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Literature review on the Remote Health Monitoring Vision in EU and Asia

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1 Introduction

A large part of the world population is residing in a spread remote or rural area. In these rural and remote areas, besides other basic needs of life, the overall access to medical facilities is difficult if existent and is mainly deficient, and the availability of doctors is scarce. The situation is not getting better even in developed countries. Indeed, accessibility to primary health care seems to be threatened by the existence or the emergence of undeserved areas often called “medical deserts”. The deficiency of timely medical advice and assistance to the patients, due to distance and lack of adequate infrastructure, is the source of critical situations and may lead to death in some cases.

Remote health care is considered as one of the serious candidates to facilitate the access to health services for all. Sensing and actuating technologies along with big data analysis provide basic building blocks for Remote Health Monitoring. These technologies are continuously evolving from miniaturization of sensors to collectively making sense out of varied data types in different forms of structured, unstructured, video, or sensory data. These technologies greatly influence the capabilities and opportunities provided by Remote Health Monitoring and shape its vision to solve problems aiming to reduce the infant and maternal mortality rate, continuous health monitoring of entire population, and well-being of elderly people in general.

In this report, we have focused on compiling a comprehensive literature review on smart and remote health monitoring and its adoption within some countries of Europe and Asia. This report aims also to explore the national and international policies and frameworks and observe how they facilitate the adoption of modern technologies in Smart and remote health monitoring especially in rural and remote areas with insufficient healthcare services. It covers the approaches already practised by SAFE-RH partner countries towards the realisation of the Smart health monitoring vision and framework, and in addition presents complementary features and best practices to be adopted in the future by all partners for an optimized and sustainable smart and remote health monitoring. This report will serve as a guideline for transferring and integrating the Smart health monitoring techniques from the European regions with the remote health practices to Asian countries.

The report is organized as follows: in section 2, we give a general description of remote health monitoring systems with a focus on wearable and contactless systems. Policy and framework related to the project are given in section 3. Sections 4, 5 and 6 give the detailed state of the art for three use cases corresponding to the pilots of SAFE-RH project, which are maternal infant, new-born and infant, and elderly people. The importance of data security and privacy and related requirement are given in section 7. Section 8 concludes the report by giving the research opportunities and challenges.

2 Remote health monitoring systems

2.1 Background

Remote Monitoring Systems (RMS) can be categorized as Control Systems (CS) whose main role is to manage multiple devices in a highly connected networked system. A common example of a generalized desktop computer-based RMS is the Microsoft’s Remote Desktop client. A user can easily access a Remote Computer from any other self-authorized system while being anywhere globally. One can access his/her workplace system remotely from home as if they were in front of their workplace system. More applications of RMS include (but are not limited to) structure monitoring, power plants, network operation centres, airports, smart grids etc. The main goal of RMS is to provide a semi or fully automated system which can manage, maintain, and monitor a specific set of tasks efficiently over a network with reduced cost. This network can be an IoT system or a local network system with a series of immobile connected devices. RMS reduces the cost associated with Manual Monitoring Systems in multiple ways. It decreases the cost of data-gathering, as manual data collecting requires multiple workers to perform this task and greatly multiplies chances of errors. However, RMS can perform these tasks in an automated way while reducing needed maintenance staffs and providing an efficient error observation system. Moreover, RMS are scalable and provide multiple opportunities to system implementation evolutions. RMS use vision-based devices such as cameras or sensor-based devices such as Accelerometer, Gyroscope etc to sense and observe the environment(s) of importance. The selection of sensing devices for the RMS depends on the observed environment and initial requirements of remote monitoring.

Alongside commercial and household applications, RMS are also being used in sensor-based technologies in a large variety of applications such as Radars, Satellites, Airplanes etc. For instance, Radar Systems use sensors emitting radio waves whose collision and reflection with objects helps in the interpretation of the presence of potential objects in the observed environment [1]. Another impactful application of RMS with sensors is the Remote Health Monitoring (RHM) or Remote Patient Monitoring (RPM). Real-time Health monitoring of patients by a doctor from a remote location has a great impact on the avoidance of irregularities and provide First Aid within the nick of time. RHM shows great promise especially when it comes to elderly and physically disabled patients [2]. Different types of wearable sensors or health-monitoring sensors such as heart rate sensor, pulse sensor, Oxygen sensors, Blood pressure sensors etc. are used in open or closed environments to observe the patients [3]. Any kind of abnormality in the patient's behaviour prompts the caretaker or doctor which enables them to take certain measures as soon as possible. Vision-based sensors are also used to monitor health conditions of patients. For instance, a camera can be mounted in the patient's vicinity allowing to keep track of patient's movements; if the system detects any abnormal movement made by the patient, it prompts an alarm to notify the caretaker. However, vision-based devices do have some shortcomings such as, environmental limitations, camera angle, lightening and contrast limitations etc. Similarly, sensor-based devices also have shortcomings of their own such as magnetic interferences, faulty sensor operation etc. The concept of RHM and RPM is not news [4] but newer and efficient systems are still being designed to overcome the shortcomings of current systems.

Figure 1: Block diagram of overall RHM System

Though various RMS applications are easy to implement, they also produce a lot of data that must be analysed and exploited to attain satisfactory results. Many of these applications usually run on web servers and require continuous sending and retrieving of data which causes delay in the provided service, and high latencies which are mainly inacceptable in Real-time monitoring of patients. Moreover, these delays can be impactful to life threatening scenarios. To avoid this persisting problem, an efficient RMS is analysed based on a layered structure as illustrated in Figure 1 [5]. The layers represent Edge computing, Fog computing and Cloud computing infrastructure. Cloud computing provides large scale data processing and computing over the internet. There is no need to manage and maintain local or online servers for data management and processing. Cloud servers are used to handle and compute the data over the internet thus reducing the cost and increasing the overall efficiency of RMS. Cloud-based monitoring enables effective remote monitoring and smart resource scheduling by removing the delays and data communication issues [6]. Many cloud-based health monitoring systems have been presented to overcome the limitations of manual server-based data communication. Hossain et al. [7] presented an IoT based Remote Health Monitoring System which utilized cloud-based server for data communication and processing. The data was gathered by cell phone embedded sensor and sent to the cloud-based server to be accessed by the healthcare workers. Though there are many advantages in migrating to cloud-based servers, so are some concerns. The vast distance between multiple devices can cause high latency in data communication which can cause problems for IoT apps that require low latency. Security and privacy is also a major concern as the data is globally communicated through different channels along with other users, so it may cause data loss and is not prone to cyberattacks. Remote health monitoring helps patient to reduce number of visits to the hospital and earlier prediction of the health-related anomalies [8]. Some of the most common sensors data like respiratory rate, heart rate, blood pressure, body temperature, blood glucose, electrocardiogram (ECG), and electroencephalogram (EEG) are generated frequently in the health applications [9], [10]. In IoT and cloud-based architectures, cloud servers are used to store and process a massive amount of data collected from sensor nodes. Applications that are deployed on cloud servers can take benefit of large amount of resources and computation power [11]. Regardless of the benefits we achieve from this architecture, cloud-based approach is not suitable for health applications, because of high network bandwidth, latency and scalability issues [12]. Healthcare applications are latency-sensitive, so to design an effective real time application fog-based approach put its beneficial role [13].

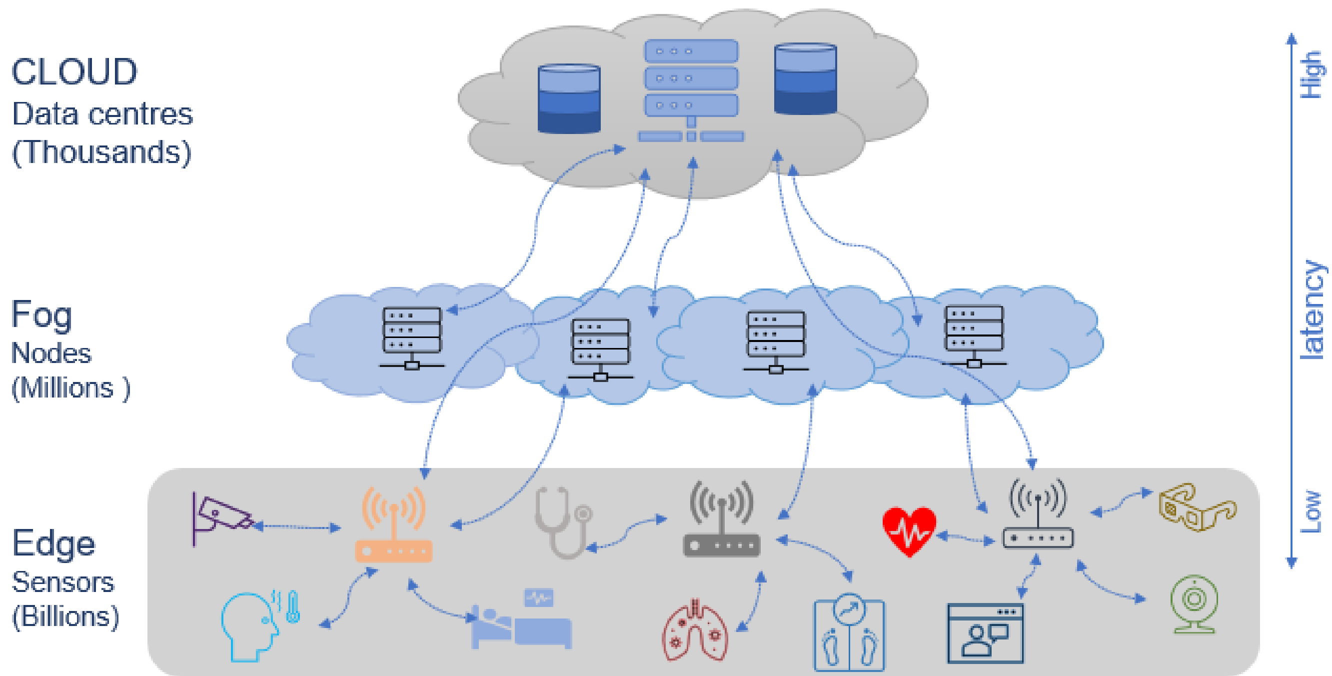

Figure 2 : Data flow in remote health monitoring system

Fog computing is an extension of Cloud computing, though both are comprised of different nodes which ultimately link to the devices. However, the nodes in Fog computing are closer to the end-user or devices as compared to Cloud computing nodes. In general, Cloud computing can be described as a centralized system while Fog computing is more of a distributed system. Fog computing is not a separate or independent system, but a mediator between device and cloud server which handles the flow of data from the devices to the Cloud. By managing which and how much data need to be sent to Cloud servers, it enables the Cloud server to work efficiently and maintain the load between the server and the client. Abundant work is being done by utilizing the Fog computing framework in healthcare monitoring as well.

Jamil et. al, [14] discussed that increasing number of Internet of everything (IoE) devices are generating huge amount data due to which Cloud computing is unable to meet requirements of real-time applications like low latency, location awareness, and mobility support. To overcome these limitations, Fog computing has emerged as a new computing paradigm that complements Cloud computing by providing support for real-time processing and analytics and storage facilities near the edge device. In the paper, authors have designed and implemented an optimized job-scheduling algorithm to minimize the delays for latency-critical applications. The proposed algorithm schedules jobs on Fog devices based on length and reduces the average loop delay and network usage. However, the proposed algorithm reduces the waiting time and can starve the tuples with larger lengths.

Jayneel et al [15] presented a Fog computing-based Health monitoring system for ambient assisted living. Movement patterns of patients are collected through inertial-sensors and the data is passed through fog gateways. The main contribution of this work is the lower data communication latency and data load management between cloud server and output devices. Sudeep et al. [16] proposed an architecture for remote monitoring of heart rate of patients using fog computing. They utilized a heart rate sensor to gather data of multiple patients with heart diseases and sent them to Fog layer. Moreover, they introduced a data compression technique for efficient bandwidth utilization at Fog layer. The results showed better accuracy compared to the state-of-the-art Cloud-based works. In health applications, wrong treatment decisions could be made with increased probability of processing and transmission of large and complex data [17]. Many articles in this paper, discussed the scalable solution for health application using fog architecture enabling real-time analysis and decision making based on local network resources [18]. In critical healthcare applications, distributed computing on fog nodes is performed on the edge of the networks (Gateways) that ensure low latency, energy consumption, execution time, scalability, privacy, and security [19]. In rural areas, where remote health monitoring of patients is a challenge because of weak coverage of internet, fog computing is a feasible solution because of its lower latency and spare capacity of locally available resources. In case of unavailability of internet, most critical tasks can be performed on patient's data at the fog nodes and forward later to cloud on availability of internet [20]. Wang et. al. [21] discussed the fog computing real-time processing and event response for healthcare applications. Experiments proved that the healthcare system utilizing fog computing responded faster and was more energy efficient than cloud-only approaches Fog computing can be used to detect falls of stroke patients efficiently by scheduling the analytic tasks to the most appropriate edge server, guaranteeing the latency and throughput.

Rahmani et, al, [22] proposed Smart e-Health system, a fog computing-based remote health monitoring architecture that can potentially utilize gateway resources in terms of performance efficient processing of health sensors data. Author demonstrated remote health monitoring system with Early Warning Scores (EWS) by using hierarchical fog-assisted cloud computing. The result shows improvement in sensing-to-actuation latency in fog computing by 140ms over cloud computing.

Stantchev et. al. [23] discussed a three-level architecture to emphasize the essentials of computing paradigm related to fog computing to provide improved performance. Prior to accessing the cloud, the sensing devices are connected to localized fog devices that cater for their needs such as computing and storage. Fog devices can in turn provide local management for the sensors and handle mobility. Interconnectivity with enhanced Quality of Service (QoS) is also sought of this computing paradigm as latency toned down due to proximity between the Fog device and sensors. The fog devices provide computing redundancy and backup in case the link to the cloud is faulty. In addition to that access control can provide better management measures for the flow of data to and from the cloud.

Though Fog computing improves the overall communication between server and client data transmission, it has some drawbacks of its own. By the addition of a new layer (Fog computing layer), the overall system becomes more complex, thus becomes difficult to debug in case of an error. Cost is also increased to implement software and hardware utilities. And the most important factor is that Fog computing is not as scalable as Cloud computing. [24] designed an application-layer approach for a Web Service based gateway. This gateway is used as a bridge among heterogeneous body sensors. The gateway application layer contacts with the web server via Web Standard Communication Protocols. The purpose of the proposed system is to prove good scalability and low delay. This system can communicate with several communication modes which depends upon RHM system objectives such as Speed, QoS, Data-Rate and Range. The security and accuracy of data is also as important as the health of an infant [25]. [26] discussed the security problems in WBANs, the importance of secure and reliable distributed databases and distributed data access control. The importance of data privacy, data integrity, accuracy, availability, authentication, data freshness (No-Delay data transmission to doctors) and secure localization and management.

Mach and Becvar [27] discussed the aspects of data computation architectures such as Mobile Cloud Computing MCC, Mobile Edge Computing MEC and fog computing. Author discussed the key challenges in MEC are like 1) computation offloading to User equipment UE in terms of energy consumption and/or execution delay, 2) efficient allocation of the computing resources to minimize execution delay and balance load of both computing resources and communication links, and 3) Mobility management for the applications offloaded to the MEC guaranteeing service continuity. The paper also discusses the computational offloading possibilities like fully offloading, partial offloading and non-offloading parts of application on MEC. Ko et. al, [28] discussed issues in conventional design for mobile computation offloading in which computation task is fetched to another server only when it is handover. This mechanism requires excessive fetching of a large volume of data for handover and thus brings long fetching latency. Moreover, it also causes heavy loads on the MEC network. Proposed solution handles this issue by pre-fetching parts of future computation data to potential servers during the server-computation time, referred to as live prefetching. This technique can not only significantly reduce the handover latency via mobility prediction, but also enable energy-efficient computation offloading by enlarging the transmission time. However, it also encounters several challenges with two most critical ones described as follows.

The first challenge arises from the trajectory prediction. Accurate prediction can allow seamless handovers among edge servers and reduce the prefetching redundancy.

The second challenge lies in the selection of the pre-fetched computation data. To maximize the successful offloading probability of edge users, the computation-intensive components should be pre-fetched earlier with adaptive transmission power control.

2.2 Wearable and Contact-Based RHM systems

Traditional RHM systems emerged with contact-based approaches. These contact-based RHM systems use different types of sensors, communication networks, data processing algorithms, post-processing decisions, and required actions and end-terminals. Contact-based RHMs also target different diseases and groups of patients. The variety in contact based RHM systems exists due to the required outcomes of special features (low power, low cost, etc.) or the choice of system designers planned for its users. For example, the designers want to target different age groups or target a system with power efficiency.

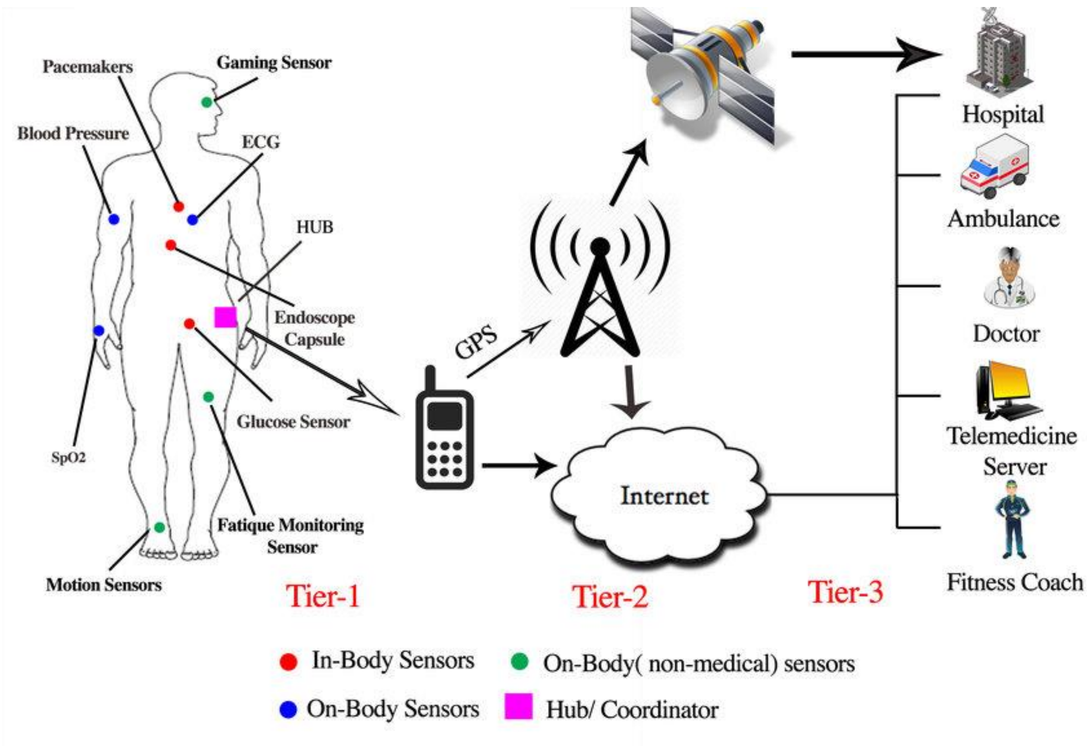

Figure 3 : Example of wearable and contact-based RHM system.

