Privacy Preserving Context-Aware Framework for Cardiac Health Monitoring

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Abstract

The impact of digital technology on healthcare delivery services is increasing as new technologies evolve and current technologies expand. These technologies have the potential to provide a platform to reason about the health condition of a patient using relevant contextual information. Context-aware reasoning is particularly important in cardiac health monitoring because of the increasing number of deaths resulting from cardiac diseases. As a result, several efforts have been made to develop intelligent systems for cardiac condition monitoring. Nevertheless, most of the existing systems for cardiac health monitoring are generally based on physiological information, mainly the heart rate or electrocardiogram(ECG) signals, while the few research that does integrate contextual information has not considered the privacy of the patients in the development process. This research proposes a privacy-preserving context-aware framework for cardiac health monitoring using contextual information from the patient's behavior data to facilitate physicians' decision-making.

The framework considers patient's privacy by allowing the user to take control of the data generated from the sensors as information is stored in the user's device and not transferred to any server. Furthermore, the user's privacy is also considered at the algorithm training and model generation stage by adopting a federated machine learning technique. Using federated learning for model development which is a key contribution of this research aims to maintain user privacy by allowing clients from different locations to collaboratively learn a machine learning model without sending datasets to a central server.

In addition, the framework addresses the issue of context acquisition by engaging healthcare professionals in the development process. A prototype tagged "mCardiac" is presented as a proof of concept. The design, implementation, and evaluation of mCardiac was made possible by constant interaction with healthcare professionals. mCardiac was also evaluated with cardiac patients who were asked to use the system to validate the effectiveness of the approach.

Chapter 1

Introduction

1.1 Background

Health monitoring assists physicians in the decision-making process, which in turn, improves the quality of life for patients. It involves the use of digital technologies to monitor the health status of a patient in an intelligent environment. These technologies vary from sensors attached to the patient to sensors installed in the patient environment [2]. Monitoring a patient within the clinical area requires the presence of the patient in the hospital, while outpatient monitoring involves the use of wireless communication technologies alongside digital sensors to transmit patient details to a server [3]. Remote patient monitoring targets different categories of people such as the elderly, chronically ill, and disabled patients [2].

Cardiac diseases such as arrhythmia, stroke, and coronary heart disease have been shown to be managed by monitoring patients' physiological signals in real-time. The symptoms of these diseases are diverse, ranging from minor chest palpitations, chest pain, fainting (syncope), to sudden heart attack, depending on the type and severity of heart disease [4]. Fortunately, with the most recent advances in ECG monitoring and the help of modern mobile phone technology, monitoring patients in remote areas has become easier and more accessible [5]. The most widely used tool for cardiac health monitoring is the Holter monitor. A Holter monitor is a portable and continuous monitoring device used to generate and record ECG signals [181]. Some modern Holter monitors allow users to wear the device while doing their normal activities and can transmit users' details to physicians through mobile phones. Research has shown that Holter monitor could be used to collect and aggregate a large amount of data from patients' biosignals and analyze them to assist doctors in the decision-making process. However, it is essential to note that in order to predict cardiovascular abnormalities, using a specific vital sign such as heart rate, ECG signals alone will not be sufficient to assist physicians in the decision-making process [6]. Hence the research question:

Can context-awareness inform cardiac rehabilitation monitoring?

Based on discussions with a health professional at the early stage of this research, the challenge was posed on the possibility of context-awareness helping professionals in cardiology to understand the recovery of patients during rehabilitation. Context-awareness is an essential part of systems implemented in areas such as Intelligent Environment, Ambient Intelligence, Pervasive and Ubiquitous Computing [123]. The fundamental idea behind context-awareness in healthcare is to develop a proactive and efficient system that can correlate patient's contextual information and adapt to the changes in the patient's condition and environment [144]. This information can be used to enable selective responses such as triggering alarms or retrieving relevant information, which plays an essential role in the healthcare delivery decision-making process. Recently, researchers and software engineers have developed a significant number of systems and solutions using context-aware techniques. Though the goal differs depending on the project and the system requirements, the fact remains that these systems aim to enhance the quality of service delivery. It provides an opportunity for healthcare professionals to assess the health condition of a patient; however, there are a few challenges in developing a context-aware system in an intelligent environment. By "intelligent environment", this work refers to any space or station where artificial intelligence is used to develop a system in order to provide relevant services to the people in that domain [1]. These challenges include context acquisition, energy efficiency, and security and privacy. Hence, the main research question leads to two subsidiary questions, which are presented below and discussed in section 1.2

RQ1: What contextual information is essential for cardiac rehabilitation monitoring?.

