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# 5G network slice for digital real-time healthcare system powered by network data analytics

Hemant Jain [a], Vinay Chamola [b,*], Yash Jain [c], Naren [c]

[a] Technology and Services strategy, Samsung Networks, Mumbai, 400063, India
[b] Department of Electrical and Electronics Engineering & APPCAIR, BITS-Pilani, Pilani Campus, 333031, India
[c] Department of Electrical and Electronics Engineering, BITS-Pilani, Pilani Campus, 333031, India

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ABSTRACT

In the wake of the COVID-19 pandemic, where almost the entire global healthcare ecosystem struggled to handle patients, it's evident that the healthcare segment needs a virtual real-time digital support system. The recent advancements in technology have enabled machine-to-machine communication, enhanced mobile broadband, and real-time biometric data analytics. These could potentially fulfill the requirements of an end-to-end digital healthcare system. For building such a system, there is also a need for a dedicated and specialized communication network. Such a system will not only support dynamic throughput, latency and payload but also provide guaranteed QoS (Quality of Service) at every instant. The motive of our study was to define an implementable low-level architecture for the digital healthcare system by using the 5G Network Slice that incorporates all these features. Best-in-class wearable devices will collect the biometric data and transmit it via the 5G network slice. Data analytics is then applied to the collected data to build a knowledge graph used for quick predictions and prescriptions. The architecture also keeps in mind the security and integrity aspects of healthcare data.

## 1. Introduction

Building a real-time healthcare system with assured QoS is the need of the hour and could potentially save lives in some situations. Wearable devices such as smartwatches can help save people in case they suffer an accident, sharing the critical health parameters with the family members and doctors. In case of a natural disaster like an earthquake the authorities can locate the victims with the help of such wearable devices. Moreover, contact tracing solutions such as the ones proposed in Ref. [1] can also be enhanced with the proposed architecture. As suggested by H. Leite et al. in their study [2], most of the countries in the world have not been able to cope up with the increase in demand for medical supplies and infrastructure that has arisen during the COVID-19 pandemic. In such situations, it is recommended to move appointments to telemedicine whenever possible. This could only be possible when there is a system in place that is capable of withstanding the demand and provide real-time data transfer capabilities.

There are many advantages to such a system. However, the limiting factor for the current scenario is the inability to transfer data in real-time. This paper proposes an architecture that tackles this problem. For managing the highly complex heterogeneous Internet of Medical things (IoMT) for patient-specific services, we will need to adapt and shift from legacy general-purpose telecom networks and services to a dedicated 5G network slice. This should be powered by an augmented cognitive computing approach with sophisticated data analytics and machine learning algorithms to dynamically adjust the network as per patient-specific dynamic healthcare needs.

In this paper, we have evaluated all the attributes essential for the digital real-time healthcare system and proposed a collaborative end-to-end patient-specific dynamic healthcare solution that uses an amalgamation of 5G and Machine Learning. The paper starts with describing the main drivers of digitization in healthcare, followed by the implementation steps, then the proposed architecture and dimensioning of 5G network slice and integrated network data analytics framework. The paper also comprehensively covers the biometric data security aspects in the healthcare ecosystem.

## 2. Related work

Currently, research is going on for utilizing the 5G network slice technique for healthcare digitization and solving various associated challenges, including technical framework, architecture,

* Corresponding author.
*E-mail addresses:* hejain12@gmail.com (H. Jain), vinay.chamola@pilani.bits-pilani.ac.in, vinay.chamola@pilani.bits-pilani.ac.in (V. Chamola), f20180333@pilani.bits-pilani.ac.in (Y. Jain), f2015547@pilani.bits-pilani.ac.in (Naren).

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implementation, and security aspects. The work done by Yushan Siriwardhana et al. [3] suggests the use of 5G technology to realize a comprehensive use-case model to handle the complete healthcare ecosystem remotely. This study also gives an overview of the deployment aspects of 5G for telehealth in hospitals. Y. Hao et al. [4] and A. Vergutz et al. [5] suggested using 5G slicing technology for wearable device connectivity to process biometric data with guaranteed bandwidth and quality of services to ensure real-time data processing at a central location. The architecture envisioned by A. Vergutz et al. [5], relies on fingerprinting healthcare applications to quickly customize resources and meet the level of reliability required for each smart healthcare application. However, none of these studies focus on the low-level 5G architectural aspects of the network slice. Our study builds on top of these studies and defines an implementable architecture of 5G network slice for healthcare applications.