In this review paper [29], the development in patient health surveillance platforms through internet-of-things (IoT) based smart devices and making them secure with block chain technology are discussed. This paper focused on IOT based smart devices which are being developed for patient monitoring, which gather patient physiological data in real-time and process data to end-terminals such as doctors, parents or healthcare providers for assessment. For example, [30] Stretchable and transparent contact lens for glucose level detection in tears by enabling LED pixel and glucose sensor through electric power wirelessly transmitted by antenna. [31] Electrochemical sensors that are powered by batteries for digital signals monitoring and Bluetooth data transmission are combined in wrist smart devices to monitor the concentration of potassium, lactate, and glucose in sweat. They explored the state-of-the-art RHM devices and potential ways to integrate blockchain and cloud computing, which may provide tremendous throughputs in on-demand health facilities. IoT enables smart devices through block chain and cloud computing enables safe and efficient transmission of health-related data from multiple sources. In addition, both real-time and AI-based remote patient surveillance enables patients to monitor their health regularly.

Most of the health monitoring system works in offline mode which can be crucial in the emergency situations for the patients especially for infants. Infants are not capable of monitoring themselves. They always need a caretaker who continuously monitors their health and vital readings such as heartbeat and temperature etc. In this paper [32] proposed a system which can monitor heartbeats and body temperature through sensors remotely in real time. Arduino ATmega328, temperature sensor LM35, Heartbeat sensor (LM358) and nRF24L01 are embedded. The system is controlled by a microcontroller. Observed data is monitored and transmitted from remote locations through wireless systems and displayed to the doctor through NRF technology. Both heartbeat readings per minute and body temperature is measured and transmitted to end-terminals (family or doctor) via microcontroller.

[33] proposed a Wireless area network for monitoring patients at any place and at any time. Different types of sensors TMP 36 (Temperature sensor for measuring temperature at real time), heart rate sensor (cardiac frequency) normal heart rate set for new-borns is 120-160 and other infants 1-12 months is 80-140, Arduino UNO microcontroller based on Atmega328 and Raspberry Pi (a tiny credit card size computer) are embedded in RHM system. Biomedical sensors measure vital body readings. The sensory data is then processed by microcontroller and sent to the Raspberry Pi via Bluetooth which represents data on a webpage.

2.3 Contactless RHM systems

COVID-19 has accelerated adoption of contactless patient monitoring technology [34]–[36]. Contactless remote health monitoring systems are categorized into two main sections. Image-based RHM and radar-based RHMs. Image-based systems detect patient illness or fall through analysing images as data. Radar-Based systems receive radio frequencies as data of patients. Sometimes, radar-based also used for patient localization. Because of the novelty of these systems, there are many improvements to be made. But the existing systems have achieved good outcomes.

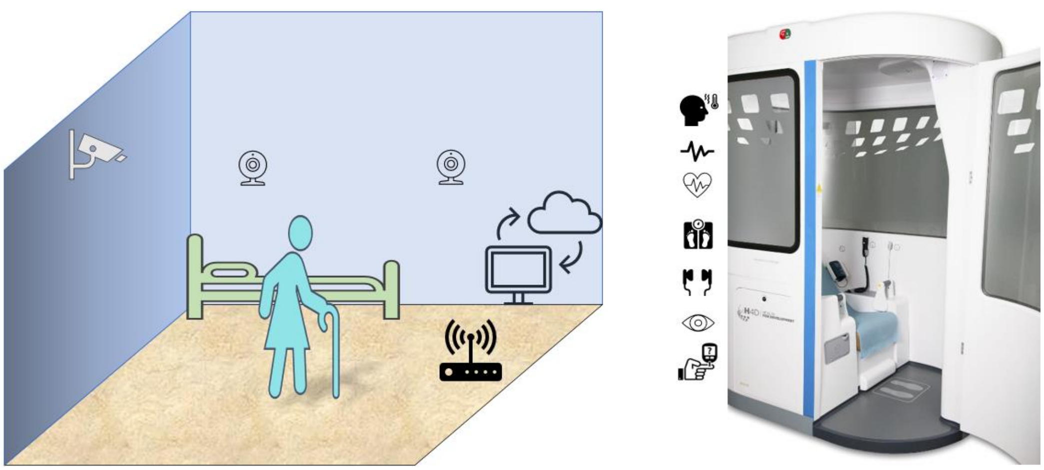

Figure 4: Contactless RHS: fall detection, and teleconsultation box.

In this paper [37] the author highly focuses on the contextualization of data monitored by sensors. This article represents a non-intrusive sensor system which is effective for monitoring and detecting high risk factors in the air that can cause the Sudden Infant Death Syndrome (SIDS). A context-aware-framework BDCaM (Big Data Context-Aware Monitoring) is used that makes it possible to personalize knowledge for the users by allowing them for the removal of precise rule-based on the context. The collection of context data like air quality and weather conditions enable sensitization systems for highly accurate results in analysis. Agent-based virtual organization coordinates with different sensors such as DHT22 (ambient temperature and humidity of air), MG811 (measure the Carbon-Dioxide (CO_2) concentration in environment), MQ2 (measure smoke in environment and liquified petroleum gas, methane, hydrogen, alcohol, propane) and MQ7 (measure the concentration of carbon monoxide) with the integration of different communication protocols such as wired or wireless, which are deployed in sensorization system. All the context data can be monitored by a web application or mobile application. [38] add reviews to photoplethysmographic imaging methods for contactless remote infant patient monitoring. This method, vital body data like pulse rate variability, pulse rate, blood oxygen level and respiratory rate are obtained by processing them camera colours signals.

3 Policy and Framework

Remote health monitoring is growing at a rapid pace, especially with covid-19 pandemic where we are witnessing in general record growth of the telemedicine [39]. It is a crucial policy area for almost all developed or developing countries. Most of the European and other developed countries have built a firm policy and framework for telemedicine. The governments are working with the health industry to explore ways to develop a large-scale teleconsultations and other telemedicine applications. In this section, we are observing the policy and framework of the governments in some of the Asian and European countries.

The World Health Organisation (WHO) defines eHealth as *the use of information and communication technologies (ICT) for health* [40]. The terms *eHealth* (electronic health) and *mHealth* (mobile health) have been used in the last decade to describe all technological solutions based on high connectivity (via Internet) and accessibility (through mobile devices) to provide various types of healthcare [41].

There are a variety of projects led by European Commission trying to define a common framework related to eHealth [42]. According to the European Commission, eHealth comprises the following categories: (a) clinical information systems; (b) telemedicine and home care in a general sense with personalized health systems and services for remote patient monitoring (teleconsultation, telecare, telemedicine and teleradiology); (c) integrated regional/ national health information networks, distributed electronic health record systems and associated services such as e-prescriptions or e-referrals; and (d) secondary usage of non-clinical systems (such as specialized systems for researchers, or support systems such as billing systems) [43].

For instance, *eHAction - Joint Action supporting eHealth Network* is one of the projects funded by the European Commission related to the eHealth field [44]. The main objective of this project is to give an overview of EU member states strategies in order to design new strategies for eHealth and to propose a cross-border policy framework and regulation to be adopted by member states in their national policies. The successful achievement of these objectives is first based on exchange, among countries at the EU level, of frameworks, rules, principles, and best practices, and in the second phase on their alignment and integration into the national policies of the EU member states.

One of the objectives is also to collect present and future eHealth strategies and propose a direction to support their alignment in the above-mentioned common policy framework. It should be mentioned that all eHealth initiatives led by the European member states are mostly coordinated at the national with few exceptions at federal or regional level.

Among the objectives clearly defined within these eHealth initiatives, the opportunity to access and share health data and information between all actors in the health framework is stated as primordial [44]. The successful achievement of this goal should lead to more independence and autonomy of all actors in the health system and place the patients in the heart of the health managing system. Thus, patients become the actors of their own health and are by this fact encouraged to improve and keep the existing health capital through adoption and applying of healthy practices and behaviours.

A large variety of different programmes related to eHealth have been carried out by the member states [44]. These programmes cover the following health-related areas such as Electronic Health Record (EHR); ePrescription (eP); Electronic Identification (eID); Telemedicine; Research; eHealth Strategy; eGuidelines; Cross-border.

Among the cited initiatives, different enablers can be distinguished [44]: standards & interoperability where the main goal is to describe national and/or international standards allowing accurate collection and exchange of health information across different health systems and services; innovation where the key technologies from different domains can find their use in the healthcare sectors; infrastructure and building blocks or services where technical foundations (physical infrastructure such as networks) and infrastructures for electronic information exchange (via national registers) through secure use of data and services (such as ePresription) across geographical and health-sector boundaries;

The enabler which is considered as one of the key enablers of the future eHealth strategies is Innovation at different levels. This enabler is mainly focused on the new technologies such as Big and open Data, Artificial Intelligence in a general sense, Internet of Things through sensors and sensing connected systems; Blockchain technologies for secure communication and data privacy, deported Health services such as mobile Health (mHealth). This non-exhaustive list of large technology domains are not directly related to the health sector, but the innovation in these different domains can be transferable and applied to the healthcare sectors. For this enabler, a huge number of digital players in different application fields and domains makes it one of the most present and proactive enablers. Numerous digital initiatives putting in the heart not only the patients but also the health professionals relying on the use of different cutting-edge technologies (AI, Big Data, IoT, BlockChain …) is the proof of the very strong dynamism in the digital part of the health related initiatives.

As stated in this report [44], a lack of global digitalisation strategies applied at the national level is currently the main problem of wide adoption of these digital solutions. The current state of the eHealth digitalisation is limited to certain health sectors and healthcare pathways applied to the management of very specific pathologies such as chronic diseases (cardiopathies such as hypertension, diabetes etc) in the limited geographical regions. Some examples of these digital healthcare initiatives with cutting-edge technologies and implemented at the regional level can be found in some regions of Spain [44].

One of the conclusions which can be drawn is that there is no unique approach or method of designing and implementing the eHealth-related solutions. Each member state country applies its own strategies based on the political, health and national priorities. The above mentioned initiatives being identified as the principal enablers of the existing and future strategies should share more common grounds in order to achieve the better interoperability at the European level. Even though that most of the key enablers can lead to a better health strategy and healthcare at the European level and cross-border healthcare, the international dimension is not one of the main drivers of presented and future initiatives.

One of the key categories in the presented eHealth framework is telemedicine and telehealth care. The telemedicine solutions primarily target the telemonitoring and prevention in primary care and are mostly related to chronic diseases with an increasing number of solutions also targeting well-being and selfcare. The telemedicine is generally perceived as a cost-effective solution with a low degree of negative effects and a huge potential to increase the patient healthcare conditions, life quality and even its survival [41]. The biggest barriers for its wide acceptance by the health systems of the Member States is a lack of acceptance at the national level by stakeholders and insufficient regulatory framework. Not to mention the non-existing or inadequate infrastructures (at the global level) for its deployment [41].

The presented policy and framework related to the EU are in a general way very similar to those adopted or in the adoption phase in France. In France, the main motivations for the adoption of eHealth solutions in the current healthcare systems are the huge territorial inequalities in the terms of medical care which are commonly called *medical healthcare deserts* (*déserts médicaux*) [45]. The recent studies show that the number of telemedicine and eHealth related projects are constantly growing in France [46]. As in the eHealth projects at the European level, most of the reported projects are related to the telemonitoring of chronic diseases such as cardiopathies, diabetes, respiratory and pulmonary failures, etc.

4 Maternal infant

4.1 Introduction

Maternal and infant health is indispensable for a healthy society. The major issues that cause maternal health problems and even deaths include ectopic pregnancy [47], miscarriage [48], high blood pressure that leads to preeclampsia [49], [50], and failure in progress of labour that might leads to C-section [51]. In addition, iron deficiency is another vital factor of prenatal and postnatal health complications that can be caused due to antepartum or post-partum haemorrhage [52], retained placenta [53], vaginal infection during delivery [54], [55], and many other similar problems. In case of neonatal or newly born baby few of the major issues that may cause problems of health include growth retardation in uterus, birth asphyxia during delivery, infection due to maternal vaginal delivery at the time of birth, shoulder dystocia, meconium aspiration, septicaemia, and premature delivery / premature lungs or any other congenital abnormalities. The complications of both maternal and infant health need to be identified and communicated timely to health caretakers and professionals to take in time action against them. However, approaching medical assistance in time is a difficult job especially in rural areas. In the current era, Information and Communication Technology has enabled the medical field to timely address complications of maternal and infant health.

Indeed, development in the technology empowers the health sector to offer improvised services for maternal and infant health using sensing, Artificial Intelligence (AI), and computing platforms at doorstep. These strands are depicted in a general taxonomy as shown in Figure 5. The sensors enabled systems detect biological information, AI approaches exploit this biological information to predict the health condition, and computing platforms offer optimized communication, huge storage, and computing capabilities for exponentially increasing data with increasing IoTs.

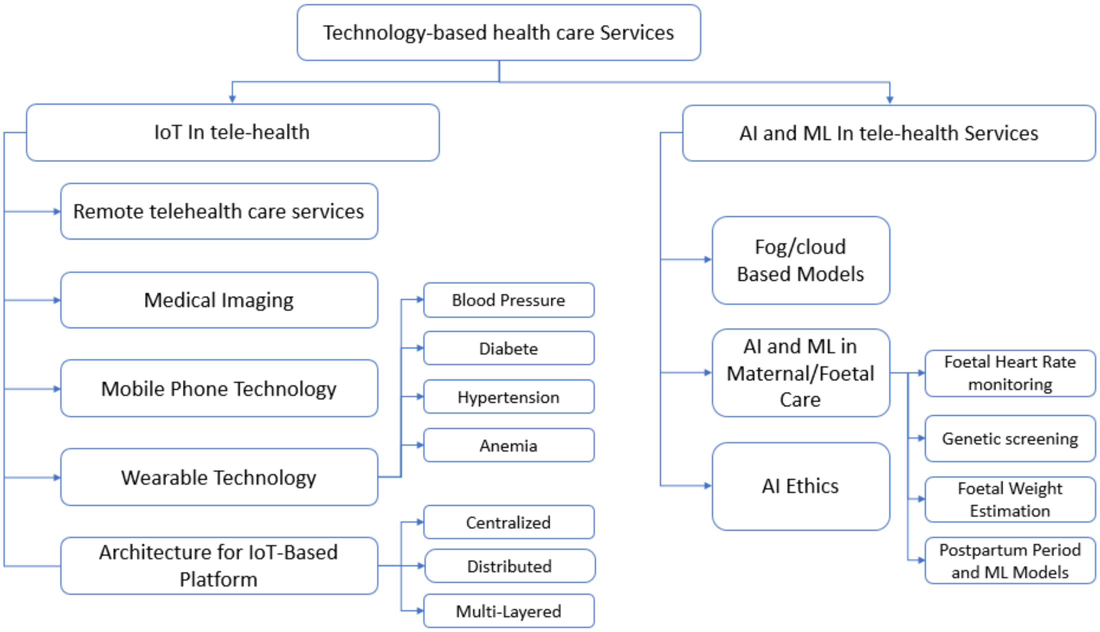

Figure 5: General Classification of Health Care Services

Nowadays, sensing technology has improved patient pregnancy care, infant health care, patient communication, and real-time monitoring of several diseases using sensors, wearable gadgets and devices [56]. The relevant literature reports the use of a variety of solutions such as ectopic pregnancy can be detected early through scans and blood tests by using high resolution and portable ultrasound [57] and Complete Blood Count (CBC) blood test machines [58]. In the case of a miscarriage scans, timely Dilation and Curettage (D&C) and Haemoglobin (Hb) level monitoring can help to minimize the relevant complications. Similarly, for Blood Pressure (BP) [59] monitoring variety of digital devices have been designed. Cardiotocography (CTG)/ tracing of foetal heart [58] and anomaly scans can reduce foetal deaths, still births, and help early detection of congenital abnormalities, pregnancy care [60], hypertension monitoring [61], diabetes monitoring [62]–[65], detection of postpartum depression [66], and similar pregnancy complications. Consequently, wearable sensors' advances can improve patient-supplier connections for successful pregnancy wellbeing. Also, for infant health care, technology enabled well equipped and intelligent incubators and NG tubes for nasogastric feed premature infants can improve in time response [67], [68].

Similarly, Machine Learning (ML) approaches may help predicting abnormal behaviour in a mother and infant's health. The immense growth of ML algorithms to monitor mother and infant health in the earlier stage of pregnancy may help doctors to tackle complications. In the present era, the ML approaches are being used for the prediction of preterm birth risk [69], detection of wild-stress [70], prenatal risk [71], postpartum depression [72], congenital heart disease [73] among pregnant women. Also, the ML approaches have potential to predict the infant's health status, to monitor the brain and general growth of baby. A variety of algorithms such as Support Vector Machine (SVM) [74], Artificial Neural Networks (ANN) [75], Regression Analysis (RA), and Random Forest are among those popular methods that are being applied to determine the best pregnancy outcomes [76]. Therefore, with this recently discovered interest in the possibilities of ML in medical services and specifically for the maternal and infant health, it has been expressed to be the foundation in maternal and infant care transmission [77].

The sensing and artificially intelligent healthcare systems must store and compute huge volume of data. To address the issues of big data and computing capabilities, different computing platforms such as edge

[78]–[81], fog [19], [82]–[86], and cloud [87]–[90] provide great support to store, process and classify the data. A general architecture exploiting these technologies for maternal and infant healthcare systems is depicted in Figure 6 .Firstly, data is collected from the sensors which monitor the patients' condition by measurable health parameters. Secondly, fog layer plays a mediating role between the edge / IoT devices and the cloud to enhance the computing efficiency and response time. The fog layer uses protocols to generate effective outcomes. Moreover, the data is analyzed, processed, and classified using classification algorithms for decision making at fog layer. Later on, the data is stored on cloud layer for further processing. In the cloud layer, messages and alerts are generated to the doctors, health workers, family in case of emergency to take the immediate action [91].

