from other sources for deeper insights. However, waiting for the data to reach this tier can delay getting the results.

5) Applications Tier

Healthcare applications are the consumers of the results of the data streams processing. The applications tier offers a broad set of techniques and tools for effective design, implementation, deployment, and operation of the healthcare services and applications. Smart applications could be developed in the areas of facility management, resource management, safety monitoring, remote patient monitoring, etc. These smart applications could be used to improve the performance of different healthcare departments, improve the efficiency of resource management, save lives, minimize the risk of loss of life and resources, improve quality of life of patients, and many more benefits.

Web services technology has emerged over the last two decades as the principal technology for delivering services and applications over the Web. Also, the microservices technology has recently emerged as a promising technology to support the design and implementation of scalable systems versus traditional systems designed as monoliths. It promotes the creation of a system from a collection of small, loosely coupled services, each isolated, scalable and resilient to failure, and with its data. Services integrate with other services to create a coherent and extremely flexible system compared to the usual systems built today. In the healthcare context, service orientation and the microservices technology represent the main design principles to ensure interoperability between healthcare systems and facilitate data integration, and the creation of healthcare processes that span several healthcare systems.

V. Data Streams Processing at the Fog

The data streams processing components at the fog typically include a distributed messaging system, a data stream processing engine, and data storage. Several publish-subscribe messaging system have been developed in recent years. The most popular are ActiveMQ, RabbitMQ, and Kafka. They support protocols such as AMQP, MQTT, and many others to interact with IoT gateways. Apache Kafka is recognized as the most advanced messaging system that can handle data streams efficiently and in a scalable manner. Kafka is ideal for real-time scenarios such as telemetry from sensors and connected devices, click-stream analysis, financial alerts, social analytics, and network monitoring. In general, Kafka integrates well with several stream processing engines such as Apache Storm, Apache Spark, Apache Flink, Google Cloud Dataflow, and Amazon IoT.

Fig. 3 depicts the stream processing components in a Fog Node. These components include a Kafka cluster, a Storm topology, a MongoDB database (or Neo4j graph database, which promises to offer better queries execution time [15]), and query tools (i.e., Apache Drill) and visualization and monitoring dashboards. Kafka usually runs on a cluster of one or more brokers. It immutably stores messages from multiple sources (producers) in queues (topics) organized into multiple partitions.

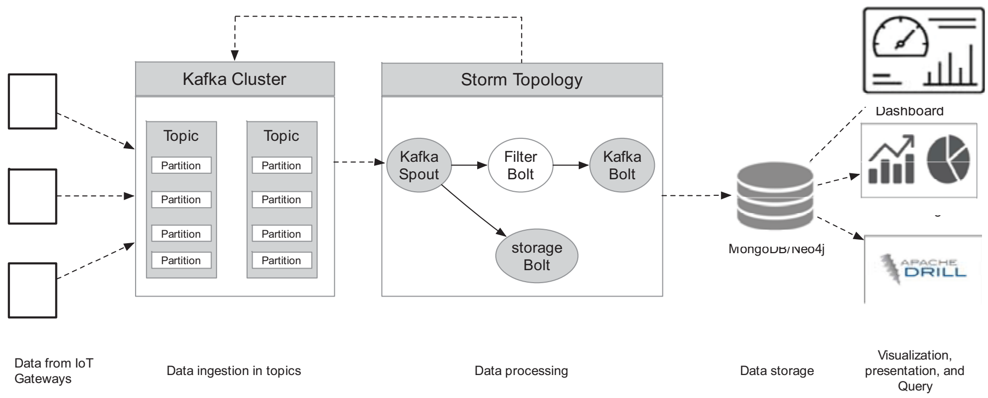

Fig. **3.** Real-time stream processing at the Fog tier

The messages in a partition are indexed and saved with a timestamp. Other processes (consumers) can query messages stored in Kafka partitions. Kafka partitions are replicated across brokers in the cluster to ensure fault tolerance. Apache Storm is a distributed open-source framework that facilitates real-time data processing. It works for processing data in real-time, just as Hadoop works for batch processing of data. Apache Storm relies heavily on Apache Zookeeper for its cluster state management operations, such as message acknowledgments, processing reports, and other similar messages.

A Storm application is designed as a workflow, called a topology, in the form of a directed acyclic graph (DAG) with spouts and bolts as vertices of the graph. The edges of the graph are named streams and direct data from one vertex to another. Apache Storm can handle more than one million tuples per second per node, which is highly scalable and offers processing work guarantees. Apache Storm provides several components for working with Apache Kafka. KafkaSpout and KafkaBolt can be used to read and write data from Kafka respectively. Also, The Storm/Trident integration package for MongoDB includes the core bolts and trident states that allow a storm topology to insert storm tuples into a database collection or to execute update queries on a database collection in a storm topology.

VI. Conclusion

The Internet of Things (IoT) is a disruptive technology that can radically transform the health ecosystem. It could potentially change the way healthcare facilities and hospitals collect and use data to improve the delivery of patient care. This change will be possible by combining IoT with the main trends in big data analytics, mobility and process automation.

Furthermore, effective governance and management of healthcare facilities and systems rely heavily on the deployment of a large number of smart sensors and devices to monitor patient conditions, medical equipment, and different aspects of healthcare facilities. The vast amounts of data generated by these sensors and devices need to be harnessed to enable caregivers and decision makers to make informed decisions. For this to happen, it is essential to process IoT data streams in near real-time and use data analytics tools to gain insights from the events happening in the healthcare facility or the current health conditions of a patient. Data streams are typically sent to cloud servers for storage and processing. The abundance and elasticity of cloud resources make this scenario feasible in many use cases. However, time-sensitive applications, such as processing videos recorded by surveillance cameras, cannot tolerate sending data streams to the cloud for processing due to network bandwidth requirements and high latency.

In this paper, we have described a fog-based architecture, which aims to manage the streaming and processing of data generated by various devices and equipment of healthcare systems. Processing healthcare data streams at the edge, closer to data sources, can reduce network traffic and improve the latency of time-sensitive healthcare applications. The fog computing tier of the architecture relies on a popular and advanced messaging system, Apache Kafka, and a powerful stream processing engine, Apache Storm, capable of handling large data volumes. Besides, IoT gateways are an essential component of the system. Several open source IoT platforms provide an implementation of IoT gateway. A prototype of the system is being developed using the ThingsBoard IoT gateway to ingest data streams into the system using a Kafka plugin. We intend to consider real life healthcare scenarios that will evaluate our system and application latency.

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