## 3. Three drivers of digitization of the healthcare system

The following are the three main drivers [6] that have brought about the digitization of the healthcare system because of the recent technological growth in these respective fields. Moreover, an amalgamation of these provides a more robust and real-time system that can be relied upon for critical healthcare applications.

### 3.1. Wearables

The recent growth in the wearable devices industry has brought about more accurate and feature-rich wearable devices into the market. These are now IoT-enabled with a lot more biometric parameter measuring capabilities. Some of the most common available wearable devices [7] along with their features are:

- *Wristbands/Bracelets for* – Heart-Rate, Pulse Rate, Sleep-time, Steps counting, and calories burnt.
- *Smart Shirt/Jacket for* – Body Temperature, Oximeters for blood oxygen, ECG, Myocardial, EEG, Sweat meters for blood sugar level.
- *AR Smart Glasses and Mio Slice for* – Blind and hearing aid patients.
- *Implantable medical devices for* – Heart Pacemakers, Implantable Cardioverter Defibrillator (ICD), etc.

Further 5G Network Slicing powered by data analytics and AI will allow upcoming wearable devices to be smarter, with more bandwidth and real-time data transfer capabilities.

### 3.2. 5G network slicing

To address the complexity of heterogeneous healthcare data transmission from patient's wearables, we would need enhanced mobile broadband, low latency, and guaranteed bit-rate quality of services along with no compromise in security. Thus, 5G Network slicing will be a catalyst [8] to trigger internet of medical things (IoMT) innovation [9] of new products and services in the healthcare domain by integrating the following [10]:

- Multi-connectivity and dynamic spectrum sharing distributed cloud RAN [11] for medical application-specific requirements, e.g., data upload from patient's wearables, remote patient diagnosis, and treatment.
- Software defined network (SDN) for dynamic throughput and payload in transport layer [12].
- Dedicated virtualized cloud core structure for patient-centric QoS and security of healthcare data.

### 3.3. Big data analytics and machine learning in healthcare

Significant research is being carried out on using artificial intelligence, machine learning, deep learning, etc, for various healthcare applications [13,14]. Big data aggregates the information collected from various medical devices (wearables and clinical) in the form of biometric text and data reports. The data is processed to extract information in near real-time for clinicians and doctors:

Analytics work-flow based on biometric data patterns:

- Inconsistency detection in patient's biometric data based on maximum thresholds defined.
- Inconsistency detection based on the historical biometric data pattern of the same patient.
- Pre and post-impact of drugs prescribed and consumed by patients.

The role of AI and ML would be crucial for the predictive and prescriptive treatment of the patient:

- With AI and ML sophisticated algorithms, illnesses and diseases can be predicted well in advance, which could potentially save human lives.
- Biometric data patterns powered by AI are best observed in areas like precision medicine, medical imaging, and analysis of thousands of pathology images of various cancers to provide highly accurate diagnosis and predict the best possible anti-cancer drug combination.
- There is another massive opportunity for the biotechnology domain for DNA sampling and modeling by using ML algorithms for critical diseases.

## 4. Healthcare network slice implementation steps

Taking learning from work done by A. Ahad et al. [15] and Y. Zhai et al. [16], we have come up with a high-level execution approach, as shown in Fig. 1. It can be divided into following the five steps:

Step 1: The IoT wearable devices (explained in section II) are connected through the mechanism provided by the 5G Radio Access Network (RAN).

Step 2: Collection of heterogeneous medical data from a variety of medical devices that are connected through 5G RAN and transmitted through an SDN for dynamic interconnection needs.

Step 3: Each of the medical devices follows IoT-oriented architecture that aims to dynamically provision 5G Slices to collect and process the data with diverse patient-level QoS requirements.

Step 4: Medical device network slices are successfully deployed in the respective virtual network function (VNFs) for real-time data processing and handling dynamic patient-specific biometric data on the control plane.

Step 5: Data analytics and machine learning techniques would be applied on both processed data (as learning data set) and unprocessed raw data for the real-time machine-to-machine communication for patient-specific quick predictions and prescriptions.