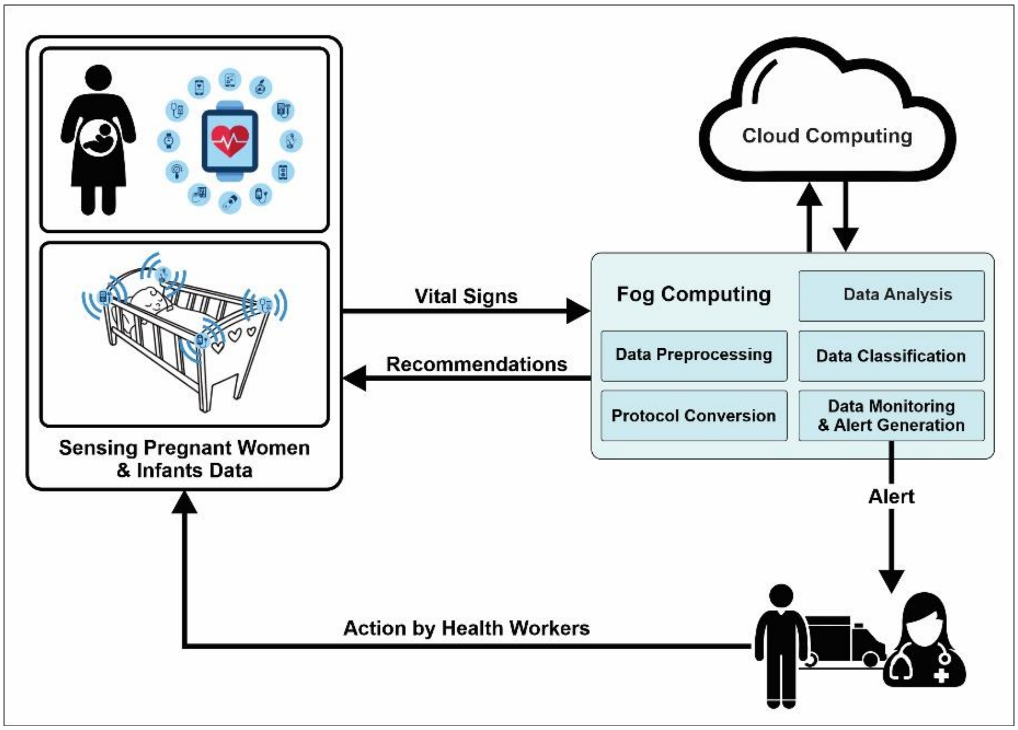

Figure 6: Architecture of Health Care Systems

Since, wearable sensor-based technologies and ML approaches have the potential to improve patient-provider interactions for effective pregnancy health management, thus replacing the traditional health care settings with a high positive rate [56], [92], [93]. This study reviews existing wearable sensing technologies and ML techniques used for better diagnosis of various pregnancy complications and infant's health monitoring. In this survey, our research contributions can be summarized as follows:

- Classification of the health care systems based on sensors used and ML techniques exploited.
- Each healthcare system, framework or model reviewed in the chronological order.
- Discourse on the real-world datasets and their details in terms of attributes, size, format etc.
- Comprehensive discussion about current research issues and challenges linked with these systems.
- Explore potential future work directions for researchers in the relevant domain.

Maternal and infant monitoring systems continuously monitor the condition of mother and foetus throughout the pregnancy and help them to get treatment on time in case of risky factors like blood pressure, hypertension disorders, diabetes, anaemia, and other related issues. The models for infant which monitors the condition and risk factors that includes the foetal growth, congenital abnormalities, heart rate, glucose level and other related issues of baby after birth are also discussed. The classification framework of health care system is shown in Figure 7.

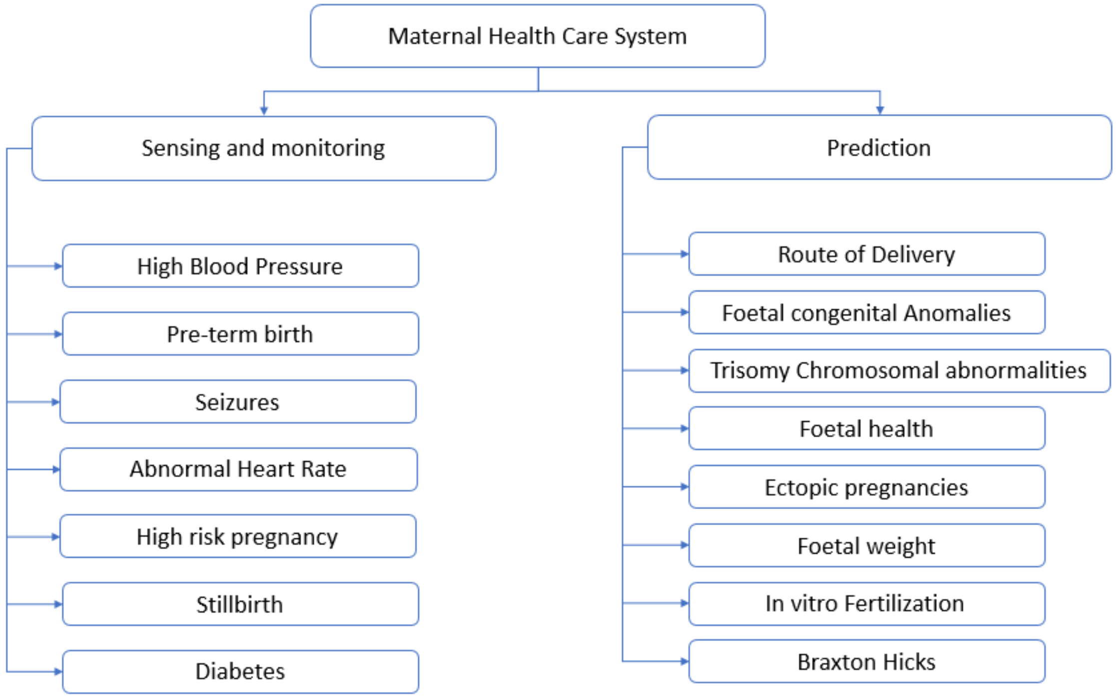

Figure 7: Classification of Maternal Health Care Systems

4.2 Sensing and monitoring systems by diseases

The use of wearable and wireless sensors for the health care of pregnant women reported a great improvement in the women's health as well as in solving pregnancy complications. These wearable wireless sensors help to provide knowledge, to detect breast cancer, chronic diseases and to motivate women to control their weights, diabetes, and mental health [94], [95]. In health status of pregnancy, the use of wearable wireless sensors provides remote monitoring to pregnant women [56]. The advance development of different eHealth applications and the use of wearable and wireless sensors explore the new opportunities to provide better clinical monitoring and diagnosis to the pregnant women as compared to the conventional health care techniques. The use of advanced sensor technology in the field of maternal health helps to detect the complications of pregnancy in early stage, to motivate and provide better health facilities to improve these complications. Nowadays these wireless or wearable sensors are used to detect risk factors like Blood Pressure, Heart Rate, Breathing Rate etc. comprising on the patient's lifestyle and behaviour in the subclinical period of an un-favourable pregnancy result [96].

4.2.1 Hypertension, preeclampsia

Hypertension or preeclampsia is one of the major complications in pregnancy. The outcomes of this can be a danger to the life of the mother or child, pre-birth or low birth weight. A wearable technology model is proposed [97] that can be used to control and monitor preeclampsia in pregnant women and can do real-time data analysis. The prior models are improved by including a chain of new health care parameters. These health care parameters can put a stop to preeclampsia issues in pregnancy. This study was carried out in a health centre in Lima, Peru. In the study, "VO7" wearable device that can measure blood pressure, heart rate, and steps were distributed among different pregnant women along with the usage instructions. The device transfers all the recorded data of about 30 minutes of the patients to a mobile application which further stores data in the SAP HANA database. The wearable device needs to be connected to the mobile application via Bluetooth and it also needs be connected to the internet. The results are presented in graphs that show patients' heart rate and blood pressure. The results can further help health centre professionals to monitor them. According to the reported results, 7% of maternal deaths were reduced, and 11% of patients were controlled by using the proposed method. The pregnant women felt confident as they can monitor themselves and expressed their satisfaction with the model. Due to the better graphics, friendliness GUI and alerts, the model is easy to use and non-invasive. The health centre assured the model's remarkable impact on their patients to prevent them from hypertension or preeclampsia.

4.2.2 Seizures

One of the most significant preeclampsia complications is Eclampsia, which is quite rare but a severe issue. Eclampsia causes seizures during pregnancy which happens as a result of high blood pressure. For monitoring eclamptic pregnant patients to avoid severe pregnancy problems, a method is proposed in [98] that exploits wireless 5G sensors. In the study, an indoor environment experiment is performed using a wireless transceiver to watch an eclamptic seizure patient's body motion. The experiment provides unique wireless data, which in results, fetch information on the wireless channel. The recorded data is divided into four different body motions: sitting, walking, lying on a bed, and seizures. Four classifiers KNN, SVM, K-mean, and RF were used during the experiment to classify the data. The results for each classifier were compared to check the performance of classification algorithms. These results recorded using the six-performance metrics, including accuracy, specificity, f-measures, recall, kappa, and precision. According to the results, SVM outperformed other classifier in term of accuracy with a 0.97 kappa coefficient value and very low error rate. The proposed method achieved promising results in detection of seizures through body movements. The future challenge can be to design a process that can predict the seizure disease timely to prevent severe injury to the pregnant patient.

4.2.3 Gestational diabetes mellitus

Gestational diabetes mellitus (GDM) is a severe threat to the mother and child's health which is often neglected. Patients with GDM experience several pregnancy complications, including high blood pressure, obstructed labour, and considerable birth weight. Existence of two proteins including Haemoglobin (Hb) and glycated Haemoglobin (HbA1c) helps to determine GDM. For the determination of Hb and HbA1c, a model is proposed that uses flexible electrochemical sensors comprising double imprinted nanocubes [99]. In the study, blood samples of diabetic and healthy pregnant women were examined. The performed experiments show that the proposed sensor has the potential for the simultaneous redox reaction of electrochemically catalyse for both Hb and HbA1c. Moreover, the response generated remain unchanged after the 450 bends. The reported results show that the sensor has potential for a wide range of applications in diabetes mellitus monitoring.

4.2.4 Cardiotocography

Due to physicians' shortages in rural geography, access to health care during pregnancy can be challenging for pregnant women. Multiple numbers of pregnant women visit for health care check-ups can also consume time and burden a doctor. Nowadays, cardiotocography is used for foetal heart rate (FHR) and maternal heart rate (MHR) monitoring as a standard health care tool for pregnant women. All medical and health care professionals need to adopt this cardiotocography technique setting. For cardiotocography, a wireless electrical and acoustic sensor wearable belt system known as Invu System is proposed to compare and monitor FHR and MHR [100]. . The Invu system is evaluated through study in which 147 women with singleton pregnancies of more than 32 weeks of gestations, aged between 18 to 50 years, participated. The tests of Invu System and cardiotocography were performed simultaneously for about equal to or more than 30 minutes, the passive eight electrical sensors and four acoustic sensors embedded on the belt gather the data. The acquired data then digitized and shared wirelessly to an algorithm in a cloud server for analysis purpose. An algorithm removes noisy data by pre-processing and encounters the independent heartbeats from electrical and acoustic sensors in that cloud server. The resultant detected heartbeats array then fused to calculate FHR and MHR. According to the reported results, a high significance correlation between Invu System and cardiotocography for FHR ($r=0.92$; $P<0.0001$) and MHR ($r=0.97$; $P<0.0001$) is recorded. The output of FHR and MHR with Invu System show that the results are very similar to the current care standards. The Invu System is a passive technology that ensures safe and convenient patient monitoring remotely or in a clinic, so no adverse situations were reported during this study.

4.2.5 Normoglycemia

The presence of normoglycemia (NGA) and GDM in pregnant women makes it hard for them to fight against different severe issues. These issues may cause danger to the life of both maternal and infant. Due to the burden of NGA and GDM in the South Asian region, a study was carried out [64] to detect NGA and GDM at the initial pregnancy level. For this study, a continuous glucose monitoring system (CGMS) is used that extract and evaluate several glucose-related parameters in women with NGA and GDM. Women having pregnancies between 8 to 20 weeks are considered for this study. The study aimed to perform a comparison among those who have NGA and GDM. These eligible pregnant women then followed CGMS treatment. Out of 96 pregnant women, 58 were with NGA, and 38 were with GDM. The study results show that women with GDM have high peak glucose values (64.3 +- 11.6) than women with NGA (60.0 +- 12.3). Time spent in this study with the NGA women group is slightly higher with 98.2% than the GDM women with 92.1%. This study observed that comparative data CGMS shows glycemic pattern's differences in women with NGA and women with GDM during early pregnancy. The evaluation of perinatal outcomes in pregnant women may be a future challenge that can reveal further confusion in such conditions.

4.2.6 Foetal hemodynamics

In [101], to examine foetal hemodynamics and to evaluate health factors during pregnancy, intelligent ultrasound sensors (IUSS) are used in the proposed system. For evaluation of the system, experiment was performed where 237 pregnant women were selected and divided into three different groups. Group IA has 93 cases of gestational diabetes women, Group IB having 19 instances of pre-pregnancy diabetes women, and Group II having 125 standard control women. During experiment, it is observed that women's blood glucose content in group IA and IB is relatively more significant than group II women after glucose tolerance test and fasting. According to the results, group IB women's blood glucose content is higher than that of group IA women. Group IA and IB hemodynamic parameters were recorded differently from that of standard control group II. Thus, using intelligent ultrasound sensors in the later pregnancy period to measure hemodynamics can predict pregnancy outcomes. Patient's health status with abnormal glucose metabolism can be evaluated in the last pregnancy period using intelligent ultrasound sensors.

For the last few years, advancements in Internet of Things (IoT) technology have helped a lot in the health industry, especially for pregnant women. Exploiting the IoT technology, a system having an IoT platform, wearable devices, and cloud computing for smart maternal healthcare is proposed [90]. This platform makes it easy for pregnant women to improve their treatment quality and facilitate them to have a check up with their doctors. It also reduces the workload for healthcare professionals and staff. The proposed IoT platform consists of three layers. The first layer is the *Perception* layer that authenticates the user, take intelligent control and gather physiological data. This data, later transferred to the second layer that is the *Network* layer that performs routing on the data, transmit the data to cloud computing, and sense if there are any extended devices. The third layer is the *Application layer*s which perform health management functions, detects diseases, and monitors foetal health. The result was calculated over the data gathered from the questionnaire. SPSS statistical software is used for the analysis task. Almost 29.84% and 65.08% of pregnant women agreed and showed faith in the increased use of IoT technology and wearable devices in the medical healthcare field.

The death of babies during or before delivery is one of the major issues nowadays across the world. To check whether a baby is alive multiple works on foetal movement have been recorded till now. Foetal movement is essential to monitor foetal growth, the umbilical cord's complications, gestational age, etc. Counting foetal movement daily can help health professionals to examine about a child's health and pregnancy difficulties. For estimating foetal movement, a system based on optical fibre sensors is proposed in [102]. The data for this study was collected through strain management with the help of sensors. Independent component analysis (ICS) was applied to post-process the collected data. Foetal movement instances were observed by using high filtering. The collected information shows that the proposed prototype's foetal movements are sensitive, much higher, and better against a mother's perception. There are many devices for measuring foetal movement, but optical fibre sensors proved beneficial. Multiplex capability, minimal size, and flexibility are few important advantages of using optical fibre sensors for foetal movement counting. For the future, a wearable belt can be designed and developed with optical fibre sensors that can reduce motion artifacts, classify moment type, and use ultrasound imaging validated with the proposed prototype. The above discussed sensors based maternal health care systems are summarized in Table 1.

Table 1: Sensors based Maternal Health Care Systems

Method	Features	Year	Disease	Dataset
Wearable Technology, a solution to hypertension during pregnancy[97]	VO7 wearable model	2018	High Blood Pressure, Pre-term birth	Data collected from mobile app.
Eclamptic Seizures monitoring by wireless sensors network [98]	5G wireless sensing system	2019	Seizures	…………
Nanocubes based flexible sensors for detection of Haemoglobin and glycated Haemoglobin [99]	Electrochemical sensors comprising double imprinted nanocubes	2019	Diabetes	Blood samples of healthy and diabetic pregnant women
Invu System: Home foetal and maternal heart rate monitoring [100]	Wireless electrical and acoustic sensors	2020	Abnormal heart rate of mother and child	147 women participated in the analysis
Normoglycemia and GDM in early pregnancy through a continuous glucose monitoring system [64]	Continuous glucose monitoring system	2020	Diabetes	96 women participated for the study
Measurement of foetal hemodynamics and evaluation of health factors through intelligent ultrasound sensors [101]	Intelligent ultrasound sensors	2020	Diabetes	Data collected using questionnaire
IoT platform for smart maternal healthcare using wearable devices and cloud computing. [90]	IoT based platform with wearable devices and cloud computing	2021	High risk pregnancy	Data collected using questionnaire
Use of optical fiber sensors for foetal movement counting [102]	Optical Fiber Sensors	2021	Stillbirth	3 volunteers participated for testing

4.3 Prediction of health conditions systems

AI and ML methodologies including modern Deep Learning methods are helpful in detecting pregnancy outcomes. Accurate prediction methods and diagnosis during prenatal healthcare can help detect problems as early as possible. According to the relevant literature, supervised learning methods are more popular as compared to unsupervised learning methods [76]. Moreover, use of state-of-the-art ML methods to predict stillbirth, late stillbirth and preterm birth pregnancies is common [103]. It is reported that postpartum depression can often be severe, and its early prediction can help with preventive intervention or timely psychiatric admission the new mother. In this regard, researchers developed a prediction model for women at risk of psychiatric admission [104]. Maternal data including delivery and neonatal data was used as predictor. In addition, many efforts aim at evaluating adverse pregnancy outcomes using ML. Different studies carried out to build the environment factors which have immense impact on pregnancy outcomes. One of the studies was conducted using the electronic health data (EHR) of pregnant women who had live delivery at an urban medical centre during 2015 to 2017. The reported results show that women living in high-quality built environments experience a different pattern of clinical events as compared to women in low-quality built environments. The reason behind such reported results was multi-purpose and walk able communities have a low risk of postpartum depression (PPD) in urban setting [105]. ML techniques are being used in predicting the weight of new born baby on features of mother [106]. Although, ML has made a lot of progress in maternal healthcare, however still many areas in maternal healthcare where advancements can be made using ML techniques. Figure 8 shows the general methodology to predict the patient's health status using ML algorithms whereas all models exist for prediction and discussed in this section are summarized in Table 2.