To design a better health monitoring system that typically draws information from various sources, there is a need for a better understanding of the contextual properties that impact the design, development, and delivery of such services. Feedback gathered from relevant professionals shows that physical activity recognition is an essential part of cardiac condition monitoring. However, most of the existing technologies for cardiac health monitoring overlook the importance of this information in quality health service delivery.

RQ2: How can we maintain cardiac patient privacy in context-aware system development?

Privacy is one of the top concerns in developing a context-aware system for patient monitoring due to the need to ensure that sensitive patient information is not compromised. Deploying technology-based systems without adequate consideration of patient's privacy often makes service users vulnerable. Moreover, context-aware applications targeting mobile devices could generate the feeling in a user that they are being constantly monitored [132].

This research proposes a privacy-preserving context-aware framework for cardiac health monitoring using contextual information from the patient's behaviour data to facilitate physician's decision-making. The proposed framework uses a federated machine learning approach for activity recognition in order to maintain users' privacy. Federated learning (FL) is a machine learning technique that allows clients from different locations to learn a machine learning model collaboratively without sending their data to a central server. In addition, the framework provides a platform enabling healthcare professionals to offer personalized recommendations following contextual analysis. The research demonstrates the feasibility of the framework by presenting an intelligent and privacy-focused context-aware decision support system for cardiac rehabilitation monitoring (mCardiac). The formulated scenario below was used to help understand the proposed system in a real working environment.

Scenario: Mike was recently discharged from hospital after suffering from coronary heart disease. In order to avoid cardiac readmission, his physician, Dr. Charles, needs to keep in touch with him regularly. However, Mike lives about 20 miles from the hospital, creating a barrier to constant visit to the hospital. In order to frequently monitor Mike's health status and offer personalized recommendations, Dr. Charles needs a platform that will generate and correlate Mike's physiological signals and activity details from a distance. The proposed framework will collect, aggregate and process Mike's contextual information and present it as a decision support tool.

An intelligent analysis of Mike's contextual information will assist Dr. Charles in decision-making and offer a better platform for healthcare delivery services. In addition, it will enable Dr. Charles to understand mike's daily activity pattern, changes in daily behavior, changes in physiological information, and the effects on the recovery process.

1.2 Problem Statement

Health monitoring plays an essential role in handling critical situations, especially for those in remote areas [6]. However, most of the studies on cardiac condition monitoring focus on identifying irregularities in a specific vital sign [126]. This approach may not provide enough information for effective and efficient cardiac health monitoring. Considering contextual information (patient's activity) when reading the physiological parameters can provide an improvement in medical services and assist physicians in the decision-making process [7]. The significant challenges of developing context-aware systems that this research aims to address are (1) Context acquisition and (2)Security and Privacy issue.

Context Acquisition: Context-aware system development starts with the acquisition of contextual information. This process varies based on context source, sensor type, acquisition process, responsibility, and frequency [129].

There are much contextual data to consider when designing a context-aware system for health monitoring; however, not all of this data might be relevant. This context can be made of information from ECG signals, heart rate, blood pressure, temperature, medical profile, oxygen saturation, time of the day, or activity data. A detailed understanding of the relevant context is necessary to understand what the context-aware system should sense and adapt. Crowley [130] stated that designers should only include entities and relationships that are relevant to a system task in order to prevent the system from becoming very complex. This research propose to address the challenge of context acquisition by consulting healthcare professionals through interviews and frequent conversations with people in the healthcare domain to determine necessary contextual information for cardiac condition monitoring.

Security and Privacy: Security and privacy is one of the top concerns in the healthcare industry due to the need to ensure that sensitive information of both patients and staff is not compromised. Health monitoring systems primarily rely on different technologies that can pose security and privacy threats and attacks such as the modification of medical data, denial of services, activity tracking, and physical tampering with devices [131]. Deploying technology-based systems without adequate consideration of security and privacy often makes service users vulnerable. Context-aware applications targeting mobile devices could generate the feeling in a user that they are being constantly monitored [132]. Therefore, the security and privacy of users need to be considered while developing such a sensitive system.