## 5. Proposed architecture of 5G network slice for digital real-time healthcare system

Legacy 2G/3G/4G telecom networks are good enough if we are using simple voice and data applications or running a retail enterprise business. But when health – and even life depend on connectivity, as they will in the real-time healthcare future application proposed in this paper, the typical legacy networks are simply not good enough. Instead, we need a carrier-grade network - extremely reliable, thoroughly tested, and engineered to meet the high availability and security, guaranteed quality of services, ultra-reliable low latency carrier (uRLLC) for absolute real-time patient-centric data with mobility. This unique digital healthcare requirement will be fulfilled by the proposed 5G network slice architecture [17].

The proposed 5G Network Slice Architecture for the Digital Healthcare System, as shown in Fig. 2, is divided into two planes, the User Plane

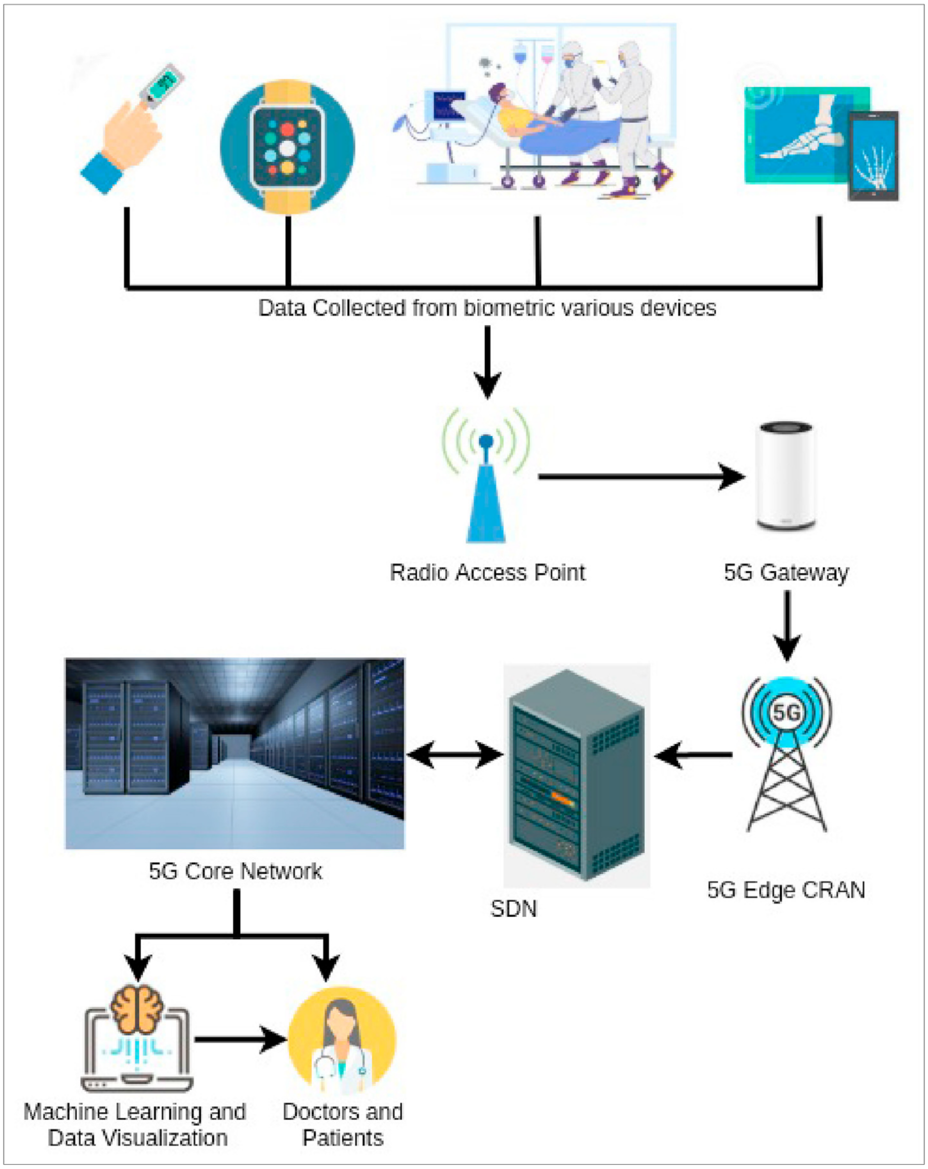


**Fig. 1.** 5G healthcare flow diagram.

(for Patient-Centric on-line biometric data transfer and mobility) and the Control Plane. The architecture proposed here uses the components defined by the 3GPP standards. The following points show the overall working of the architecture:

- Before the data transmission on the 5G network slice begins, the Authentication Sever Function (AUSF) authenticates the wearable device. Then the Policy Control Function (PCF) ensures that the user is allocated the subscribed resources.
- The mobility and accessibility of the wearables are controlled by AMF. The User Plane Function (UPF) then allocates the required resources as per the subscription conformed by the PCF. Potty
- Then the data is collected from the non-3GPP wearable and is transmitted through the non-3GPP Inter Working Function (N3IWF) and stored in the central server.
- Finally, the Network Data Analytics Framework (NWDAF) performs analytics on the collected data.

The components, along with their descriptions, have been mentioned in detail in Table 1. The connections among these components are made using the standard interfaces defined by 3GPP, these are denoted by N followed by an integer.

### 5.1. User Plane

This consists of UPF, which is responsible for playing an anchor role for user session interconnection and traffic flow as per user-specific QoS. The 5G Network slice assignment will be done by using a dynamic slice allocation mechanism based on the feasibility study of the data collection mechanism and the amount of data to be processed. This would ensure the patient-centric quality of service commitments.

### 5.2. Control plane

This consists of a combination of shared and dedicated network function components such as AMF, AUSF, UDM, NSSF, CHF, UDSF, SEPP for controlling the healthcare slice, assigning dynamic resources, interconnecting healthcare network slice with legacy telecom network for voice and data communication.

The Authentication Server Function (AUSF). It acts as a common authentication function for all device types (3GPP and non-3GPP), ensuring the privacy of patient's electronic health records (EHR). And

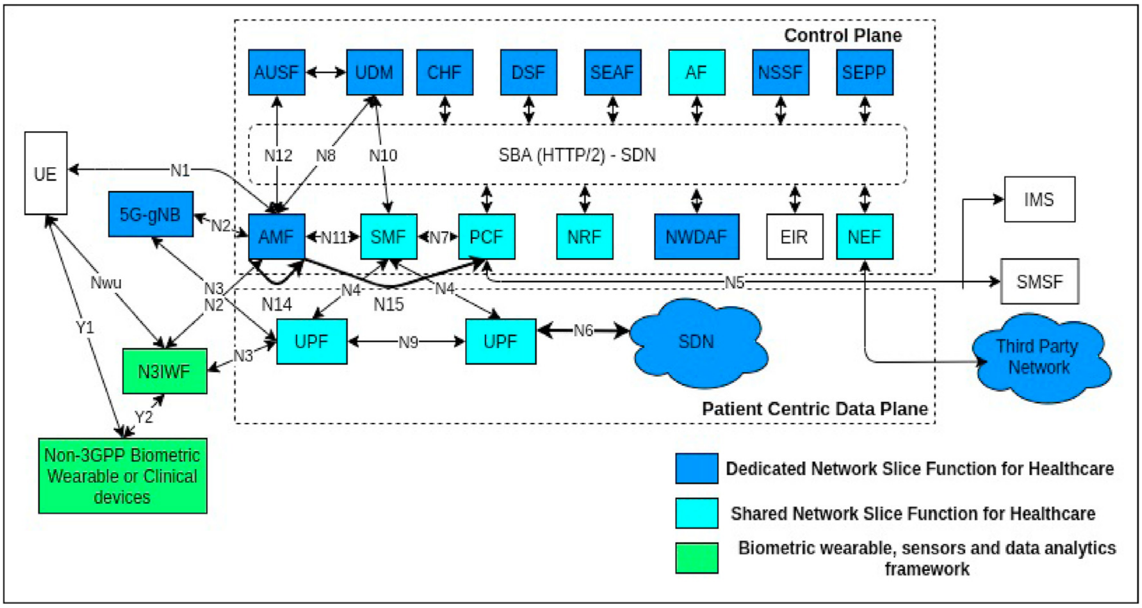


**Fig. 2.** 5G network slice architecture for digital healthcare system.

Security Edge Protection Proxy (SEPP) function handles the network layer EHR protection.