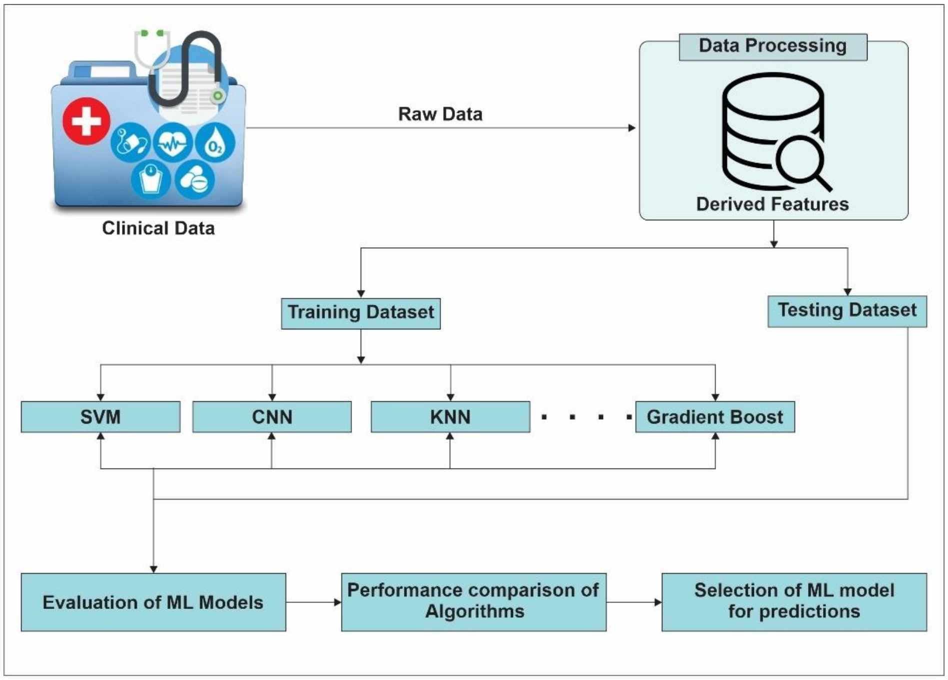

Figure 8 : General Framework to Predict Patient's Health Status using ML

4.3.1 Route of delivery

In order to predict the route of delivery, a supervised Artificial Neural Network (ANN) [107] has been developed. The variables used for the input of ANN are gestational age at birth, maternal age, risk factors or disorders of maternal. The algorithm gives output in two forms including Cesarean (CS) or Vaginal delivery (VI). For the experiment, data was obtained from the patients admitted for delivery and it was randomly selected to train the algorithm. The reported results show that the ANN based system gives the efficiency rate of 97% and performs best in other statistical measures as well.

4.3.2 Congenital anomalies

In [108], a prediction system was proposed to predict the congenital anomalies in foetal. Different binary classification models including SVM, Decision Forest, neural network, decision jungle and others were used to train and process the data to predict the foetal anomaly status. The data was obtained through questionnaire from RadyoEmar radio diagnostics centre in Istanbul, Turkey, and an e-health application was designed to get the parameters as an input. Experiments were performed and results show that when Decision Forest algorithm used to train the data, gives best prediction in terms of accuracy, Area Under the Curve (AUC) and F1 score.

4.3.3 Foetal trisomy

To monitor the chromosomal abnormalities and the risk of foetal trisomy, ANN diagnostic system was proposed [109]. The system uses ANN to train the attributes of data. The two-stage approach which consists of diagnosis of aneuploidy cases and stratification of risk is used. Firstly, blind set of pregnancies was classified into risk or no risk using four markers. Then, the data with risky pregnancies was sent for further examination. Secondly, the risky pregnancies further classified in to three types including high risk, no risk or moderate risk using seven markers. The reported results show that the proposed approach outperformed the system using mixture model as a classifier. In addition, the system has potential to be used in real-world applications in medical field.

4.3.4 3D pose estimation

In [110], a deep-learning based method was proposed to accelerate the performance of subject-to-template 3D rigid registration and inter subjects and to estimate the capture range. The model was trained to find the volume of medical images, 3D position of arbitrarily oriented subjects. In the proposed system, regression-based CNN method is exploited to predict the 3D rotations and translations using image features. Finally, models were trained using MRI scans of foetal brain and 3D pose of foetal brain. The results of study show that the trained models achieved the 3D pose estimation with the wide capture range in real-time in terms of mean squared error.

4.3.5 Ectopic pregnancy

Ectopic pregnancy is one of the major causes of mortality and morbidity. To avoid the complications, early diagnosis and the choice of treatment for such patients is decisive. In this regard, AI algorithms based clinical decision support system was developed [47]. The system uses two architectures: 1) considers the classifiers individually and 2) considers the combination of classifiers in one integrated classifier. The algorithms used for the system are MLP, SVM, deep learning and Naïve Bayes classifier. Experiments performed using Rapid Miner on the clinical database of ectopic pregnancies collected from 'Virgen de la Arrixaca' hospital in Spain. The reported results show that the SVM improves accuracy for both single classifier and three stage classifiers. Moreover, SVM and MLP both performed better in terms of sensitivity, accuracy, and specificity. The system helps doctors to take their decision for initial treatment on time.

4.3.6 Foetal weight

In low resource areas, the facility of sonographers and ultrasound machines are not easily accessible. To address the issue, ML approach [111] was proposed for predicting the foetal weight at fluctuating gestational age. Ensemble models of ML including random Forest, XG Boost, Light GBM was used as such models creates multiple models to enhance the accuracy of the approach. Firstly, parameters of genetic algorithm were initialized then the optimization parameters were selected. Experiments were performed to predict the foetal weight, and the reported results show that the multiple model approach gives better results as compared to individual algorithm in terms of accuracy.

4.3.7 In Vitro Fertilization

Around the world, the effects of infertility are common in one out of seven couples. In Vitro Fertilization (IVF) is a best suggested treatment for such couples. The main concern of such patients is the successful results of IVF treatment which mainly depends on the factors and number of attributes. For this purpose, automated classification with ML integrated hill climbing feature selection algorithm is proposed [112]. To assess the prediction ability of IVF, 25 attributes and well-known ML algorithms including MLP, SVM, C4.5, CART and RF were used. Experiments performed using MATLAB and results show that the proposed approach gives the better prediction accuracy than the existing techniques like neural network-based image analysis method, and Total Recognition by Adaptive Classification Experiments (TRACE). Prediction accuracy was measured in terms of well-known evaluation measures including F-measure, AUC and accuracy.

4.3.8 False labour or contractions

A Braxton hick which is normally known as false labour or contractions during pregnancy has been experienced by mostly women. Mostly women failed to identify such pains. For pain track analysis, prediction model was proposed [113]. Firstly, SVM is used by the model for sentiment analysis. Later, images are taken as input and their facial expressions are extracted using facial recognition algorithm. To differentiate the pains like false labour or true labour, SVM is used. Experiments performed using MATLAB and results show that model performs better as compared to existing ones in terms of accuracy.

Table 2 : Summary of AI based Maternal Health Care Systems

Model	Year	ML Algorithms Used	Disease	Dataset
Computerized Prediction System [107]	2018	ANN	Route of Delivery	Data consist of 2127, 3548 and 1723 deliveries for the years 1976, 1986 and 1996
Foetal Health status Prediction using ML [108]	2018	Logistic Regression, Locally Deep SVM, Neural Networks, SVM, Averaged Perception, Decision Jungle, Decision Forest, Bayes Point Machine, Boosted Decision Trees	Foetal congenital anomalies	Clinical database of 96 pregnant women
Two-stage approach using computational Intelligence System [109]	2018	ANN	Foetal trisomy and other chromosomal abnormalities	Dataset comprises of 72,054 euploid pregnancies
Deep CNN Regression Model for 3D Pose Estimation [110]	2019	CNN	Foetal health	MRI scans of 40 newborns and 93 reconstructed MRI scan of fetus
Decision Support System [47]	2019	Multi-Layer Perception (MLP), Deep learning, SVM, Naïve Bayes classifier	Ectopic pregnancies	406 cases of ectopic pregnancies collected from 'Virgen de la Arrixaca' hospital in Spain
Prediction of Foetal Weight using Ensemble Learning [111]	2020	Random Forest, XG Boost, Light GBM algorithm Genetic algorithm	Foetal weight	Dataset comprising of 4212 intrapartum recordings
Machine learning approach for IVF treatment [112]	2020	Multi-Layer Perception (MLP), SVM, C4.5, CART, RF	Vitro Fertilization (IVF)	Data from infertility clinic at Istanbul
Pain Track Analysis [113]	2021	Facial recognition algorithm accompanied by SVM, Decision tree	Braxton Hicks	Database of images

5 New-born and Infant

5.1 Introduction

The rise in technology has had an enormous impact on the field of healthcare. Besides, the internet of things and ubiquitous computing methodologies when applied to remote healthcare monitoring helps physicians better monitor their patients and thus provide faster treatment. Monitoring of patients outside the hospitals through Remote healthcare technologies (e.g., mobile health, telemedicine). The main advantages of remote healthcare monitoring of infants are the ability to continuously monitor their illness, real-time detection of illness, prevention of descending illness and untimely deaths, reduce the number of infant's hospitalization, cost reduction, emergency medical treatment, mobility problem for patients, emergency first aids for traffic road accidents and other damages and usage of non-invasive medical interposing.

Remote surveillance for infants targets many groups of infants, like neonates diagnosed with chronic illness or any other disability and premature babies with underdeveloped organs and apnea issues. All these conditions of infants are better be monitored regularly. Most researchers follow the policy of permitting mobility and a parental environment for infants which can be more beneficial than the expensive hospital rooms. So, several systems are developed to support the idea of remote patient monitoring with the use of the latest technologies. However, the infants cannot interact with remote sensors without the help of a caretaker.

For the infants, victims of accidents and sudden injuries, the time is taken by the monitoring system can be the only time to take the infants to the hospitals in an ambulance. Nevertheless, first aid medication is also very important, and efforts should be made for the safe journey to the hospital because an infant's body organs are not as much developed to bear critical injuries. The doctors can also monitor the patient and continually guide the paramedics about the deterioration and the maintenance of patients as much as required.

Key features for a remote infant patient surveillance system are data monitoring, data processing and a communication network to transmit data to end-terminal. Data monitoring systems are formed of different combined sensors having wireless data carrying ability. With the evolution in remote monitoring technologies, not only medical devices are used as sensors; cameras and smartphones can also be used as sensors. Recent researchers are focusing on the contactless techniques in which devices could monitor without touching a patient's body [114]. Contact-based sensors in Wireless Sensor Network (WSN) can be divided into Wireless Body Area Network (WBAN) and Personal Area Network (PAN). Data processing systems have the capabilities of receiving data from sensors and transmitting data and a processing unit. The server terminal can be a computing device or a smartphone of a doctor in the hospital. The communication networks connect the data monitoring systems to the data processing systems and transmit the monitored data and results to a paramedic person who is linked with the system through the network.

There are several challenges that exist when we are coming to design a remote infant patient monitoring system. The main decisions in developing a remote monitoring system using contact-based or contactless-based techniques is selection of sensors, algorithms, and communication medium and further consent of the medical staff and mainly the approval of the patient. Accuracy and reliability are also challenging.

With the advancements of research in the RPM field, new researchers must come up with a basic overview of previously used technologies. Most of the research discuss technologies in the last three decades but this work discusses the current developments in remote infant healthcare surveillance systems from 2010 to 2020. The difference of this paper is, it discusses both with-contact and contactless sensors, algorithms, and overall systems from the most recent literature that is proposed or developed between 2010 to 2020.

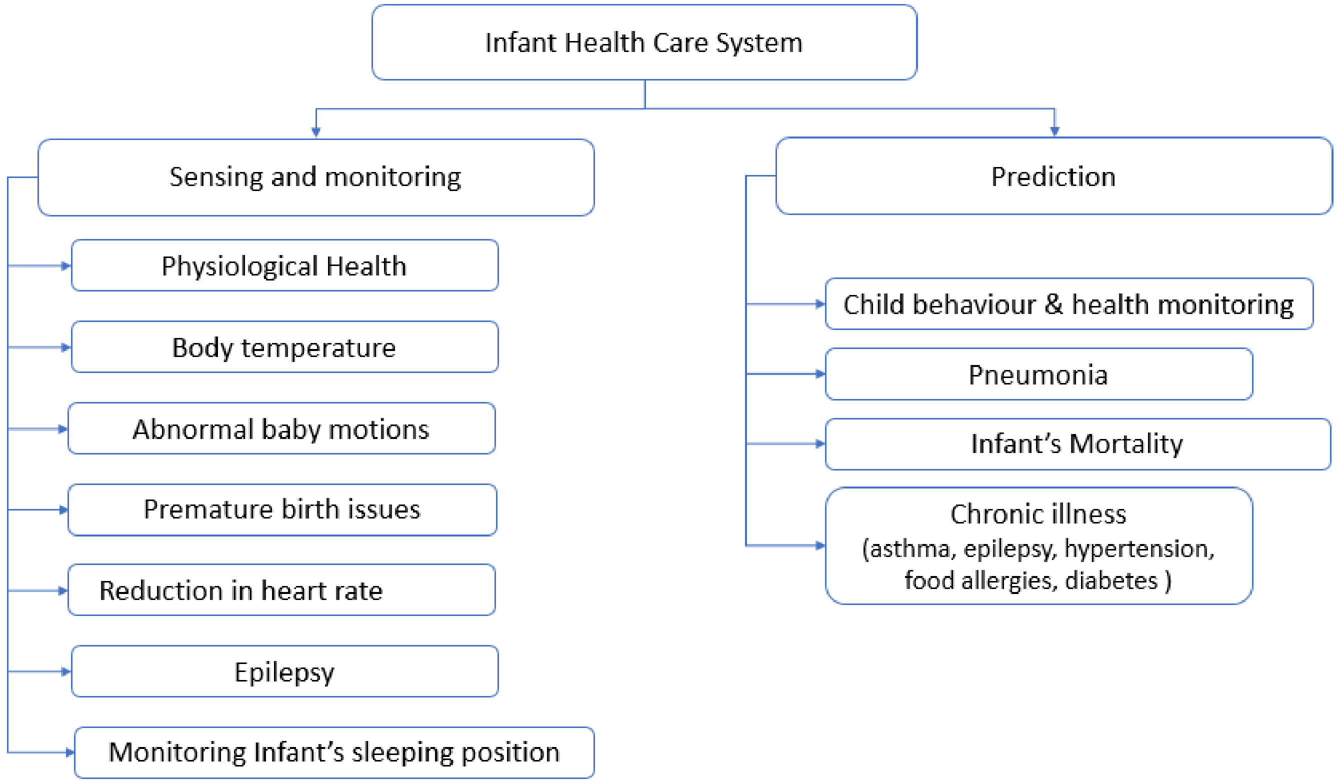

Figure 9 : Classification of Infant Health Care Systems

5.2 Remote infant patient monitoring system by diseases

Physiological data from infant patients is detected by a remote infant patient monitoring system. The most common data are heartbeat rate, oxygen volume in blood, Electroencephalogram (EEG), Electrocardiogram (ECG), respiration rate, body temperature, blood pressure, blood sugar level, and the signal from the nervous system are collected. Besides, sometimes, the weight of the infant and imaging data during sleep are also collected. Some researchers have also worked on wound monitoring applications. The typical traditional systems collect data through the sensors linked to the body. But the main issues with the traditional system are mobility and daily activity of infants. These devices have an impact on infant's comfort and critical physiological data gets impacted. So, the reading may not be accurate but rather the discomfort for the infants. While there are some circumstances where invasive and contact-based approaches are necessary, novel research tries to obtain physiological data in non-invasive way as possible. In recent research, a lot of work is being done on contactless methods.

5.2.1 Heart rate,

Heart monitoring systems are very common and critical in use. The main reason is that the vital signs of a body linked with heart can lead to many other diseases at same time. Chronic heart failure, blood clotting, strokes, cardiac arrhythmia, and high blood pressure are the most common diseases that can occur in an infant. Various technologies like ECG (Electrocardiography) monitors or wearable devices used to get these data. Although the gathered data cannot be 100% accurate. There may be chances of impurities in data. Various applications and devices that use smart phones such as monitoring patients remotely and to prevent cardiac diseases are discussed in this paper. Many security issues can occur while sharing patient data associated with patient's privacy. Health Insurance Portability and Accountability Act (HIPAA) has listed many factors for defining measures that can be implemented while defending health information.

But this information is still not enough against various health databases, which risks the patient's privacy [115]. According to latest published reports, many remote patient monitoring systems were designed for patients suffering from chronic illness such as cardiovascular diseases, cardiomyopathy, and cardiopulmonary diseases which can cause heart failure in infant patients living in remote and urban areas, who cannot seek immediate medical assistance [116].

These types of remote monitoring systems are very common because heart related diseases are the leading causes of deaths in the world. These monitoring systems provide combined results with respiration and heart related. One of the crucial challenges is to get accurate readings from the patient's body. Traditional contact-based methods usually use Electrocardiography (ECG) and photoplethysmographic methods which have been proven useful. These methods use light-incident on small veins.

[117] proposed a real-time monitoring system compatible with various sensors to detect medical parameters such as heart rate, body and skin temperature and blood pressure at same time. These parameters help in early detection of various diseases such as high blood pressure, low blood pressure, hyperthermia, and arrhythmia via an alarming system based on upper and lower threshold value. The developed monitoring system has two interfaces, one for the doctor or any paramedic person and one for the patient. The patient interface is composed of wearable sensors and transmission means to extract and transmit medical data via Bluetooth low energy to android based listening port. The android based listening port transfers this extracted medical data to a web server. Web portal extract data from SQLite database and transfer this to online database MySQL via Wi-fi or GPRS/3G. After processing this data is shown on the doctor interface along with location and patient identity information.

Some existing systems Smart Vest [118] and LOBIN [119] have the similar approach to monitor remote patients by using wearable clothes. Smart vest uses wireless data transmission from clothes to remote servers whereas LOBIN uses wireless data transmission boards and distribution points. There are some disadvantages of these systems like wearing weird clothes can be discomfort for an infant.

Researchers proposed a cloud-based RPM system for monitoring Heart rate variability (HRV) of infants and premature [120]. This system is developed after considering low-cost factors, accuracy, and security of HRV data. This system acts as an interface between patient and doctor. The purpose of this system is to provide better and timely healthcare monitoring to infants and new-borns belonging to rural areas and have very less facility of medication due to small doctor-patient ratio. In this study, the developed remote and diagnostic system to monitor an infant's heart conditions. This also helps patients in prevention of heart diseases who are recovering from their illnesses. The researcher configured a wearable Electrocardiographic device to get HRV data. The data reflects the patient's health condition and helps to detect the heart abnormalities like high blood pressure, low blood pressure, arrhythmia, and ischemia. System's architecture is composed of wearable ECG devices, ECG system nodes, a main processing server, data files and web GUI (Graphical user interface). Two types of MIT Physionet databases are used for storing patient data: MIT-St. Petersburg and MIT-BIH sinus rhythm. After analysing the performance of the proposed system, the obtained results for specificity, sensitivity and accuracy were 99.17%, 98.78% and 99.02% respectively. Achieved promising results concluded that the proposed system was quite reliable, valuable, and robust.

Contactless physiological parameters using cameras are short but advanced technology these days. Recently, contactless systems have been developed in both offline and real-time mode by using different colour spaces such as RBG [121], Lab [122], YCbCr [123]. Heart Rate Variability (HBV) is an important physiological parameter which is used to detect many fatal diseases. In this paper [124], a contactless remote Heart Rate Variability (HRV) monitoring system has been developed by using the facial video based on colour disruption of facial skin caused by cardiac pulse. The Lab colour space is used to extract physiological data from facial video recording by using a simple webcam with daylight provides illumination and signal processing algorithms such as Independent Component analysis (ICA), Principal Component Analysis (PCA) and Fast Fourier Transform (FFT) are employed to detect HRV. IBI (Inter-beat-interval) based HRV features: time domain and frequency domain are extracted with a reference sensor system. The system is proposed for server-side languages PHP and MySQL. Currently, the system is executing on a personal computer where HRV features are monitored by a website.