The proposed framework considers the security and privacy of the patient at every stage of development. It allows the user to take control of the data generated from the sensors as information is stored in the user's device and not transferred to any server, thereby allowing the patient to determine who can access their private information. This minimizes the mishandling and the misuses of patients private data. The user's privacy is also considered at the algorithm training and model generation stage by adopting a federated machine learning approach. Federated learning allows different clients in different locations to train a global model without sending their dataset to a central server.

Our initial approach to handling this challenge was to provide a personalized physical activity recognition process by generating a personalized model for each user [128]. In the personalized approach, the user generates a model, and the model is used to recognize his/her activities. One major challenge of this approach is the chances of model overfitting, as the user may not generate enough dataset for algorithm training. Model overfitting is one of the machine learning problems that result when a model does not generalize to the population due to an insufficient training dataset. Generalization is the ability of a machine learning model to correctly classify data not in the training dataset.

Federated machine learning has the potential to address this issue in that it allows knowledge sharing among the generated models while preserving the privacy of the user. In this approach, the machine learning model learns from large and diverse data sets, resulting in a better global model.

1.3 Research Goal

This research aims to propose a context-aware framework for developing an intelligent and privacy-focused decision support system for cardiac condition monitoring [126]. This became necessary after a comprehensive review of the current technologies and techniques used to develop context-aware systems targeting cardiac health monitoring. The framework supports context acquisition, context modeling and storage, context reasoning and visualization, and personalized recommendations. This research demonstrates the feasibility of the framework by developing and evaluating a context-aware decision support system for cardiac rehabilitation monitoring. In addition, a federated machine learning approach was adopted to develop a model for physical activity recognition in order to maintain users' privacy.

1.4 Key Research Contributions

At the initial stage of this research, a comprehensive survey was conducted to investigate different technologies and techniques used for cardiac condition monitoring and management [126]. The results of the study demonstrated necessity for the development of a better system that is privacy-focused and allows the healthcare professional to offer personalized recommendations to the patient. The major contributions of this research are summarized below.

- This research proposes a context-aware framework for developing a decision support system for cardiac condition monitoring in an intelligent environment. The framework aims to improve the existing approach by offering a better intelligent and privacy-focused system.

- A user-friendly mobile app is developed to collect sensor data for algorithm training and can be used for future research. The mobile app is available for both Android and IOS devices. It collects the x-axis, y-axis, z-axis of the accelerometer sensor embedded within smartphones and stores this data on the user's device.

- Federated machine learning technique is adopted for physical activity recognition. This approach allows different clients from different locations to collaboratively learn a machine learning model without sending their data to a central server [127]. The experimental analysis of this approach demonstrates its ability to maintain clients' privacy.

- The feasibility of the framework is demonstrated by designing and implementing a context-aware decision support system for cardiac rehabilitation monitoring.

- The system is evaluated with real cardiac patients and presented to healthcare professionals. The feedback from healthcare professionals through questionnaire attests to its usefulness and effectiveness.

1.5 Thesis Organization

The thesis is divided into seven chapters as presented here.

Chapter two: Presents the literature review of previous works on health monitoring, more specifically on cardiac condition monitoring, discussing different technologies and methods used to develop context-aware systems for cardiac health monitoring. Challenges of developing context-aware systems in the healthcare domain as well as possible areas for improvement are also discussed in this chapter.

Chapter three: Outlines the research methodology. The User-Centred Intelligent Environments Development Process (U-CIEDP) was adopted for the research design, development, and evaluation. The methodology is created to guide system developers in implementing systems that are robust and meet stakeholders' expectations in an intelligent environment. The features of the proposed framework are also discussed in this chapter.

Chapter Four: Focusses on different areas of health monitoring using machine learning techniques. Various machine learning approaches and algorithms are discussed here. Federated machine learning techniques are also discussed, including their ability to maintain users' privacy. Experimental analysis using the federated machine learning approach is also presented. The results of the analysis show that the chosen approach has the capacity to maintain users' privacy.