The Network Data Analytics Framework (NWDAF) facilitates analytics on a real-time basis on the patient-centric data collected by the 5G network. The detailed architecture and implementation model will be discussed in the next section.

As the whole E2E 5G Network slices would be built on the Virtual Network Functions (VNFs) on cloud infrastructure, adding more hardware resources on RAN, Core, and SDN could be done very quickly without any impact on the quality of healthcare services.

### 5.3. Cybersecurity aspect

It is also worth highlighting that the privacy and security of patient data are essential. The 3GPP, a telecom standard body, has released a guideline for security assurance methodology specifying cybersecurity for 5G networks and devices. The cybersecurity framework and standards are also specified by International Telecommunication Union (ITU), the European Telecommunication Standard Institute (ETSI), and the National Institute of Standards and Technology (NIST) for the respective regions. The proposed architecture will follow the cybersecurity model specified by the authorities. Moreover, the authentication protocol proposed in Ref. [18], and [19] can be used here to further enhance the security of the system. And security aspects of implanted medical devices have been proposed in Ref. [20].

### 5.4. Dimensioning model

Further to the proposed 5G network slice architecture for healthcare, a slice dimensioning model [21] would be needed to assess the capacity, coverage, and cost of the 5G network slice infrastructure [22]. From the Mobile Network Operator's point of view, such a model is also needed to identify what are the most consuming slices in terms of hardware and radio resources to reserve the resources and pricing. To work out a dimensioning model, On the core network side, a slice is a chain of VNFs and physical network functions. On the transport network part, the slice can be seen as a pipe or tunnel with a specific bandwidth reserved for this slice. However, on the RAN side, the slicing is made through a frequency sub-channel reservation. Now, the question that arises here is how to derive the dimensioning of the slice given its exigence in terms of these different resource types?

Therefore, we propose a cost allocation model that aims, first, to fairly allocate network resources to deployed slices (services) and, second, to show that network slicing makes more efficient use of the network. The proposed model is built on the following assumptions:

- A network slice will support one specific service, which is healthcare in our proposed model.
- A predefined throughput is reserved per service on the RAN and the transport network in a dynamic way.
- On the core network side, a service/slice consists of a chain of (virtual) network functions, such as 5G functions besides physical network functions.
- Virtual network functions (VNFs) are running on virtual machines (VMs), which are in turn executed on servers, and one VM can only host one VNF.

Both the resource model of the RAN and the backhaul network and the resource model of the core network are used as inputs to the dimensioning model. Consequently, we propose an allocation model for network slicing based on the hardware requirements and the throughput required for each slice. This model aims at allocating the right amount of resources to each slice. To accomplish this, we have to distinguish between the three types of network resources discussed previously: RAN, transport network, and core network resources. The RAN and transport network resources will be allocated by reserving a predefined throughput per slice on the base station and the backhaul network.

Yet, for the core network resources, this allocation is done in two steps:

(i) identify the hardware requirements for each 5G VNF
(ii) map the 5G NFs onto VMs and then onto servers.

Finally, based on the above assumptions and resources required in the 5G network Slice for healthcare, Core Hardware (VNFs and PNFs), Transport and RAN (Throughput). The dimensioning model for the healthcare slice is represented using equation (1).

$$D_{slice} = D_{throughput} + \sum_{i=1}^{K} D_{VNF}(i) + \sum_{j=1}^{L} D_{phNF}(j) \tag{1}$$

where.