By using a telemedicine framework, where two or more paramedics from an ambulance can communicate to a 'Tele-EMS (Emergency medical service) physician' who is located in 'teleconsultation centre', it is showed that instead of using different specialized protocols, simple devices and applications interfaces are better and easy to use. [125]. The system is [126] capable to detect vital signs such as pulse rate and oxygen saturation instead of monitoring the system for joint angle and hydrotherapy. [127], [128] presented PAN upper layer architecture for android phones which works in 'hub + sensor + processor' manners. A comparison in 5 RPM systems represented in [129]. This comparison shows the results observed by contact-based systems are very promising. Ambient lightning causes incorrect results in contactless approaches. [130] Explains the disadvantage of deterioration monitoring have been minimized with patient guard 300 (PG300) wearable apparatus that measure heart rate, Electrocardiography (ECG), temperature and respiration information. [131] presented an approach to measure physiological data which is related to pulmonary artery pressure (PAP) and Electrocardiography (ECG) and encode the detected data in a text message. 5th Generation (5G) can improve dedicated channels for medical data. Pupillary fluctuations can also be used to measure heart rate variability [132]. Boundary segmentation of a remote eye tracker and eye pupil are used here to observe the change in eye pupil's diameter that occurs with heartbeat.

[133] discusses an RPM system that uses both contactless and contact-based approaches for detection of physiological data of infants. A wearable device detects infant's coughing and a wireless system monitors respiration of infants. Micro-Electro-Mechanical-System based microphone is utilized to record the coughing sound of infant patients and mutual measurement units are utilized to record the thoracic and cavity motions for monitoring respiration. This system is a fully contactless system for measuring respiration, but it is not fully contactless as the IMU units are placed on the infant's chest. The measurement or parameters are only sent wirelessly. However, the IMU units are very small in size and lightweight. So, these units cannot discomfort the infants.

[134] proposed and implemented a Remote Mobile health monitoring system based on smart phones and web browsers with chronic illnesses, especially in infants. Vital sign sensors are integrated by portable terminals to monitor physiological data such as heart rate, body temperature and respiratory rate. A smart phone can be used as both an information transmission platform and an intuitive human-machine interface so that the patient's health status can be monitored continuously. Patient's current location can be acquired by GPS for outdoor and Wi-Fi signals for indoor. The remote server uses browser/server architecture to acquire data query, patient location and observation curve. The portable terminal is integrated with heart rate sensors, respiratory sensors, temperature, and posture sensors. Zephyr BioHarnessTM sensor is used as a portable terminal. With no need for multiple sensors, it detects comprehensive physiological data like RR intervals, ECG, respiratory rate, heart rate, skin temperature, breathing wave altitude, vector magnitude peak acceleration, and posture. Of being lightweight of 35 grams, it can be easily fixed with a patient's chest with a belt. But for infants, it can be uncomfortable because of the tightening belt. Furthermore, the system was only capable of monitoring a patient's status in real-time and not professional analysis and instruction.

Vital parameters (Respiratory rate, ECG, heart rate, body temperature) of term and preterm infants during their incubators care are monitored with sensors or self-adhesive electrodes directly on skin such as electrocardiography (ECG) and photoplethysmography (PPG) is an important part of routine care in infant intensive care unit to ensure their good health. For many reasons, these kinds of monitoring systems can be stressful for infants [135]. Therefore, it is necessary to measure viral parameters (temperature, respiratory rate, pulse and oxygen saturation) without mechanical or conductive contact with infants. As a contactless method of monitoring, [135] proposed an adaptive style of camera-based photoplethysmography imaging (PPGI) according to neonatal requirements. The PPGI camera is directly placed above the incubator of the infant illuminated by infrared light-emitting-diode (LED) array (850nm). 5 minutes video is recorded from each preterm infant and analysed post hoc. Infants are not limited to moving in front of the camera to keep the balance as accurate as possible. In this way the blood perfusion is recorded successfully according to the heart rate.

In [136] 3-tier architecture is presented the infant healthcare monitoring system using Wireless sensor network (WSN) which constantly monitor infant's body parameters. Various biosensors are attached to the Arduino Nano board to measure body oxygen level, heart rate and temperature and recorded signals are sent to the server by using Node MCU ESP8266 wireless communication. Data is uploaded on a remote server and is available for para medical staff and caregivers by using an IOT application ThingSpeak. In case of emergency, paramedics or caregivers are notified through smart phone alerts. The system is beneficial for cardiac patients and can be utilized for elderly care in homes and hospitals. Accuracy of the system is 99% with 10 seconds response time.

Monitoring the physiological health of infants is crucial. In the past, the traditional methods were used where various equipment were attached to the infant's body which causes discomfort to the subjects. In order to overcome this issue, a sensor based bed was designed that monitors infants' physiological health of infant [137]. The proposed technology exploits Ballisto Cardio Graphs (BCGs) which provides the heart's mechanical activity and efficiently records the physiological measurement. The proposed bed includes Heart Rate (HR) and Breathing Rate (BR) using load-cell sensors signalling. To validate the proposed bed 13 experiments were carried out in which four infants participated. As a reference signal, a commercial device was used to measure electrocardiogram signals and breathing signs simultaneously. Then both the signal results of load-cell sensors and reference signal were compared by using the proposed algorithm. The comparison verified that the proposed technology of BCG performed acceptably well for both HR and BR with average error rate of 2.55% and 2.66% respectively. Although, promising results were recorded from experiment, however it has limitation such as minimum number of measurements and insufficient recording time. Future work can be done on these two limitations for better respiratory distress solutions for infants using the proposed method.

To monitor the patients' health by the physicians at a distance and take necessary actions on time in case of emergency, smart health monitoring system is developed [138]. Firstly, health parameters like ECG, heart rate, blood pressure, fall detection and temperature were sensed using body sensors. Then, SVM is used as a classifier to classify the sensed data and generates alert if emergency occurs. It also informs the ambulance, if required. The developed system implemented in rural areas to connect the patients with specialist doctors in big cities and hospitals for timely treatment.

The Heart Rate (HR) of new-born matters a lot for monitoring his future health. If a new-born baby's breath does not start, it may cause a reduction in heart rate. Also, it badly affects the circulation of blood to the baby's organ. At the time of birth, the neonatal staff manually records the baby's HR by listening to the baby's heart. This technique is neither efficient nor accurate. To overcome this issue, a novel device is proposed [139]. The proposed device uses a smart mattress with electrometer-based amplifier sensors and the screen-printing technique. The device records and monitors the breathing and electrocardiogram of a baby. To illustrate the suitability of ECG monitoring based smart-mattress, many concept tests were performed and proved. According to the reported results, the device is accurate and quick that gives ECG readings of a young infant is less than 30 seconds. This novel development has potential to help neonatal staff in resuscitation procedure for new-born babies and the delivery room for the new-born baby's stabilization. The proposed device reduces the times for the assessment of resuscitation process success. The device performance is four times quicker than the pulse oximetry.

5.2.2 Respiration and apnea

Respiratory system consists of two phases: inhaling oxygen from air and expiration of carbon dioxide during energy-producing reactions [140]. Thus, the monitoring of the respiration system and respiratory rate (RR) are very significant for an infant patient. Respiratory rate (RR) is an important parameter in intensive care medicine [141]. RR is measured in breaths per minute. The normal RR is different in adults and preterm infants. Normal RR in adults is 12-20 breaths/minute and RR in preterm infants is 40/60 breaths/minute [142].

Detecting respiratory diseases and breathing abnormalities challenge the remote monitoring system because these systems detect breathing sounds. Upper body of humans produces different sounds, so this can be challenging for a monitoring system to differentiate these sounds.

Critical diseases are the main cause of respiratory disorder. Which are identified by abnormal respiratory rate or typical waveform (disrupted breathing depth or rhythm) [143], [144]. Tachypnea's increased respiratory rate can be an early sign of lungs and heart diseases. A decreased respiratory rate caused by hypothermia, certain medication or by diseases which affect the central nervous system is called Bradypnea [145]. In terms of premature neonate, continuous monitoring of respiratory rate along with its variations is most important. Apnea and bradycardia occur in infants frequently and may lead to lack of oxygen in the organs and results in deficiency in neurodevelopmental outcome if not detected early [146]. Furthermore, tachypnea is one the critical bacterial pulmonary infection [147]. This vital sign identifies the sudden infant’s death syndrome, which is the major cause of deaths in infants and adults as well [148].

Chronic Obstructive Pulmonary Disease (COPD) was appraised as sixth leading cause of death in 1990 and could be fourth in 2030. Skeletal muscles dysfunction can lead to poor health and even morality. In this paper [149], [150] e-Health system with smart sensor-based devices that is used in real-time monitoring of respiratory frequencies is considered a good approach of timely treatment and prevention of respiratory diseases. The main aim of the approaches is not only to the recording and telemonitoring physiological readings but also to encourage parents to adopt promising health-care skills for infants for improving their well-being.

Spirometry and capnography are common approaches to monitor respiratory and cardiac variables. But these are uncomfortable for infants and new-borns and can disturb the nature of breathing. This can disrupt health readings.

[151] presented a remote respiratory system to monitor an infant’s respiratory rate and respiratory cycle timing variables. The system illustrates that the respiratory rate can be monitored by using a DSLR video camera, imaging the chest of the infant even in the unclear ROI or in the blanket. This system is effective even in changing light conditions because it relies on motion magnification not on skin colour analysis. [151] designed a magnification technique for videos to meet the measurements by using elliptic filter and wavelet decomposition and after that frame subtraction technique based on motion detection is used to monitor respiratory rate of the infant’s chest in the magnified videos. The accuracy of respiratory rate and their timing cycles at different positions of infants is 99%. The system can be a candidate for replacing

traditional contact-based sensors that are utilized for breath sensing and this technique can also be considered to replace other contact-based systems.

[152] numerous sensorization technologies have been proposed to continuous respiratory monitoring. An accelerometer captures the processed information to detect the respiratory rate from rib cage movements.

[153] and [154] are designed for infants are accelerometer-based commercial devices. This paper [155] shows a technique for designing and implementation of a smart sensor-based device for respiration rate monitoring integrated with smart vest. Such devices can be implemented for respiratory rate monitoring of COPD (Chronic Obstructive Pulmonary Disease) infant patients during their rest time. The requirements to design such devices are low cost and easy to use. This system capacitive sensing principles based non-intrusive technologies of low-cost LC-Oscillators with high sensitivity.

Mobile communication and wearable sensors integration shifted the healthcare service from clinic-centred to patient-centred, and is known as telemedicine [156].

This paper [157] represents a smart sensing strip for infants for non-invasively real-time monitoring of respiration rate. The monitoring system represents a monolithically integrated flexible hot-film flow sensor attached on a moulded flexible silicone case and Bluetooth 4.0 LE module (containing a 12-bit ADC, a MCU part, a GPIO part and Bluetooth 4.0 LE transceiver) with miniaturized conditioning circuit packaged. The respiratory rate is wirelessly acquired respiratory data through flow sensor, process acquisition of important signs for health diagnosis by personal mobile device. This system offers a simple wearable device to continuously monitor respiratory flow eliminating the uncomfortable nasal cannula. The respiratory sensor is a flexible flow sensor combined of four elements of a Wheatstone bridge on a single chip. These elements include a hot-film resistor, two balancing-resistors and a temperature compensating-resistor. All these elements are packaged in a silicon case. The smart strip can be attached to the upper lips of infants avoiding uncomfortable nasal canal. The tube-free configuration of this wearable device makes it non-invasive and least-resistance.

The World health Organization [158] reported that respiratory diseases have become top killers in the past few decades. Asthma, apnea syndrome and Chronic Obstructive Pulmonary Disease (COPD) are the common respiratory diseases among infants that cause some serious health issues and even morality.[159] Sleep apnea is a critical respiration disease that occurs during a patient's sleep. Obstructive sleep apnea is a common breathing disorder during sleep in infants that occur due to partial or complete obstruction in airflow. Sleep apnea disturbs sleep duration as well as sleeps quality. This may lead to chronic partial sleep deprivation. Overnight polysomnography (PSG) is developed in hospitals to diagnose sleep apnea disorders. Respiratory Inductive Plethysmography (RIP) is used to measure the respiratory rate of the patient [160]. In RIP, the patient wears an elastic belt and it measures the respiratory rate by detecting the change in its inductance. This approach is much invasive and causes discomfort for infants as an infant cannot manage the overtightening of the belt around the chest or abdomen and could cause suffocation. In contrast, the loosening of the belt can lose the signal. [161] reported new development in fabricating capacitive sensors for clothes to monitor respiration without being invasive. These may produce inaccurate results because of the infant patient's movements and crying. Other methods are introduced to measure respiratory rate from the unobstructed sensors and on-body wearable devices [162].

[163] developed a non-invasive, contactless, and wireless system for respiration monitoring. This can be utilized in Polysomnography (PSG) studies, home respiratory systems, and physiotherapies applications. In this paper, ultrawideband (UWB) is used because of its large bandwidth that facilitates in location estimation, allowing precise ranging and high time resolution. This RPM system monitors infant's respiration accurately, HMM to jointly estimate the direction an infant is facing, and RSS-propagation

delay profile estimates the chest wall movements. A single segmentation algorithm is developed to estimate the infant's respiratory motion from backscattered signals at the ultra-wideband receivers. To estimate the number of apnea and hypopnea-episodes, another algorithm is proposed to segment the breaking patterns.

In this paper [164] proposed a contactless respiratory system that monitors respiration rate through camera sensors reliably. Respiration monitoring is important in application. Variations in breathing rate and shallowness of breath are vital signs of health problems. Respiratory shambles are the early sign of health abasement. Even though, it is a vital sign for health measurement [165]. [164] deployed and implemented an efficient approach to extract raw breathing signals form video movements. In addition, a camera detects motion information in the explored scenes. This improves subsequent breath-to-breath classification. The purpose of the proposed work is to develop an efficient image processing algorithm that integrates low-complexity and high sensitivity. It uses an off-the-shelf-camera without light pattern projecting on the body. It provides directionality information to reconstruct inhale and exhale signals in real-time without excessive post-processing.

[166] investigates the problems in RPM systems for detection of respiration rate as well as breath information accurately. It reduces the diagnostic time and helps to improve medical services. [166] Introduced a method to extract respiratory rate and tidal volume variability through an accelerometer data as a reliable and unostentatious technique over an extended period. A method is also proposed for Tidal volume variability (TVvar) estimation, and it is validated by using Pearson correlation. They designed an alert system for the feedback of tidal volume emergency situations. When the system receives signals from the cloud, it can perform essential functions to process them and set the emergency alert eventually. The system is composed of wearable sensors, standard BLE (Bluetooth low energy) and backend cloud storage with important benefits of convenience, cost, quality of service and patient comfort.

Table 3: AI based Infant Health Care Systems

Model	Year	ML Algorithms Used	Disease	Dataset
IoT based child behavior & health monitoring system [167]	2017	C4.5, ID3 algorithm Decision Tree	To monitor child behavior & health	Medical Dataset
Automatic Classification of Pneumonia using ANN [168]	2018	Artificial Neural Network (ANN)	Pneumonia	60 digital images of ultrasound
PROMPT [169]	2019	CNN	Infants' mortality	1977 patients
ML based Health monitoring system [138]	2020	SVM	To monitor chronically ill patients or infants	Data collected through body sensors

5.2.3 Fever, sneeze, and cough

Fever, sneeze, and cough are some of the few common infant diseases. Among these three, fever is the one that fights against the infections attacked infants. In some cases, this fever can be very dangerous for an infant's health. Sometimes, infants have a severe increase in their body temperature for a very short interval of time, and it remains unnoticed for either their parents or caretaker. This sudden increase in body temperature may lead to severe injuries like epilepsy. In this regard, a lightweight device is proposed [170] and developed in Malaysia to alert the infant's parents about their abnormal body temperature. The device is small and comfortable to wear for an infant that continuously monitor its body temperature. The wearable device has LM35 sensors in it, which gathers an infant's body temperature and sends the information to parents via a wireless network. A micro-controller named Arduino ESPresso Lite 2.0 controls the LM35 sensor to measure the temperature. After collecting the temperature data, the micro-controller ESPresso transfer and store this data to the cloud server. Later on the data is processed and sent via Wi-Fi interface to the mother's or caretaker's mobile phone. To establish a wireless connection for the Wi-Fi interface, an ESP8266 is used. The proposed device is easy to implement and less expensive. This device can provide better communication between a mother and an infant. For future work, more sensors can be exploited to the proposed device to give information about heart rate, oxygen saturation, etc.

5.2.4 Behaviour disorders

Vision sensors are used to examine babies' behaviour employing the intelligent multimodal system [171]. The proposed method is different from traditional wearable devices that make babies uncomfortable when attached to their bodies. This vision sensor-based monitoring system uses control chart techniques. This control chart technique provides baby behaviour in an analysed manner. The proposed method's control chart is constructed using Raspberry Pi (RPi) attached vision sensors which provide real-time frames. On the control chart, there are two points: 1) Upper Control Limit (UCL) and 2) Lower Control Limit (LCL). If the baby's motion drops down below LCL or the baby's movement surpasses UCL, an alert is transferred via interconnected IoT devices to baby caretakers. Performance evaluation measures on collected data are entirely accurate and efficient, which shows the proposed system's success. The proposed system can be developed for home use with only one RPi, and a network can be made by using multiple RPi for a health care centre or nursery.

To enhance the health and behavioural monitoring system, a new method proposed in [167]. Gaming data and body parameters are used to analyse the health of child. For large scale data management and comparison, Hadoop is used whereas C4.5 and ID3 algorithms are used for classification. A class label represents different types of disorders such as disruptive behaviour disorders and attentiondeficit/hyperactivity disorders. The reported results show that the predictions made using C4.5 achieves better results than ID3 algorithm in terms of accuracy and execution time. In future, more mind games can be added and using more body sensors may help to monitor the physical and psychological state of child in early time.

5.2.5 Seizure disorder

Epilepsy is becoming a common disorder nowadays, causing sudden seizures or sensations, awareness loss and unusual behaviour. This neurological disorder affects any human being of any age. There was a dire need for seizures' early detection as it may improve treatments and give timely warning to the patient. In this regard a system is proposed to assess the utility of ANS metrics for the identification of early seizures to delineate the period of preictal in terms of specificity and sensitivity [172]. This system uses wearable devices like ANS (automatic nervous system) which offer promising results. It is easy to use and cost-effective as compared to impractical EEG. The investigation includes 66 people with epilepsy who have a continuous recorded unique dataset of multi-day wristband data and statistical testing with seizure surrogate data, including temperature, heart rate, and electrodermal activity that did not exhibit consistent trends. These investigations result in differences between the preictal and inter periods regarding these signals' entropy, variance, and mean and potentially afford to search for more personalized seizure makers. EDA signal entropy was used to increase the before seizures in patients' small subsets, whose findings may give deep insight into the epileptic seizure pathophysiology with respect to ANS function. Through these wearable devices, the detection of changes becomes easy and more feasible. Therefore, provides latest opportunities in seizure risk evaluation and forecasting based on easy-to-use and non-invasive devices.