Chapter Five: Presents the context-aware decision support system for cardiac health monitoring. Details about the system evaluation are discussed in this chapter. The developed context-aware system was evaluated with cardiac patients and presented to healthcare professionals. The cardiac patients were required to put on the Holter monitor and carry smartphones which ran the mobile app to collect data concurrently. The working principles of the system was presented to the healthcare professionals whose assessments of the system were gathered through a questionnaire.

Chapter Six: Presents the conclusions relating to the contributions to knowledge in this thesis and proffers possible areas of future work for further contribution in areas involving cardiac health monitoring.

Chapter 2

Literature Review

2.1 Cardiovascular Diseases

Cardiovascular diseases are diseases affecting the heart and blood vessels [4]. They are usually caused by the accumulation of fat inside the arteries, which blocks the flow of blood to the heart [10]. Figure 1 shows that cardiovascular diseases are the number one cause of death across the globe [11]. The chart indicates that in the year 2016, about 17.65 million people, representing 31% of all global deaths, died as a result of cardiac diseases [11], and this might increase massively in the future [4]. Benjamin et al.[12] reported that about 2,300 Americans die of cardiac disease each day, an average of one death every 38 seconds. The report also stated that cardiovascular diseases claim more lives each year than all forms of cancer and chronic lower respiratory disease combined, and that they cost more than $329.7 billion in both health expenditures and lost productivity. According to the British Heart Foundation report, heart and circulatory diseases cause about 28% of all deaths in the UK, accounting for nearly 170,000 deaths each year - an average of 460 people each day or one death every three minutes [13]. Public Health England reports that healthcare relating to cardiovascular diseases costs around £7.4 billion every year. [14].

As the effects of cardiovascular disease and the financial burden it imposes upon society continue at an alarming rate, Celermajer et al.[15] pointed out that the major challenges in tackling the burden of cardiovascular disease in developing countries are low health budgets and lack of professionals in the field.

Though there are different examples of cardiac diseases, such as cardiac arrhythmias, atherosclerotic disease, and cerebrovascular disease, Celermajer et al [15] state that most of the cardiovascular challenges in the world are due to atherosclerosis. Atherosclerosis is a condition where arteries become blocked with fatty substances called plaques, which can result in a stroke or heart attack [16]. Its symptoms include pain or discomfort in the chest, shortness of breath (dyspnea), fatigue, and nausea. In 2014, Bhatnagar et al.[17] conducted research and discovered that 46% of cardiovascular disease deaths in the UK resulted from atherosclerosis.

Arrhythmia is another cardiac disease that needs paying attention to. A cardiac arrhythmia occurs when the electrical impulses that coordinate heartbeats do not work properly, causing the heart to beat too fast, too slow, or irregularly [16]. Its symptoms include palpitation, weakness, and chest pain.

2.2 Cardiac Rehabilitation

"Cardiac rehabilitation is the non-pharmacological intervention using any combination of exercise, education or psychological support to restore by their own actions, the patient's pre-disease or pre-cardiac event physical, psychological and social level of function" [125]. It is the main aspect of secondary prevention of cardiovascular disease [19], which assists patients in the recovery process and creates an opportunity for healthcare professionals to frequently assess the health status of patients and offer timely advice in order to avoid deterioration, or perhaps death. In addition, it provides training and support which assist patients in returning to their normal work and activities [20].

Gimenez et al.[21] proposed a framework which aims to develop and validate a system for integral community cardiac rehabilitation programs based on technological platform for lifestyle change supporting system. The system