**Table 1**
Description of Components used in the Architecture.

| Type of 5G Network Function | Name of 5G Network Function | Full-Form of Network Function | Functional Description |
|---|---|---|---|
| **Shared Network Function** | AMF | Access and Mobility Management Function | This control plane component interfaces from the access network and User device and manages access control and mobility, and plays a key role in network slicing functionality by serving all slices of User plane accessibility. |
| | AUSF | Authentication Server Function | Common authentication framework for all devices access (3GPP and non-3GPP). |
| | UDM | Unified Data Management | Stores subscriber data and profiles. |
| | NSSF | Network Slice Selection Function | Selects the set of network slice instances serving the application. This function will select the health-care slice in the overall 5G Network Architecture. |
| | CHF | Charging Function | This function is responsible for slice specific or uses specific billing. |
| | UDSF | Unstructured Data Storage Function | This function is responsible for the storage and retrieval of information by any network function (e.g. Context, State, Session). |
| | SEPP | Security Edge Protection Proxy | Protect the interactions among PLMN, message filtering, and topology hiding. This function is responsible for patient data protection as well. |
| | IMS | IP Multimedia Subsystem | This function handles machine originated voice calls to patients. |
| | SMSF | Short Message Service Function | This function handles text messaging service of any patient information only if data network is unavailable. |
| **Dedicated Network Function for Health-Care** | UPF | User Plane Function | This is the anchor function for mobility and user session interconnection and traffic flows as per user-specific QoS (Quality of Service) |
| | SMF | Session Management Function | The only function that establishes and manages sessions for all access types according to the network policy. |
| | PCF | Policy Control Function | Provides a common framework by exposing policies as a service for a user-specific subscription. |
| | NRF | Network Repository Function | It provides registration and discovery functionality to enable other network functions/ services to discuss and communicate with each other. |
| | NEF | Network Exposure Function | This function receives information from other network functions and applications and used for purposes such as analytics. |
| | NWDAF | Network Data Analytics Framework | This function has distributed architecture to provide analytics on a real-time basis on the data collected by the 5G network. |
| **Non-3GPP (Medical Devices, Wearables) Functions** | N3IIWF | Non-3GPP Interworking Function | This network function is responsible for the integration of stand-alone untrusted non-3GPP access. |

- $D_{slcie}$ is the dimensioning of the slice
- $D_{throughput}$ is the dimensioning of the throughput required in the healthcare slice
- K is the number of VNFs in the slice
- $D_{VNF}(i)$ is the dimensioning of the ith VNF
- L is the number of physical NFs in the slice
- $D_{phNF}(j)$ is the dimensioning of the jth phNF

The parameters such as throughput, number of required VNFs, and number of required physical NFs are set according to the requirements of the healthcare application. These requirements vary based on the nature of the data transmission (real-time or non-realtime) and the number of concurrent patients that need to be handled on the slice.

## 6. Network data analytics framework for healthcare

This section proposes an end-to-end data analytics framework to cater to the need for dynamic quality of services in the healthcare domain. The section details the data analytics frameworks of RAN, SDN, and Core Network Slice (CNS) [23], along with patient-specific biometric data analytics required for the proposed real-time solution [24] which is not feasible through legacy non-real-time data analytics techniques. Overall data analytics framework [25,26] for all the components of 5G Network slice for healthcare service is presented in Table 2.

### 6.1. RAN DAF

Here are two possible proactive actions that will be performed by RAN DAF to ensure meeting the requirements of the patient-specific quality of services (QoS) on a real-time basis. Firstly, the dynamic adjustment of 5G QoS indicator (5QI) attributes for UEs with good or bad channel conditions to avoid service discontinuity due to poor coverage or cell-edge channel quality. Secondly, the pro-active adjustment of Resource Block (RB) selection using multi-cell joint scheduling to avoid interference.

### 6.2. SDN DAF

The major action of this analytics component is to ensure enough backhaul capacity available for patient-specific biometric data payload and throughput, as per the committed QoS data analytics algorithms will learn to optimize the network backhaul provisioning.

### 6.3. CNS DAF

As explained in section-4, CNS DAF will direct 5G Network slice to allocate dedicated user-plane components as per healthcare application

**Table 2**
Data Analytics Components for digital Healthcare.

| NWDAF Component for Healthcare | Key Functionality | Type of Data Analytics & ML Algorithm |
|---|---|---|
| RAN DAF (Radio Access Network Data Analytics Framework) | Real-time dynamic optimization of radio resources (Mobility, Spectrum selection, Traffic & Number of Subscribers) for Quality of Service commitment. | Diagnostic Algorithm Prescriptive Algorithm Predictive Algorithm |
| SDN DAF (Software defined Networking Data Analytics Framework) | Real-time dynamic optimization of SDN resources (Backhaul transport for data throughput and payload) for Quality of Service commitment | Diagnostic Algorithm Prescriptive Algorithm Predictive Algorithm |
| CNS DAF (Core Network Slice DAF) | Real-time dynamic optimization of Core Slice Components (UPF, AMF, SMF etc) for Quality of Service commitment. | Diagnostic Algorithm Prescriptive Algorithm Predictive Algorithm |
| Healthcare DAF | Patient specific real-time biometric data analytics | Diagnostic Algorithm Prescriptive Algorithm Predictive Algorithm |

need in terms of the number of patients and QoS.