5.2.6 Circadian rhythms

Human detection regarding human health and development through high resolution and sensitivity image sensors is common in present era. However, these biological and environmental sensors are expensive and demand a powerful processing capability. Thus, it is undoubtedly challenging to analyse humans during their regular daily life routine at home. Coping these challenges, a detection system is proposed that uses low-cost IR technology-based location, thermal environment, motion, and temperature sensors [173]. It is beneficial for long-term evaluation in the home environment. This latest technology is tested to visualize the thermal environment and parental care effects on the common marmoset known as circadian rhythms. Firstly, a comparison of this system is made with a manual analysis technique for validating the design. Afterwards, circadian rhythms are assessed from the postnatal day in the standard four marmosets. In the circadian phase, patterns of age-dependent shifts are shown through the biological indices of body surface temperature and locomotion velocity. The development of these circadian rhythms and principal analysis of components was affected by environmental variables. A novel basic pattern of BD-BT correlation is revealed by signal superimposing imaging methods in correlation day/night animal switching older than a postnatal day which is also one of the limitations of this study. The switch origin was associated with BT and BD rhythms around earlier times of feeding. In the future, this technique has value for understanding care conditions in which non-invasive home monitoring is beneficial and useful that also further suggests the potential in adapting this technique that well facilitates home AI programs implementation and development for healthy development support.

5.2.7 Sleep monitoring

Wearable sensors play important role in the field of medical because these sensors can conveniently give important physical information in real-time without bulky instruments. However, these sensors have many drawbacks such as frequent battery charging cycles and user inconvenience. These drawbacks can be removed after reducing power consumption, which arises due to the battery's capacity or size. To overcome the drawbacks, ultra-low power sensor was proposed [174], in which signal repeater and a particular switch has been introduced that significantly reduce the use of power as both provide power when there is a dire need. Afterwards, the characteristics of antenna radiation were observed that are an essential factor in the wearable sensors. Improved soft encapsulation method improved the antenna radiation that maintains good wear ability in daily life degraded by the polymeric encapsulation layer. The human body's safety is also verified in this proposal through RF (Radio Frequency) and absorption rate simulations. Furthermore, the infant's sleep position was monitored in the wearable sensor part by an accelerometer sensor. As infants cannot communicate well and cannot talk about their harmful situations, it is also challenging for caregivers to keep an eye on them; so this infant sleep monitoring system helps the caregivers be alert in the infant's unsafe situations.

5.2.8 Motor skills

The framework of locomotion is laid on the infant's earliest motor skills that determine developmental progression. On the other hand, motor dysfunction negatively impacts physical insight, spatial, balance, and cognizance, and it is considered significant in infants' Autism Spectrum Disorder (ASD). ASD refers to an infant's sitting and standing delay and head lag. A system is proposed in [175] which uses a wireless device known as opal sensors, comprising of a 3D- magnetometer, 3D-gyroscope, and 3D accelerometer to study the full-day HR infant's movement. Motion complexity in an infant is measured through these sensors which is important for normal motor development as less body movement reflects one of the ASD symptoms. These lightweight sensors report only 14-bits resolution and have a range of 6g that results in the recording at 20 Hz. The data is synchronized from both the left and right sensors and stored on the individual sensor's internal memory. At every visit, the data can be downloaded. The data records include the infant's sleep and wake status. ASD outcome and motion complexity have the most vital relationship with each other than adaptive skills and cognitive ability results. Primary motor development measuring objectives are required to identify a typical infant performance of motor that can show later ASD risks. Early infant's motor development can easily be tracked by motion complexity and removes the risk of ASD in HR infants. Table 4 provides an overview of latest models proposed in recent years as discussed above.

5.2.9 Mortality prediction

In [169], to predict the paediatric mortality in ICUs, ML based model is developed. The model named as Paediatric Risk of Mortality Prediction Tool (PROMPT) and Convolutional Neural Network (CNN) is used to develop the model. It consists of two layers; first layer has one-dimensional convolutional operations, and second layer has max pooling. Performance of PROMPT was compared with other ML algorithms such as Long Short-Term Memory (LSTM), and Gradient Boosting Decision Trees (GBDT). The results show that the developed tool achieves high sensitivity and tool has the better ability to predicts the patients at high-risk of mortality.

Table 4: Sensors based Infant Health Care Systems

Method	Features	Year	Disease	Dataset
Load-cell sensors based physiological signal monitoring bed for infants [137]	Load-cell signal sensors	2016	Physiological health	Total 4 infants participated in 13 experiments.
Body temperature monitoring of infant using IoTs [170]	LM35 sensor	2018	Body Temperature	…………..
Use of vision sensors in IoT for intelligent baby behavior monitoring [171]	Vision sensors	2019	Abnormal baby motions	Live baby video
Computationally efficient mutual authentication protocol for remote infant incubator monitoring system [176]	Wireless medical sensors	2019	Premature birth issues	…………..
Cardiac monitoring of babies through non-invasive smart sensing mattress [139]	Electrometer-based amplifier sensors	2019	Reduction in HR	Concept tests
Autonomic nervous system changes detected with peripheral sensors in the setting of epileptic seizures [172]	Peripheral sensors	2020	Epilepsy	66 people participated for the study.
Inexpensive Home Infrared Living/Environment Sensor with Regional Thermal Information [173]	Infrared sensors	2020	Infant's Physical and psychological health	……..
Ultra-Low Power Wearable Infant Sleep Position Sensor [174]	Switch sensors	2020	To monitor infant's sleeping positions	24 infants were recorded
Measurement of infant complex motions using wearable sensor technology [175]	Wearable opal sensor technology	2021	ASD	Data collected from 5 infants

5.3 Datasets

This section represents the real-world datasets used for the experimentation purpose in such domain. Different datasets which have the data collection of infant images to monitor baby position [177], MRI database [178], [179], infant mortality etc. Datasets of such domain has different types such as data consists of images and videos; some has the training and testing data to make predictions [180], text-based data. Table 5 presents the summarized view of the datasets.

Pregnancy Risk Assessment Monitoring System (PRAMS) is designed to monitor and identify the risk factors that occur before, during and after the pregnancy. Participants have been selected randomly from the birth certificate of New York City. The dataset size is 1.11 KB and freely available for research purpose. The infant mortality dataset contains the counts of death of infants those which are less than 1 year based on the death certificates of New York City. The rate has been calculated by dividing number of infant deaths by the counts of live births. The dataset size is 2.44 KB and available freely for research utilization.

UNICEF together with their key partners are analysing the health status for maternal and child. They have different collections of data like antenatal care, new-born care, delivery care and maternal mortality [181]. UNICEF also contains the child mortality data of different stages like still birth, neonatal mortality, under-five mortality [68], [182]. Data has been collected from different countries. Maternal and child health data and statistics [183] is a digital library which provides different datasets about births, infant deaths, child care, indicators of child including stages of maternal and child. The website has a variety of toolkits to analyse the data and statistics online as well as provides statistics about the adolescents, pregnant women, infants, and their families.

Table 5 : Summary of Datasets

Dataset	Source	Attributes	Format	Language
Pregnancy Risk Assessment Monitoring System (PRAMS)	https://data.cityofnewyork.us/d/rqgf-94xs	Year, source, question, prevalence%, lower 95% confidence interval, upper 95% confidence interval	csv	English
Infant Mortality	https://data.cityofnewyork.us/d/fcau-jc6k	Year, Maternal race, infant's mortality rate, neonatal mortality rate, post neonatal mortality rate, infant death, neonatal infant death, post neonatal mortality rate, No. of live birth	csv	English
Baby Monitor Forecast	https://www.kaggle.com/c/fiap-fsbds-baby-monitor forecast/data?select=test.csv	Id, date, mes, weekday, mergem, Venda, desconto, outdesc, outmg	csv	English
Maternal and Child Health Data of UNICEF	https://data.unicef.org/resources/dataset/maternal-health-data/ https://data.unicef.org/topic/child-survival/	Country, year, mothers' age, source	csv	English
Neuro Developmental MRI Database	https://jerlab.sc.edu/projects/neurodevelopmental-mri-database/	Age, 1.5T, 3.0T, total, notes	Tar.gz	English
Infant Death Dataset	https://www.cdc.gov/nchs/fastats/birth-defects.htm	No. of infant death, infant death per 100,000 live births, cause of infant death	pdf	English

5.4 Future directions

Although the technology is rapidly growing day by day, there are some significant shortcomings in the research. There are some important privacy and security issues which are not being resolved. The above literature review discusses latest technology usage but not all systems ensure data privacy and security. The other main issue is the usage of the system because each system is designed by a unique interface. The general method of acquiring physiological data from sensors can be very common for many systems. Adaptability of the system is very important for the parents of infants and the paramedics. Another issue with system usage is comfortability. As skin of infants is very sensitive and the contact-based systems can be a cause of discomfort for them. So, contactless technologies such as radar and image sensing can overcome this issue. Overall, more research is needed to see the acceptance of technology in the medical field by patients and the medical community. Still, error correction methods are not capable of winning the trust of the medical community.

6 Elderly people

An important element of RMS is the Human Activity Recognition and Interpretation. Automatic interpretation of human activities can play a pivotal role to revolutionize various routine activities. Human Activity Recognition (HAR) has been deemed as one of the quintessential research areas since past two decades due to its applications in multifarious disciplines such as remote health monitoring, security and surveillance, human computer vision and gaming [184]–[187]. Activity recognition refers to an ability to infer on-going activity by processing raw data through diversified mechanisms varying from traditional statistical measures to advanced data mining and machine learning concepts [188]–[191]. HAR systems are beneficial in inferring human activities for providing feedback to take necessary actions for intervention. Typically, human activities are classified into two broad categories: (1) Ambulation or Fitness activities and (2) Functional activities [188]. Uncountable motions like walking, jogging, walking towards upward/downward directions, fall under the category of ambulation or fitness activities. Functional activities include routine tasks such as attending calls, washing foods, cooking, etc. [192]. These behavioural or functional activities can play a consequential role to decipher human wellness [192], [193]. Human motions of the same activity may hold a significant difference due to constraints including environment, time, culture etc. [185]. Saidi [194] focused on extending elderly home care in the safest possible conditions by preventing the risks of people living alone. Proposed system is monitoring elderly person remotely and designs a method for solving the privacy protection issues for healthcare data based on F2C computing scheme.

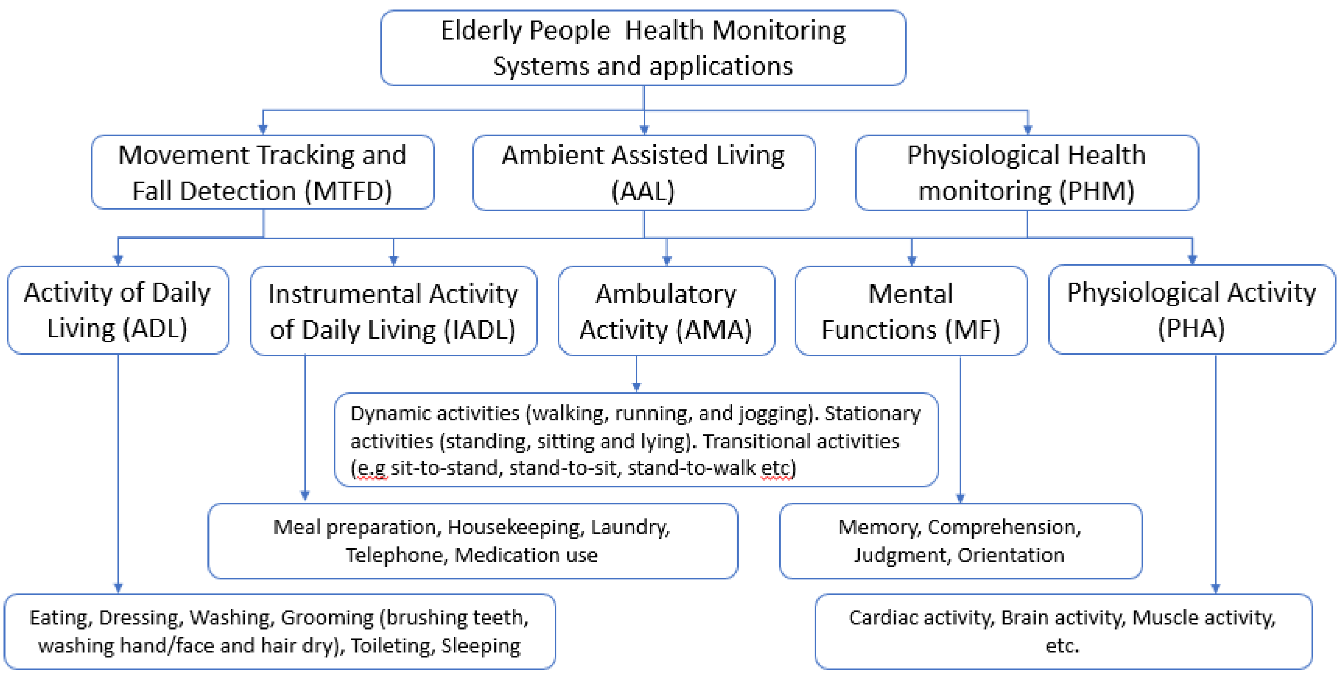

Figure 10: Taxonomy of human activities

6.1 Human Activity Recognition

Human Activity Recognition (HAR) is a process that involves the recognition, detection, interpretation, and examination of human activities. It mainly focuses on the movements and actions that humans make in their daily lives. The data collected from these actions and movements is collected through different wearable sensors and devices which can be utilized in several aspects which can make our daily life better and convenient. Vision-based devices such as cameras, video recorders etc. can be fixed in a certain place to track the movements of a person. Over a certain amount of time, enough data can be gathered to identify the movement of a person against certain action. Similarly, wearable sensors such as motion detectors, compass, accelerometer etc. can be attached to a person on different body locations and movement data can be gathered. The gathered data from these devices is then fine-tuned to remove any redundancies before feeding it to a data-processing model. In the recent years, HAR research has attracted significant attention because of its advantages and widespread applications. These widespread applications include (but are not limited to) fashion, smart homes [184], [195] self-driving cars, surveillance [185], [196] and healthcare [197]. The ability to recognize and detect human activity has been an important concept in the field of machine learning [198]. Different Human Activity Recognition systems have been designed to automate these applications; however, building a fully automated HAR system can be a very difficult task because it requires a huge pool of labelled data and efficient data classification models. Moreover, it is very difficult to accurately classify movement data as a single activity can be performed in multiple ways and different activities can be performed in similar ways. Nonetheless, progress is still being made in HAR, as hybrid models are being introduced which can efficiently differentiate between activities hence leading to a better classification of features[199]

An activity is recorded using varying modes like video cameras, RADAR, wearable physiological sensors, device-free sensing such as Wi-Fi, acoustic sensors etc. [200], [201]. Contemporary state-of-the-art has divided these modes into vision-based devices and body worn sensors. The vision-based devices harness modes like video camera to capture on-going activity and are currently being employed by numerous security applications [186], [202], [203]. However, they often suffer from veracity related issues due to camera angle, background and more importantly, they lack an ability to differentiate between targeted objects and other similar moving objects in the area of interest. For instance, a video camera is placed to capture movement of a patient in a room but it also captures activity of people other than the patient [185]. In such scenarios, vision-based approaches may produce inaccurate results for the applications wherein criticality must not be overlooked such as medical health monitoring. On the other hand, wearable physiological sensors mitigate such issues by stipulating correct information by least involvement of unwanted medium [193]. Wearable sensors like gyroscope and accelerometer sensors are worn on different parts of a human body to produce 3-axis orientation acceleration, respectively. Besides this, sensors are comparatively less expensive, environment-friendly and hold the potential to produce multi-level data resulting into a precise information [195]. Presently, ubiquitous sensing that focuses to discover knowledge from data collected via pervasive sensors is considered as a hot area of research [193]. Such kind of activity recognition is employed in two different forms, external and wearable sensors [201]. In external sensors, a predetermined point of interest is selected to place devices that capture voluntary interactions among user and sensors [204]–[208]. Whereas wearable sensors are attached to the user. Particularly, embedding powerful sensors in smartphones for human activity recognition (HAR) is receiving major attention the scientific community in order to meet escalating demands in certain areas including pervasive and mobile computing, context-aware computing etc. [186], [193], [203].

6.2 Activity of Daily Living

Lu et al. [209] proposed a feature engineering-based approach for efficient data classification. The daily life activities were divided into countable and uncountable activities. Countable activities were categorized as activities which involved fewer gestures such as, walking, sitting, eating, smoking etc. These activities involve a fixed number and iterations of gestures. Whereas uncountable activities were considered as the activities that involved complex and uncountable gestures such as, dancing, exercising etc. Even in some cases, walking can also be considered as uncountable activity. The features to be extracted were selected based on SFFS while 3 features were newly introduced. Using Sliding Window 9 features were extracted against every activity using publicly available DaLiAc dataset and self-gathered (AmA) dataset. The features extracted were based on every activity's specific patterns. The extracted features were tested on conventional M.L models such as, KNN, SVM, GBDT and Random Forest. The results showed a huge boost in classification accuracy as compared to conventional state-of-the-art M.L approaches mentioned before. However, there are certain limitations of Sliding Window such as, the computational cost. Cost can be minimized by increasing the window size; however, this will affect the accuracy of feature extraction. Moreover, as mentioned before, same activity can be performed in multiple ways and vice versa and this method does not take this factor into account.

6.3 Ambulatory Activity

Chen et al. [210] proposed an Attention based Bidirectional LSTM (ABLSTM) which used a Bidirectional LSTM (BLSTM) to train data in multi-directions. This approach is based on Wi-Fi data thus involving the need to of BLSTM which can process the state of signal data before and after processing. 2-layered BLSTM is used with one layer directing the data forward and the other one redirecting the data backwards. The output from the BLSTM is passed as input to the Attention Model. Attention Model focuses on the certain features of data which are of interest based on some speculations. These speculations involve the scoring of vector data using ReLu function and then passing through the Softmax layer for classification. The results showed superior classification accuracy compared to other similar approaches. However, the experiments were based on a single channelled Wi-Fi device without real-time data collection. These 2 factors can have a huge impact on accuracy of proposed system. Real-time data involves multiple type of interferences on the readings which can be caused due to a certain environment or magnetic interference. The dataset used for this was based on a single user data and dataset itself was supervised. A lot of potential work can be further done on this approach. Though supervised learning has had a lot of focus in past research because labelled data is not available in abundance, hence recent approaches mostly focus on semi supervised data. Zhu et al. [211] proposed a novel Deep LSTM (DLSTM) approach for efficient feature recognition. Both, labelled and unlabelled, data are used to train the model to detect human activities using smartphone sensors. Deep LSTM involves multiple LSTM layers between the input and output layer. The raw data is passed through the augmentation phase to increase the amount of data and Gaussian noise removal is performed to filter any inconsistencies in the data followed by the extraction of low-level features. These low-level features are dropped out and the rest of features are passed to DLSTM for high-level feature extraction. The unsupervised data loss, which involves unlabelled data, is calculated and is labelled based on some predictions. The results of the proposed approach were benchmarked against the UCI dataset. The results showed its supremacy on other semi supervised learning methods. However, this approach was performed in a controlled environment, in an uncontrolled environment where a single activity can be performed in multiple ways or different activities can be performed in similar way the results may vary.