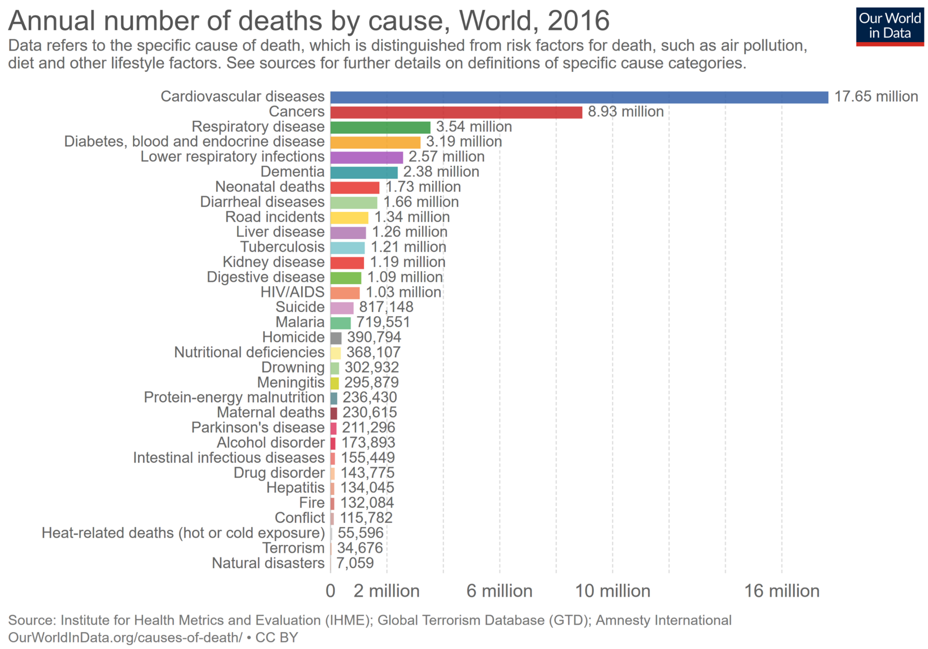


Figure 2.1: Comparison of annual number of deaths caused by different diseases

acts as a personal trainer for the patient, motivating and guiding during rehabilitation. To validate the system, sensors are placed on the patient's chest, and 6 ECG signals are recorded during the exercise. An alarm warning is triggered when ECG frequency greater than the programmed value is detected, when ectopic activity is detected and when there is an increase or decrease in the ST-segment. ST-segment is the part of the ECG from the end of the QRS complex to the beginning of the T wave [23].

Providing a rehabilitation scheme can effectively minimize cardiovascular readmission; however, patients regularly decide not to participate in center-based rehabilitation due to lack of motivation, distance to the rehabilitation center, or lack of time for the working class [25]. To alleviate this challenge, Chatzitofis et al. [24] propose a home-based rehabilitation system, HeartHealth, an exercise-based rehabilitation platform which uses gamification techniques. The system's main function is its ability to record patient movements and compare them against the exercise level prescribed by the medical expert. It consists of two front-end interfaces, the game interface and the Android application. The user-friendly game interface supports motion capturing sensors, while the Android application assists medical professionals in monitoring their patients. The system also has a back-end where the motion data and analysis are stored.

Though the home-based cardiac rehabilitation approach has proved to be effective, safe, and relatively low-cost for patients who are unable to attend the center-based programs, telerehabilitation was recently introduced to complement traditional means of cardiac rehabilitation [26]. A number of authors and medical professionals argue that telerehabilitation is the way forward for cardiac condition monitoring during rehabilitation [27]; [61]; [29]. Telerehabilitation is the use of information and communication technologies to monitor and assess patients during rehabilitation. In this approach, patients are not required to be present at the healthcare center; instead, they are monitored as they perform their normal daily activities.

Advances in technology have enabled the development of different forms of technology-based intervention, such as imaged-based, sensor-based, and virtual reality-based approaches [26]. "Using telerehabilitation allows for the continuity of cardiac rehabilitation within the patient's own environment while reducing the barriers related to transportation, physical impairment and physical distance from health care facilities" [26]. Kyriacou et al. [30] propose a web-based remote monitoring system for the smooth cardiac rehabilitation process. The application monitors different biosignals such as ECG, oxygen saturation, blood pressure, and bodyweight of the patient. Lu et al. [31] also describe CAROLS, a motion-sensing-enabled exercise system for cardiac rehabilitation. This system provides an interactive and user-friendly virtual gaming platform for rehabilitation exercises. The project aims to motivate cardiac patients to improve their exercise levels during rehabilitation.