### 6.4. Healthcare DAF

Data collected from various devices in different forms such as X-ray images, heart rate, oxygen level, etc., is used to create a Knowledge Graph (refer Fig. 3). Before creating a knowledge graph, the data needs to be processed and filtered by using various deep learning [27] and machine learning techniques. Convolutional Neural Networks (CNN or ConvNet) is one of the highly used deep learning algorithms, and it is most commonly used in image classification applications. Techniques proposed by Z. Lv, L. Qiao [28], Li, Yi and Lv et al. [29] and, V.Chamola et al. [30] can be used here. Also, it is preferable to build a Multi-modal [31] System with a provision of a multi-fusion approach to achieve exceptionally high sensitivity in scenarios where multi-dimensional biometric images and a large number of biometric readings have to be analyzed. The image fusion technique proposed by Li, Yi Zhao [32] can prove to be very useful here. Moreover, the work done by G. Bansal, V. Chamola et al. [33] on lung cancer classification would add another feature to the above scheme.

After precomputing the features among various data points, a Knowledge Graph is made. One of the main advantages of Knowledge Graphs is also being able to relate different types of data. This is very useful for extracting value by combining information from different sources. Hence, applying this to medical applications will yield much better results than just using Machine Learning on individual data points. After this step comes data visualization, which is the most important step in this process of extracting information. It is performed by using various data visualization techniques, e.g., Microsoft Power-BI, Google Charts, Tableau, etc., which makes the graphical trends and dashboards, and which can be used by the clinical and medical experts to take quick decisions on patient diagnosis and treatment.

The proposed solution can actually save a lot of lives in a number of situations for e.g., remote cardiac monitoring will be possible for heart attack prevention and prediction, wearable devices will enable for telemedicine-remote diagnosis, and prescription, remote supported robotics surgeries [34] will also be possible. Many remote monitoring techniques, such as one proposed in the paper, could be used here. Developing a real-time digital healthcare system will open a completely new domain of remote patient monitoring.

## 7. Security and integrity aspects of healthcare data

The data security, integrity, and accessibility aspects [35] of 5G Network layer, wearables devices, and patients medical database have been evaluated. 5G Network layer security is addressed through traditional authentication approaches [36] for wireless technologies like 5G AKA (Authentication and Key Agreement) and EAP (Extensible Authentication Protocol). These would be used to prevent signal-based wireless attacks or patients' medical data hacking. For wearable devices, security policies for healthcare sensor networks [37,38] are also studied. Blockchain is proposed as the most effective and widely used technique for data collection [39] to manage and protect medical data records. Blockchain is a distributed database technique that ensures that patient's data remains anonymous and auditable throughout. Blockchain technology would facilitate patient tracking, identity assurance, and managing medical data records and integrity by tokenization [40,41]. Each data record will have an immutable audit trail which is maintained in the form of a patient's healthcare data transaction ledger [42,43]. Finally, to ensure secured access to a patient's health records [44], a patient-controlled access mechanism by using finger-print and face recognition are used to generate a system trigger when abnormal and unauthorized changes in the data pattern are observed. Further, there is the role of legal and regulatory bodies of respective countries to provide a legal guideline for medical wearable devices, sensors, and data security to deploy digital healthcare services.

## 8. Future direction

We plan to validate our slice resource dimensioning model for various healthcare applications to process dynamic formats of biometric data need in rural, urban, and dense-urban areas. It would be a good exercise to apply the model on two different types of slices (e.g., IoT versus eMBB). Also, the complexity of multi-level analytics is one factor that needs to be further evaluated, especially if this affects real-time decisions. Moreover, the Security and integrity aspects of patient-specific data to be evaluated with various practical scenarios on the operator's network as well as medical practitioners. In the future, 5G network healthcare slice is proposed to be utilized for remote surgery and telemedicine-remote diagnosis as well. Hence, any adverse impact of 5G system on human health would also be a potential future work. Finally, one key direction is the confidence intervals of analytic results and how this can be calculated if analytics are performed in an integrated manner. The exploitation of the benefits of prediction strongly depends on how accurate analytics can be, and this strongly depends also on the algorithms used for mining the data and process them.