In recent study, Wang et al. [212] proposed a hybrid 1 dimensional approach. Data from multiple sensors is passed through a Convolutional neural network and the output is passed to LSTM module which classifies the data. The main achievement of this approach is the identification of activity transition along with activities in general. Most of the proposed works don't consider this factor into account wile designing an approach but in human behaviour recognition this is an important task. Moreover, activity transition detection has a significant effect on the real-time movement recognition. The data from 2 sensors (accelerometer and gyroscope) is combined into a 2d array and then passed to the CNN. The respective CNN is a three-layered architecture with 3 hidden layers, each consisting of a convolution layer and a pooling layer. The output from the CNN is passed into the LSTM module in the form of a vector. The features extracted from LSTM are passed to a fully connected layer which undergoes the process of Batch

Normalization and finally forwarded to the Softmax layer for classification. The results of this approach were benchmarked against the publicly available HAPT dataset which already contains the activity-transition data. The results showed that not only this approach had better activity recognition rate than other Deep Learning models such as, CNN, LSTM, CNN-BLSTM and CNN-GRU but also had better activity transition recognition rate. The limitations of this approach lie in the fact that only basic activity transitions (laying-standing or sitting-standing) were identified. Complex activity transitions such as, walking-smoking, driving-eating or sitting-reading may be a different case. Moreover, multiple users may have different movement on activity transition while this study is based on a smaller number of people's movements.

Xu et al. [213] proposed a hybrid neural network approach (InnoHAR) which combined RNN with Inception Neural Network (INN). INN consisting of various deep layers has multiple convolution layers parallel to pooling layers which forms an inception layer. These convolution layers are a matrix of 1x1, 1x3 and 1x5 respectively. The main idea behind the inception layer is to allow the filters to select required size itself rather than wasting resources. The output from the INN is then passed through 2 GRU layers for better time efficiency. The results tested on 3 public datasets showed better results compared to the state-of-the-art DeepConvLSTM model and CNN model. However, this approach considered the already available pre-processed datasets and did not experiment on the real-time sensor data which requires additional modules such as noise removal and data segmentation. However, INN has poor initialization which requires a lot of computation to get over it and minor changes to the model require retraining of data which is costly. A fine-tuned CNN can achieve same performance, which is the reason INN is not used much in state-of-the-art approaches.

6.4 Physiological Activity

With the increasing importance of HAR in IoT and daily life comforts, it is being applied significantly in the Internet of Health Things (IoHT) environment as well [188]. HAR is being used to help the patients with *psychological and paralysis issues*. Moreover, HAR is being used for patients with congenital diseases and conditions, especially for the children with motor disabilities, to encourage them towards physical activities [214], [215]. HAR is also being used to detect abnormalities in the Cardiac patients [216], it is even used to detect early signs of sickness and illness [217]. Another aspect of HAR includes the monitoring of elderly patients to detect their physical state. Monitoring elderly patients by attaching sensors to different parts of body or observing the patient's movement through a camera [218] can help collect motion data which can be used to predict irregularities in a patient's condition e.g. if the patient has fallen, is standing, is lying, is walking or running etc. Collecting this data and implementing an interactive method to observe their movements has a significant impact on the health-monitoring of elderly patients.

Figure 11 outlines the block diagram of individual human activity recognition system.

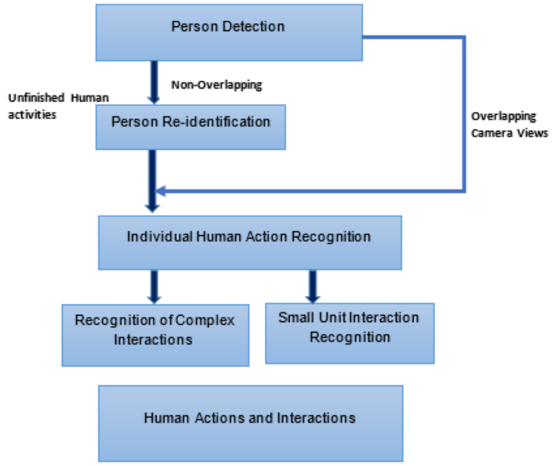

Figure 11 : Block diagram of human activity recognition

6.5 Representation of Human actions

Approaches based on motion and appearance are widely used in methods of vision-based identification of human action. Representation of incoming human actions as feature vector is an essential step for recognition of actions. Throughout the literature, silhouette-based, motion-based, body part-based, frame-based, and interest-point-based approaches to representation of actions are very popular.

In previous studies, motion feature for the representation of action was derived from input videos. The approaches to describe the motion by extracting silhouettes are very common. In these approaches, activity features are extracted from human silhouette. In general, these methods are based on background subtraction method. Motion energy image (MEI), Motion History Image (MHI), Localized motion energy image (LMEI) and NWFE are some main silhouette-based feature representations methods. MEI and MHI [219] are two of very important silhouette based features for the representation of human movements. Spatial motion energy distribution is extracted at the same time with MEI and labelled as LMEI [220]. Singh et al. [221] determined directional vectors (DVs) by describing the boundary of human silhouettes with chain codes. Wo and Shao [222] proposed to represent human actions by silhouettes building of correlogram matrix from pose sequence and named BoCP .An extension of MHI is proposed by adding inversed recording and gait energy information. The results are further improved by fusing BoCP with extended MHI. Key poses of silhouettes to produce the descriptor are represented by cells and grids. The feature vector is modelled by computing the parameters of cells and grids. The key problem of silhouette-based approaches is the computation of silhouettes which in not robust to occlusions. Such methods achieve good results only in controlled environments.

In addition to the approaches focused on silhouettes, other motion-based techniques extract motion descriptors straight from consecutive images. Motion binary pattern (MBP), optical flow, volume local binary pattern (VLBP) and weighted optical flow are some of the popular motion based techniques. Motion Binary Pattern (MBP) is a motion descriptor for the representation of multi-view actions. MBP is the combination of VLBP and optical flow. Kihl et al. [223] proposed to compute the motion descriptor with an optical flow field encoding step on input images. They conducted half-wave rectification on the optical flow vector field and the descriptor proposed is called SoPAF. Histogram of oriented optical flow features are extracted to represent human activities. Motion and pose information from frames sequence is derived by Mukherjee et al. [224] and the resulting feature is named histogram of weighted optical flow (HOWOF). Optical flow-based technologies are noise-sensitive, change of motion and scale. Optical flow variations can be used to avoid aforementioned problems.

Recently, Long Short Term Memory (LSTM) networks have shown propitious performance for the recognition of human actions in 3D skeleton sequences. These approaches mainly utilize the whole skeleton as input to the network. Often, part-based human skeletal are used as input to LSTM. They divided to skeletal into five sub parts and separately fed them to five subnets. The Original LSTM based approaches model dependencies and dynamics in sequential data by incorporating information from all joints; Liu et al. [225] proposed to limit the sequential data by limiting the number of joints to informative ones. Human actions are represented by combining the movements of skeletal joints. Human body part-based methods require robust tracking of body parts which is challenging task in occluded environments. If body parts are detected correctly, these approaches perform very well for action recognition tasks.

Frame-based feature representation is another popular technique in which the temporal relationship among images/frames is consider. HOGs and STIPs are among the most acknowledged frame-based feature descriptors. Computation of frame-based features is a direct process and is useful for images that do not involve rapid local variations. The combination of frame-based and temporal features has been used in literature to incorporate motion information. Initially, Histogram of Oriented Gradients (HOG) was proposed for the detection of human from an image. Later, human action recognition has been performed by combining HOG with other descriptors. An extension of HOG named 3DHOG is proposed achieving robustness to occlusions and multiple points of view. Cao et al. [226] proposed to combine HOG along with HOWOF for representation of the actions.

7 Data Security and privacy

7.1 Security and privacy threats in remote health monitoring

A reliable remote health monitoring must be robust against all types of the security and privacy threats. Some of the common threats are listed as follows.

- **Decentralized data collection and transmission framework.** The limited lifetime and low computation power of sensors in a decentralized system put extra limitation on the design of security systems. In this regard, lightweight symmetric encryption algorithms and elliptic-curve cryptography algorithms have been proposed to provide data security at the sensor end. Furthermore, the transmission protocol in the decentralized system should provide efficient data sharing schemes such that the data is preserved without any loss of information. The key shared by the authorized units of network to decrypt the encrypted data must be secured. Replacing the sensor after they are removed temporarily for battery recharge need extra attention as the attacker may get physical access to these sensors.
- **Data collection and processing.** A reliable health monitoring system requires that the data is collected and stored on high-speed networks. The hospitals may utilize the services of a third-party storage server for this purpose. This third-party honest-but-curious entity may be interested in learning the information in the data. Therefore, the data encryption scheme is designed to encrypt the data before storing it in the storage database provided by third party. However, the processing on encrypted data sometimes do not give the same results as obtained by processing the raw data. To tackle this problem, some encryption schemes are proposed that encrypt the data in way that the computations over both encrypted data and the raw data yield same results, for example. homomorphic encryption [227].

7.2 Requirements of reliable remote health monitoring system

The reliability of a remote health monitoring systems may depend upon the following aspects.

- **Data access control.** The system must grant selective access of the patient data to various parties. The medical data must be accessed only to medical staff and can be accessed by anyone other than medical staff. A customized policy should be provided that is decided by the patient.
- **Scalability.** The security system must not impose high computation and storage load on the whole remote monitoring system. The policy should be updated continuously with the increase in the number of users. Nevertheless, the security system should also be scalable.
- **Flexibility.** In some cases, the patient may not be in a situation to give consent about specific treatment decisions. For example, the patient's data need to be shared with other hospitals and healthcare providers in emergency situations with the patient in critical condition. The system must allow someone else to provide necessary input on behalf of the patient.
- **Accountability.** The security system must be aware and intelligent enough to identify the staff who try to breach the security and privacy of the patient's data. This information can be served as evidence in the court of law.
- **Confidentiality.** The security system must limit the use of data and restrict to authorized users only. The data storage devices should be equipped with the functionalities that can ensure these functions.
- **Integrity.** The integrity of the data against unauthorized modifications during storage periods is very important to ensure the quality of data. Any attempt of unauthorize access and modifications in the data must be timely detected.
- **Dependability.** The data must be available all the time whenever it is necessary. Unavailability of the data at the critical time may cause threat to the patient life. The system must be reliable, dependable and operable in real-time.

7.3 Vulnerable holes in remote health monitoring

The remote health monitoring requires continuous reliable systems for proper monitoring of health attributes of patients. The major parts of such systems include network of sensors, wireless communication channels, database that may be central or cloud storage, and interfaces. Each of these parts are prone to attacks and have explicit limitations that need to be considered.

7.4 Safety and Security considerations

The three main considerations of a safe and secure remote health monitoring system include privacy, integrity and authenticity to provide timely and appropriate diagnosis and treatment without abusing privacy of patient's information. These properties rely on different aspects of a remote health monitoring including [227]

- Incorrectly calibrated or non-calibrated medical devices produces unreliable data.
- Insecure database and interface of transmission of data may increase potential of attacks.
- Keeping data from being manipulated by unauthorized applications that utilize the same database.
- Unauthorized access to the database.
- Keeping or storing data in the database incorrectly, for example, giving incorrect indexing the patient data.

- Low security and privacy of the tele-consultation interface may lead to different attacks such aborting the session, learning sensitive information or disrupting the diagnosis and treatment of patients.

7.5 Security and Privacy in Implantable Medical Devices (IMDs)

IMDs are small electronic devices that are implanted inside the patient's body to monitor the medical condition, to provide treatment or to improve the functionality of a specific body part [228]. Examples of such devices include pacemakers, defibrillators, neurostimulators, and drug delivery system. The Figure 12 shows illustration of the pacemaker IMD. These devices enable different applications such as constantly monitoring patient's state. With these aided benefits, these systems come with a cost of security and privacy risks for the patient. In some cases, security, and privacy breaches of these IMDs can put the life of carrier patient at risk. The U.S. Food and Drug Administration (FDA) states that the intentional attacks on IMDs could be very difficult to detect as compared the accidental ones. Furthermore, the data shared by these devices is very sensitive medical information that requires extra protection as per the rules of European and U.S. directives. The major security risks in IMDs include vulnerable wireless communication channels that makes the remotely monitored implant device exposed in the non-medical environments. In some cases, the eavesdroppers would simply listen to extract sensitive information, such as signals, diagnosis conditions, and personal data, from these channels. Therefore, the new generations of IMDs require sophisticated security systems that guard against the confidentiality, integrity, and availability breaches. The security systems must consider two constraints of these small implantable devices, 1) the inherent limitation of energy, storage, and computing in these devices and 2) should consider adequate balance between the safety of the patient and the security level offered. The recently developed IMDs have been incorporated with communication and computing capabilities, usually called telemetry. The functionality modes of the IMDs can be classified as normal and emergency.

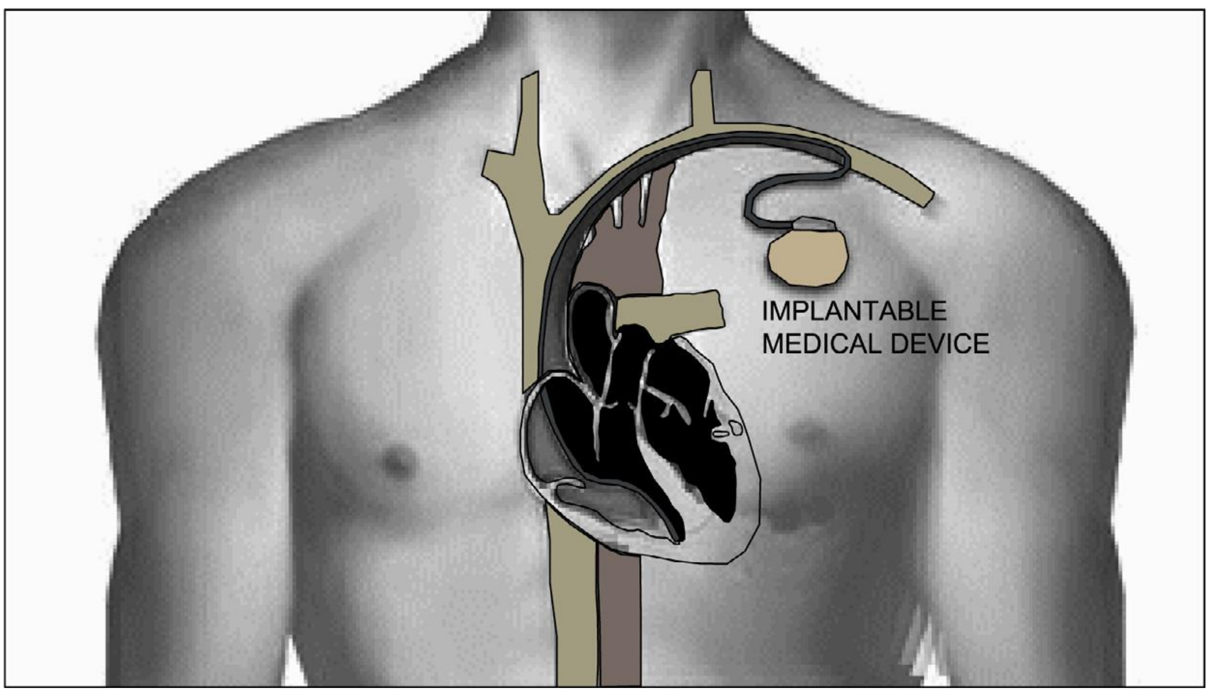

Figure 12 : Pacemaker IMD [Source: [228]]

Table 6 : Attack properties and threats in the IMD domain [source: [228]]

Attack type	Security Property	Threats
Spoofing	Authentication	Impersonate the programmer Impersonate the IMD Impersonate the external device
Tampering	Integrity	Patient data tampering Malicious inputs Modify communications
Repudiation	Non-repudiation	Delete access logs Repeated access attempts
Information disclosure	Confidentiality	Disclose medical information Determine the type of IMD Disclose the existence of the IMD Track the IMD
Denial of service	Availability	Drain the battery of the IMD Interfere with the IMD communication capabilities Flood the IMD with data
Elevation of privileges	Authorization	Reprogram the IMD Update the therapy of the patient Switch-off the IMD

The attackers are grouped as passive attackers, who only listen to the channel, and active attackers, who can send, block, or modify the information exchanged in addition to the passive capabilities. The different types of attackers are illustrated in Figure 13 . The attackers may also try to modify the IMD-specific information for their personal benefits, for example.

- Manipulating distance between the attacker and the IMD device
- Misusing the IMD functions
- Manipulating the information about patient's condition

The classification of different security systems that have been developed to guard IMDs against attacks are given in Figure 14.