Due to advancements in mobile technology, coupled with the wider use of mobile phones, researchers have also examined the effectiveness of cardiac rehabilitation systems using mobile technologies ([32]; [33]; [35]; [36]; [38]; [39]. Frederix et al. [34] present "MobileHeart", to support and monitor patients during rehabilitation. MobileHeart is a smartphone-based application that supports and monitors ischemic patients during rehabilitation. The mobile application has the potential to tailor recommendations to a patient based on the initial clinical condition, pathology, and risk factor profile. Mio Alpha 2 was used to collect heart rate and activity data (Pedometer) and presented in a dashboard for visualization. An E-learning module was also integrated into the system to educate patients on managing cardiac disease during rehabilitation. Though the system is effective and useful, the mobile application can only display the generated sensor data details and lacks the knowledge base to assist physicians in decision-making.

2.3 Health Monitoring

Patient monitoring at distance can be traced back to 1905 when Dr. Einthoven transmitted electrocardiograms (ECGs) from a hospital to his laboratory by directly connecting immersion electrodes to a remote galvanometer via telephone lines [40]. This paved the way for other researchers using modern technologies for patient monitoring. Finkelstein et al. [41], developed a web-based asthma patient monitoring system that makes use of spirometer to transmit the result of a Forced Vital Capacity (FVC) test from the patient's home to a hospital database through standard telephone landline, cellular digital packet data network and wireless RAM mobile network. A real-time diabetic patients monitoring system was also proposed by [42]. The system monitors the ketone level of the patient by constantly measuring the breath using a gas sensor. Barreto et al. [51] proposed a system for monitoring the environmental temperature, humidity, and location of Alzheimer patients using wearable devices. The device sends the acquired patient information to a server and a caregiver through a mobile application. The focus of [52] and [53] were on elderly patients. Their system monitors the sleep patterns, humidity, and ambient temperature of the elderly at home. Gjoreski et al. [22] also developed a system to monitor the elderly at home using ECG and accelerometer sensors. The application is capable of recognizing user activities and detecting a fall event.

Mobile patient monitoring was also proposed by ([54]; [44]). These systems use wearable sensors to sense, analyze and transmit patient signals while on the move. Mobile patient monitoring involves the use of mobile computing, wireless communication, and network technologies for continuous measurement and analysis of patients' physiological signals while the patient is on the move [55]. This means that the patient is not restricted in a particular domain; rather, they are able to carry out normal daily activities while being monitored.

2.4 Cardiac Health Monitoring

There have been several studies relating to cardiac patient monitoring. However, most of these studies focus on identifying irregularities in a specific vital sign. A real-time system that transmits patient ECG signals to a mobile phone was proposed by [56]. The system can detect sudden heart attacks and transmit alerts to the patient's doctor or relatives. Bessmeltsev et al. [57] introduced a prototype for continuous monitoring of cardiac activity using electrocardiography and heart rate. The system is made up of an intelligent sensor data acquisition system, a processing system based on Bluetooth technology, and a communicator for transferring data to a medical server. Triantafyllidis et al. (2014) also presented a personalized health monitoring system for heart failure patients. The platform supports the physicians' activation/deactivation of the system's components based on the patient's condition during the monitoring process. Most of these systems only display the raw data generated from the wearable sensors [59], while some researchers used smartphone to present the raw data [62]. To complement this approach, Pierleoni et al. [60] presented an android-based heart monitoring system that makes use of heart rate data to provide a detailed report about cardiac patient health status, transmit the data to an online database and generate an emergency alert when necessary. In addition, they utilized sophisticated algorithms to detect stress states, classify arrhythmia events, and compute the amount of consumed calories in real-time. Their goal was to implement a simple and inexpensive health monitoring system for heart disease patients and the elderly. The evaluation of the system proved its effectiveness; however, using only a single parameter of the considered patient might not provide enough knowledge to the clinician in the decision-making [6].

2.5 Context-Awareness

Context-awareness is the ability of a system to use relevant contextual information such as location, activity, temperature or identity to provide services to the user. This information can be used to enable selective responses such as triggering alarms or retrieving information relevant to the task at hand. This section explains what context and context-aware systems represent in the healthcare domain, discussing their applications and challenges.

2.5.1 Context and Context-aware System

Context is a concept used in different areas, and people understand it in different ways within Computer Science, and other disciplines that relate to Computer Science [63]. Several authors such as ([65]; [68]; [69]; [70]) have tried to define context and context-awareness. However, there is no consensus on its definition so far [123].

Schilit and Thiemer [65] first introduced the term "context-aware" specifically applying it to the problem of location awareness in an office environment. Their definition comprises people's locations and identities and the state of objects within their environment.