## 9. Conclusion

In this paper, we have evaluated and proposed the 5G Network Slice architecture, novel dimensioning model, along with an integrated analytics framework for Digital Real-time Healthcare systems. We explained why digitization is the need of the hour, how the next-generation 5G system and growth of wearable devices, along with data analytics and ML techniques, are making it possible to build a real-time patient-centric healthcare system. We proposed and derived a dedicated Network slice architecture with dimensioning model and real-time analytics model to ensure the patient-centric quality of services and biometric data diagnosis, predictions, and prescription to transform the legacy healthcare domain.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

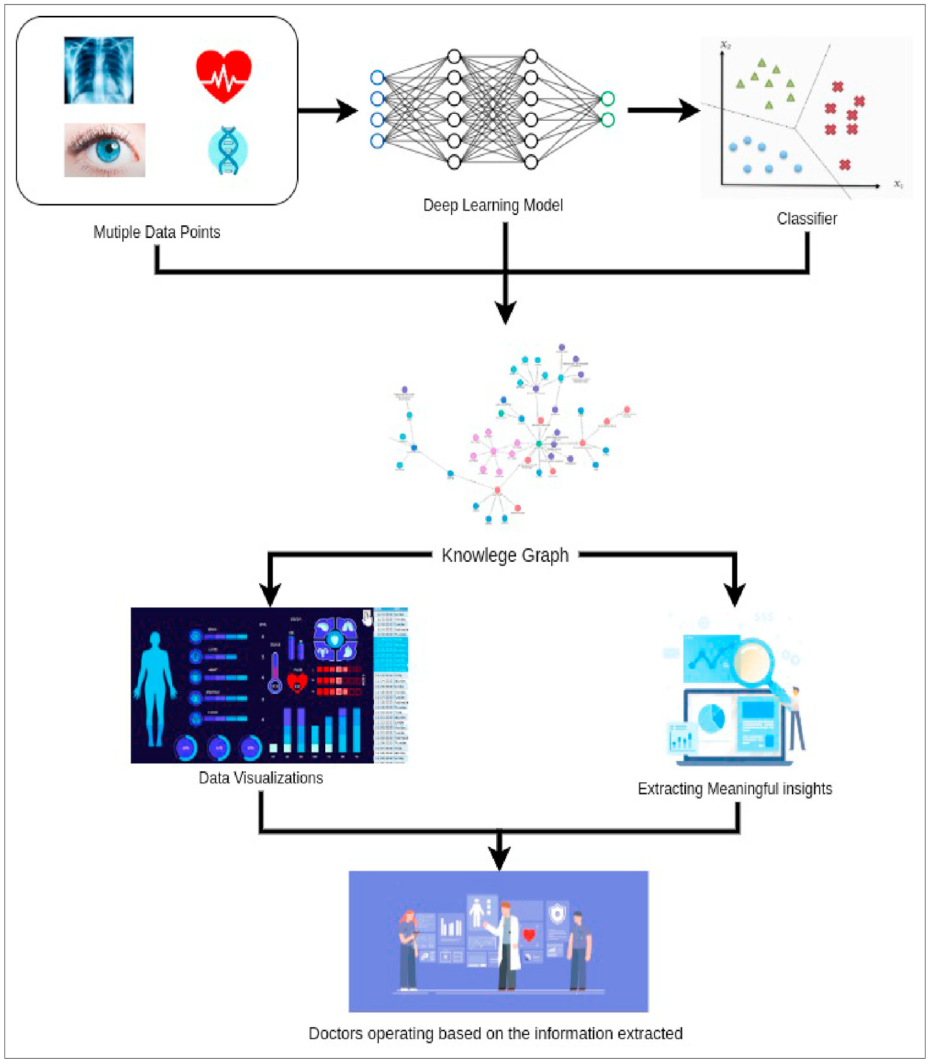


**Fig. 3.** Using Knowledge Graph to extract biometric insights.

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