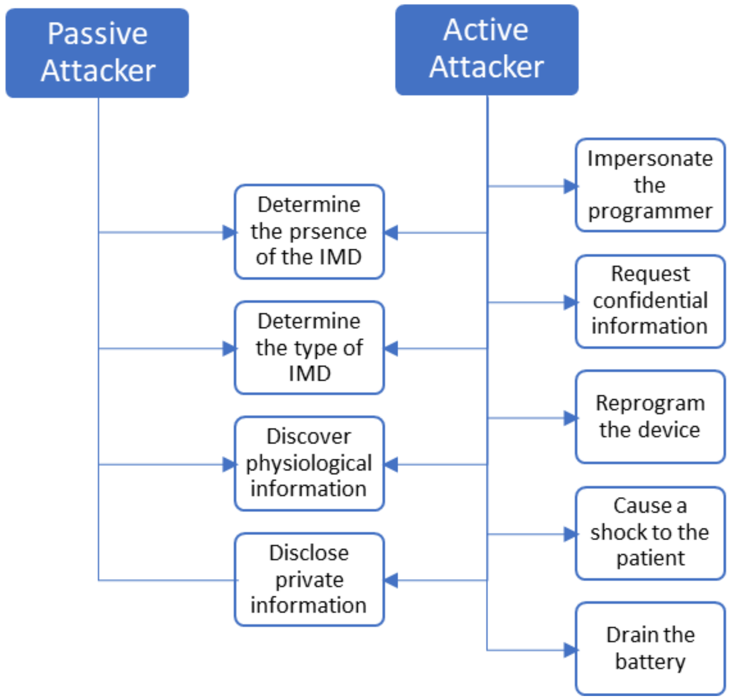

Figure 13 : Passive vs Active Attackers [Source: [228]]

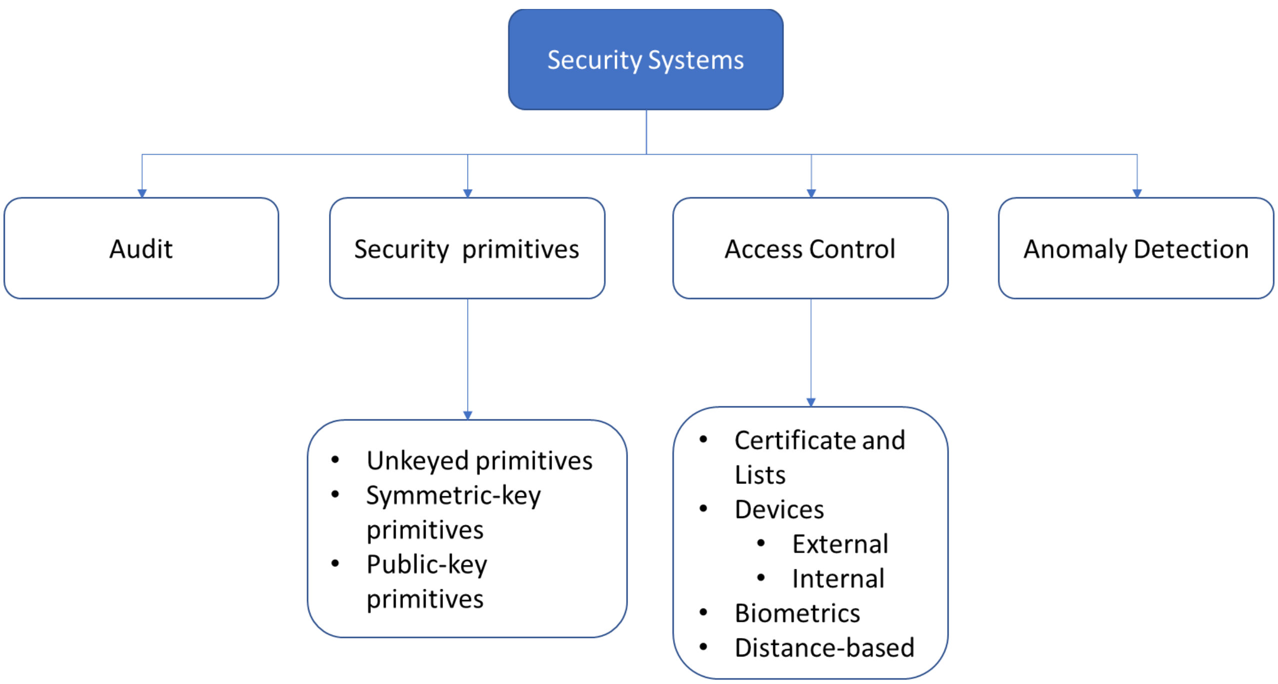

Figure 14 : Classification of security systems for IMDs [Source: [228]]

7.6 Data Privacy and Security in Cloud Computing for remote healthcare monitoring

Cloud computing is one of the most emerging technologies used these days that provides a service through which one can use computer resources online on-demand [229]. There are different components of different cloud computing models: software infrastructures, end-user computers, access control framework, etc. The data and infrastructures on Cloud computing are very beneficial as all the data is available over the cloud for different applications. However, this benefit can give rise to different types of challenges, and risks that can harm data security [230]. Many privacy, functionality, and reliability issues have been noted on cloud resources. These threats may cause due to lack of security checkups, continuously leaking user credentials, or malicious criminal attacks.

Cloud services have become essential solution to provide various services to users such as cloud as virtual desktop service, cloud as application services, and cloud as database service. The service provider offers different resources in the form of hardware, software, and network to the end users. However, the lack of integrity and privacy opens new challenges. In figure 1 to ensure security, data integrity and cloud security are integrated. In data integrity user authentication and authorization in the form of access control lists (ACLs) and MAC access control lists (MACLs) are mandatory to achieve the required minimal security. To make the cloud secure, prevention of data loss and data privacy are ensured with the aid of following concepts.

Data privacy: *Regularity compliance* measures the security program that is working to meet the specific set of security standards to continue for a particular amount of time. *Data sovereignty* is the idea that **data** are subject to the laws and governance structures within the nation it is collected. *Data remanence* is the residual representation of digital data that remains even after attempts have been made to remove or erase the data.

Data loss: *Bring your own device (BYOD)* refers to the trend of employees using personal devices to connect to their organizational networks and access work-related systems and potentially sensitive or confidential data. Personal devices could include smartphones, personal computers, tablets, or USB drives. *External Threats r*efers to the risk of external user from the outside of a company who attempts to exploit system vulnerabilities through the use of malicious software, hacking, sabotage or social engineering. *Internal Threats r*efers to the risk of somebody from the inside of a company who could exploit a system in a way to cause damage or steal **data**. These kinds of **threats** are particularly troubling, as employees are expected to be trusted individuals that are granted extended privileges, which can easily be abused.

A survey named Fugue survey [231] concluded that due to improper security setup daily, such incidents happen on cloud systems. With the passing time, a variety of attacks are encountered on cloud computing systems, including [232, p. 20] account hijacking, lack of cloud security strategy, insider threat, limited visibility of cloud usage, and many more. There must be some preventions for these threats, especially when data sensitivity is the primary concern. Here we discuss the latest techniques proposed to overcome the privacy and security concerns.

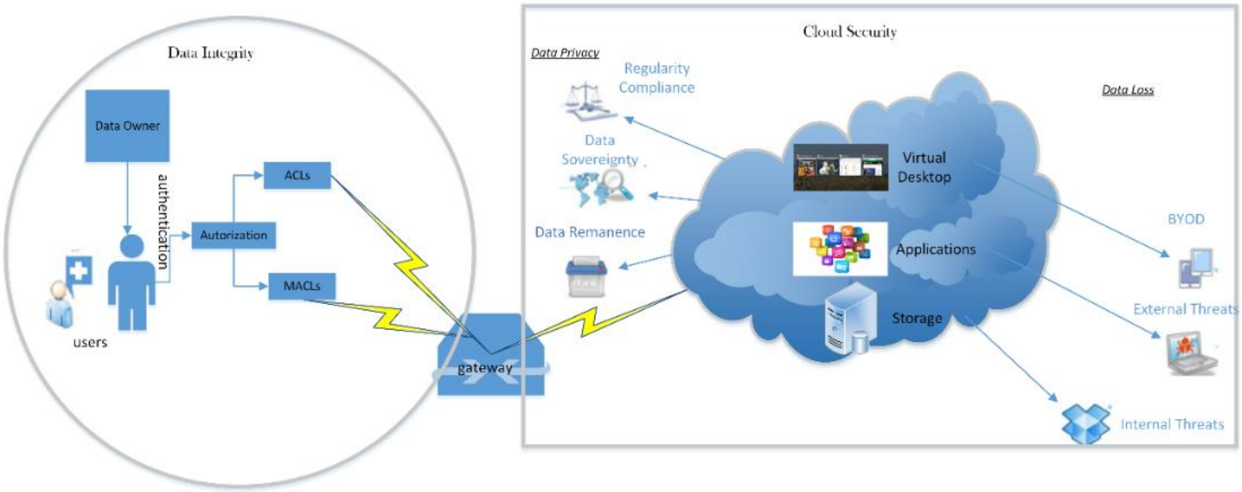

Figure 15 : Major Security and Privacy Issues in Cloud Environment.

The new advancements in interconnection healthcare data, monitoring, prevention measures about illness, and medical knowledge are essential requirements. These fundamental requirements have been solved with the use of cloud computing in healthcare. However, these healthcare data security issues are significant complications for cloud computing systems. The privacy and security issues caused by using cloud computing among healthcare providers to share healthcare-related data has been discussed [233]. There are many issues regarding this aspect. However, the microservices approach that provides managing and sharing healthcare data helps to deal with such problems. A novel model that notifies the data breach and preserves healthcare data privacy is proposed in this article to tackle cloud computing security problems.

Cloud computing in the healthcare sector is growing day by day as there will be a complete patient's medical history available for real-time. However, the hosted healthcare data within the cloud can face different privacy and security issues. Blockchain technology has been proposed [234] for the protection of healthcare data hosted within the cloud. On one side, blockchain technology can help secure the privacy of healthcare data present over the cloud. On the other side, some challenges can be faced by using blockchain for healthcare data management and privacy. As a solution to blockchain limitations, it is suggested that the healthcare data should be kept off-chain. In such a way, it can be erased, secured, and corrected when it is appropriate. Simultaneously, these healthcare data's accuracy and authenticity can be checked with the stored healthcare data's immutable hashing over on-chain.

The advancement of technology in results provides an excellent opportunity to the audience as Cloud computing. With the cloud computing paradigm, an end-user can access several resources present over the cloud at any time and place. However, the massive distance between the end-user revealed some drawbacks of cloud computing, such as high latency. The issue and its solution which is fog computing, has been discussed [235]. Fog computing is thought to be a supplement to cloud computing. Fog computing demands a variety of privacy and security requirements. These requirements include Storage data services (integrity verification, dynamics support, public audacity), Sharing data services (Access efficiency, Authorization revocation), Query data services (Secure searchability, dynamics support), and Computation data services (Verifiability of outputs). These requirements can be used to solve the challenges of data privacy and Security in fog computing.

To gear up the performance needs, cloud computing comes up with an extension known as P2P cloud systems. These cloud systems consist of decentralized architecture and can handle the cloud resources at a minimal cost. However, a wide range of threats like big data processing and protecting sensitive and private information is being noticed daily due to the heavy use of such cloud computing systems. A big-data storage solution is provided [236] after analyzing the existing layered architecture. Also, the work explored the working of P2P cloud systems concerning big data analytics and its processing. With the detailed analysis of such systems, a hybrid mobile cloud computing model and its simulation are proposed to normalize the use of such mobile cloud systems in healthcare cases. The use of mobile cloud computing systems benefits from holding and analyzing big data.

With the rapid advancement and popularity of cloud computing, various types of vulnerabilities and threats has increased. The key issues in cloud computing is privacy and data integrity as data is stored on different geographical locations. To address the key issues, Genetic Algorithm (GA) based new model CryptoGA has been proposed [237]. For encryption and decryption, GA has been used to generate keys that are combined with the cryptographic algorithm to guarantee the integrity and privacy of cloud data. Different datasets have been used to evaluate the proposed model. Experiments have been performed and performance has been judged on different parameters like throughput, execution time, avalanche effect and key size. Results show that the proposed model preserves the users' data privacy and ensures the integrity against the unauthorized users. Proposed model performs better than the traditional models like blowfish, DES and others.

Recently in healthcare services, the security of disease prediction and medical data storage becomes a significant part in cloud computing. Day by day, a large amount of data has been produced in the healthcare with the rapid development of healthcare devices. To secure the large amount if data from various attacks, cloud computing technology has been utilized to store, process and handle such data in large amount. Cloud computing based conceptual structure has been proposed [238]. Initially, datasets based on medical images ad query images has been collected for image processing. The collected images are transferred to the cloud using IoT devices and stored into the cloud. The medical images have been passed through the process of encryption to eliminate the threats before transmission. Back Propagation (BP) neural network and chaotic system is used to carry the encryption process. The images are transferred to the cloud platform after encryption where medical diagnosis takes place. The proposed algorithm called Fuzzy Convolutional Neural Network (FCNN) has been used for diagnosis process which classifies the images into normal and disease affected images. The resulted information has been sent to the experts or doctors from cloud by using IoT devices. The experiments have been performed to evaluate the proposed algorithm using BRATS and Brain MRI datasets. The results show that the proposed algorithm outperforms the existing algorithms such as Naïve Bayes, Decision Tree (DT), K-Nearest Neighbor (KNN), and Artificial Neural Network (ANN).

The providers of cloud service provide space for shoppers to network to other system of information management by moving native management system into the cloud services in cloud computing. Effective and strong use of resources has been provided by this service and it cuts down the expenses as well for the providers. But the cloud suppliers faced the limitation of preserving the information economically and secure within the cloud. To maintain the privacy, suppliers must encrypt the information before moving into the cloud. Crypto graphical storage system has been used to overcome the limitation which is based on file division and file-block key. But this system also has the issue of updating and sharing of user revocation. An anti-collusion information sharing scheme has been developed [239] which provides the secure private keys. Team manager gives keys to new customers using secure communication channels and certified authorities. Therefore, revoked user is unable to retrieve the information even using un-trusted clouds. Such scheme manages the revoked users easily.

8 Research Opportunities and Challenges

In the relevant literature, the research studies propose different approaches and provide various future research directions opening new research opportunities for the researchers in this domain. This section presents an overview of these research opportunities and challenges.

8.1 Need of Advanced Sensory and Monitory Systems using IoT

The advent of IoT devices and their ubiquitous integration in a large variety of computing platforms has marked a new era in many applications fields as well as in health care system, where several patient-care services are continuously provided and added to the current offer. For instance, the various applications like blood pressure sensing, heartbeat monitoring system, glucose level sensing using IoT with computing technologies brings great improvements in health care systems. Moreover, sensors-based bed can be used to solve the respiratory distress problem in infants [137]; or even the evaluation of perinatal outcomes in pregnant women may be a future challenge that can reveal further confusion in such conditions such as normoglycemia [64]. To monitor foetal movement, a wearable belt can be designed and developed with optical fibre sensors that can reduce motion artifacts, classify moment type [102].The wide adoption of the IoT based monitory systems increase the comfort and put the patient in the heart of the healthcare systems, but pose also some serious security and privacy issues avoiding the acquired and personalized data to be hacked and misused by non-authorized persons. This adoption goes through several phases among which the first is the comparison between the existing systems and the IoT based smart systems. This comparison may provide useful information allowing to monitor the reliability issues, area of application, implemented technique and technology [90]. **Error! Bookmark not defined.**According to study, more sensors may be adjusted to monitor the heart rate and oxygen saturation along with temperature monitoring [170]. Such cited issues and opportunities present a good starting point for potential research studies in the future.

8.2 Advanced Techniques of ML/AI in Healthcare Systems and their Explainability

Since the recent research work employing ML/AI approaches have shown extraordinary results in terms of accuracy and classification often surpassing the human capabilities, the use of ML/AI techniques in sensitive medical applications is less and less questionable. However, ML/AI techniques are data-driven and many challenges related to the acquisition, preparation and processing of these data before their use for training purposes should be carried out as well as the steps providing the decision explainability of these "black box" approaches allowing their easier adoption among healthcare workers. As labelling of acquired data for deep learning and ML is time-consuming and expensive, the supervised learning based algorithms need proper refinement and improvement to enhance for instance the pregnancy outcomes and allow such techniques to be incorporated for real-world clinical care [76], [169]. Moreover, to enhance the accuracy of complex indicators, other ensemble classifiers can also be studied, such as those related to urgency such as admission in intensive care unit. Some other examples of use of ML/AI techniques in healthcare systems suggested in the recent literature are listed here: the study on diseases related to psychological disorders in pregnancy [240]; to develop operator independent system [168]; or to monitor the behavioural changes in children, more mind related games can be added [167]; for Mobile apps for developed systems can be created for other operating systems their users as well [108]; to predict the congenital anomalies in the foetal, risk factors like pre-eclampsia can be associated with other pregnancy complications [109]; to improve the prediction accuracy of model, time series of historical data for physical examination can be used [111].

For supervised learning approaches which are used in healthcare systems as well for classification purposes, deep learning approaches are recommended to be used in the future research studies as these techniques are being widely used in other areas and their performances in terms of accuracy and other standard research evaluation measures for classification have proved to be highly effective. So, there is a need that deep learning-based algorithms such as Convolutions Neural Network, Recurrent Neural Networks and Long Short Term Memory algorithms should be used in future research studies in healthcare systems (for mothers, elderly persons, and infants). AI-based systems show that they can outperform humans in certain analytical tasks. However, in sensitive areas that affect medical, ethical, and societal aspects, the need to explain how AI takes its decisions (explainable AI - XAI) is paramount and constitutes a challenge that must be addressed for this technology to be adopted with trust.

8.3 Lack of Availability of Real-World Datasets

Another limitation faced by the researchers is the availability of real patients' data from clinical care, hospitals and medical institutions, as their patients are resistant to share publiclytheir personal data and reports. Since the medical data of patients consists of health conditions, personal information, related treatments and diagnostic reports, and are very sensitive, any mode of misuse and hacking by unauthorized persons can easily modify them which may lead to wrong treatment or diagnosis of diseases and may fatally cause increases in mortality rate [91]. It is also suggested that the databases comprising video records of monitoring a variety of movements related incidents during sleep and awake should be increased, because they represent a wealth of information necessary for health-care in near to medium term future [137]. In addition, the data labelling in health-related studies is very sensitive and thus high skill level involvement and knowledge for labelling of class attributes need experts to be hired or involved in research studies for such sensitive tasks. In addition, the common people should be encouraged and involved to provision data for research studies. In this sensitive mission, it is essential to teach about the anonymization of the patients' and/or volunteers' records resulting in such a form of data records making impossible to discover the identity of the involved individuals. This information may help and motivate them to volunteer themselves for provision of their data for research studies.

8.4 Research Issues raised due to IoT based Systems.

With the rapid advancement of IoT, some challenges like data management, security, literacy, energy etc. require to be sorted out [241]. Management of data needs storing, and processing capacities as large amount of data are continuously generated and should be processed in time. One of the possibilities to address this challenge is to provide enough cloud storage to manage and store all data properly. On the other hand, distance data management implies more stringent security protocols which are also challenging tasks. Indeed, with a myriad of connected devices in different operating environments the issues related to the compatibility of network security may occur. Moreover, security challenge may be solved by motivating the users to practice and embed built-in features in the used devices and to push more intelligence to the edge (closer to the source of data). Consequently, by embedding more intelligence in edge devices, power requirements of these IoT devices and thus needed energy supply for processing purposes will be increased. However, the communication, which is generally the most power consuming task, will be diminished. In addition, data privacy is a big concern as well. This research area is challenging in any field of applications and more specifically in health-related systems. Finally, the above-mentioned challenges and proposed state of art techniques and approaches should be considered and incorporated for data management, data security and data privacy in the healthcare systems for all level patient monitoring and healthcare (infant, maternal, elderly).

8.5 Conclusion

A large number and types of miniaturized sensors are available for measuring vital signals and patients' behaviours. Most of these sensors are in contact with the patient and in some cases require the intervention of a third party such as health worker, which, in addition to the reluctance of patients, limits the large-scale use of RHS. Some works show the increasing interest in contactless sensors, a technology which has great potential for development and the acceptability of RHMs.

The use of multiple sensors combined with continuous monitoring will generate a large amount of data. To deal with this problem, recent work shows the interest in developing advanced ML / AI techniques to extract useful information as close as possible to the sensor. The use of these ML / AI techniques has the advantage of providing higher precision with the development of new AI algorithms. However, confidence in the results is crucial since it concerns people's lives and thus requires that AI algorithms be interpretable. To train AI algorithms it is necessary to have real world datasets, which implies the importance of the intervention of experts in the field of health to help ICT developers to effectively label these data and to help their interpretability. The manipulation and transmission of patients' personal data poses a problem of confidentiality which is one of the obstacles to the development of RHS and which must be considered very seriously at all levels.

9 References

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