According to Dey and Abowd [70] "a system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the users' task." While "context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves".

Recently, Augusto et al. [144] defined context as "the information which is directly relevant to characterize a situation of interest to the stakeholders of a system", while context-awareness is "the ability of a system to use contextual information in order to tailor its services so that they are more useful to the stakeholders because they directly relate to their preferences and needs". The contextual information could be, for example, the physiological details, activity information, location, or time of the day.

This research is largely influenced by Augusto et al. [144] definition of context and context-awareness as it considers contextual information from the stockholder's point of view.

Context can be categorized into primary and secondary context [129]. Primary context is any information relevant to the stakeholder retrieved without using any existing context, while secondary context is relevant information derived from the primary context [71]. For instance, location data from a GPS sensor is primary context, while calculating the distance covered by fusion of location data is secondary context. Context-aware applications are enhancing interaction between humans and systems in areas such as industry [73], transportation [72] security [37], business [74], and healthcare [75], as well as smart home [139]. These systems provide platforms for a better and more timely decision-making process for the user. There are different application domains of context-awareness. However, this research focuses on healthcare targeting cardiac condition monitoring and management.

2.5.2 Components of Context-Aware System

This section briefly discusses different components of a context-aware system, which was presented as the life cycle in [123] and [129].

- Context acquisition: This component is responsible for sensing contextual data from sensors. Context acquisition techniques vary based on context source, sensor type, acquisition process, responsibility, and frequency [129]. Varshney[124] presented three types of context acquisition which include sensed context, derived context, and context explicitly provided. Sensed context is acquired through physical or software sensors such as pressure, temperature, lighting, and noise level. Derived context can be computed from primary contexts such as distance, time, and date. An example of context explicitly provided is the user's preferences, "when explicitly communicated by the user to the requesting application". The context-acquisition techniques is elaborated below as presented in [129].

Based on sensor types: There are different types of sensors that can be employed to generate context. In general usage, the term 'sensor' refers to sensor hardware devices. However, sensors are referred to as any data source that provides relevant context to the technical community. Three categories of sensors are physical, virtual, and logical.

Based on acquisition process: There are about three processes to generate context. These are sense context, derive context, and manually provided context. (a) Sense: The data is sensed through sensors, including the sensed data stored in databases. An example is blood pressure generated from a sensor or retrieved appointments information from a calendar. (b)Derive: The information is generated by computational operations on sensor data. These operations could be as simple as web service calls or as complex as mathematical functions run over sensed data. An example is a calculating distance between two points using GPS coordinates. The necessary data should be available to apply any numerical or logical reasoning technique.

Based on responsibility: In this category, context acquisition can be accomplished using two approaches: (a) Pull: Here, the software component which is responsible for generating sensor data makes a request from the sensor hardware at a time interval. (b) Push: The physical or virtual sensor pushes data to the software components responsible for periodically acquiring sensor data.

Based on frequency: Context can be obtained based on two different frequencies. (a) Instant: Here, events occur instantly. The events do not span across certain amounts of time. Examples of instant events are: open a door and switch on a light. Sensor data needs to be generated when the event occurs in order to detect this type of event. Both push and pull methods can be employed. (b) Interval: Raining or winter are some examples of interval events. These events span a certain period of time. In order to detect this type of event, sensor data needs to be generated periodically. Both push and pull methods can be employed.

Based on source: Here, context acquisition methods can be categorized into three based on the source. (a) Acquire directly from sensor hardware: In this method, context is directly acquired from the sensor by communicating with the sensor hardware and related APIs. This method is typically used to retrieve data from sensors attached locally. (b) Acquire through a middleware infrastructure: In this method, sensor (Context) data is acquired by middleware solutions. The applications can directly retrieve sensor data from the middleware and not from the sensor hardware. (c) Acquire from context servers: In this method, context is acquired from several other context storage; examples are databases and web services through different means such as web service calls. This mechanism is useful when the hosting device of the context-aware application has limited computing resources.

- Context modeling : Here, the sensed data is represented in an efficient and structured format for retrieval. Context modeling is defined in [66] as the "context representation that assists in the understanding of properties, relationship and details of context". There are different techniques for context modeling, such as key-value, mark-up scheme, object-oriented, logic-based, and ontology-based. These techniques are discussed in section 3.3.2.

- Context reasoning: This component involves gaining knowledge from the context data. Researchers applied different methods in order to discover hidden information from the represented context. There are different techniques of context reasoning such as fuzzy logic, rule-based, ontology-based, supervised, and unsupervised learning [123].

Fuzzy logic: Fuzzy logic is mostly used with other reasoning techniques such as ontology, probabilistic or rule-based reasoning. It is quite different from traditional logic reasoning. Everything is represented with 0 or 1 in the traditional reasoning; however, partial truth is accepted in fuzzy logic reasoning.

Ontology based reasoning: In this technique, reasoning can be achieved with ontology modelled data. Semantic Web languages, such as RDF, RDFS, and OWL can be used to implement ontology-based reasoning [66].

Rules: Reasoning can be acquired with an if-else structure in this reasoning technique. User preferences, event detection, and human thought can be modeled with rules to be used in different applications.

Supervised learning: In supervised learning, sensor data are generated alongside labels or manually labelled for algorithm training. Examples of supervised machine learning algorithms are support vector machine and logistic regression.

Unsupervised learning: In unsupervised learning, there is no class label; the goal is to model the distribution in the data to gain more useful information about the data.

- Context distribution: The context information is distributed to the consumers at this stage [123]. Perera et al.[129] stated that context acquisition techniques could also be context distribution methods. Other context distribution techniques such as querying and subscription were presented by [66]. Users create queries to produce results in the querying technique, while in the subscription method, users subscribe to the context system to retrieve specific sensor data periodically or when a specific event occurs.

2.5.3 Challenges of Context-Awareness

A context-aware system provides an opportunity for healthcare professionals to assess the health condition of a patient using relevant parameters. However, there are a few challenges in developing a context-aware system in an intelligent environment. These challenges include context acquisition, energy efficiency, the storing of context information, security and privacy. This section discusses the challenges of context-aware systems with respect to mobile devices and big data.

2.5.4 Mobile device challenges of context-aware system

As technology advances, researchers design and implement context-aware applications for mobile devices such as smartphones, tablets, and smartwatches. An example of a context-aware application for mobile devices is a mobile application that can dynamically adjust its behavior to suit the condition of the user at a particular time, or location [76]. For instance, a smartphone application that can automatically make a mobile phone silent when the user is driving or that can detect the activity of a cardiac patient while monitoring the heart rate, is regarded as a context-aware system. There are many challenges with developing context-aware systems using mobile devices. These include: sensing context data, the energy efficiency of smartphones, storing context information, security and privacy, and presenting context information on the small display of the smartphone. This research elaborates on some of the challenges faced by researchers when implementing a context-aware system for mobile devices [132].

- Context acquisition: Context is a vast concept that involves all possible parameters for handling a situation. Many categories of context can be generated through sensors embedded in mobile devices; however, identifying relevant context while developing mobile applications and frameworks might require an expert in the domain, and finding such professionals, especially in healthcare, can be costly.

- Energy efficiency: Developing context-aware applications for mobile devices is a challenging task due to their limited battery capacity. Context-aware systems involve continuous sensing of contextual information in real-time and requires a lot of energy to function effectively. Though advances in technology have improved the battery capacity of mobile devices, it is still not suitable for many context-aware applications [132].

- Security and privacy: Context provides information that helps us to better understand a situation [129]; however, it also increases the security and privacy challenges of mobile applications due to the possibility of improper handling of contextual information. Context-aware applications targeting mobile devices could give the users the feeling that they are being constantly monitored [132]. Therefore, the security and privacy of users needs to be addressed at every stage of the mobile application development process.

- Mobile device screen size: Using the small size of a mobile device to display contextual information in order to facilitate the decision-making process is a major challenge in developing mobile health(mHealth) application [84]. Mobile phones have small screens, and this makes it difficult to fit all the data and information into them" [85]. Therefore, it is essential to seek a method by which the relevant contextual information of the entity will fit onto the small display of a mobile phone. Another challenge is accessibility problems that people with visual disabilities experience with mobile devices. For problem related to non-touch-sensitive edges, Damaceno et al. [203] suggested fixing stickers on the edge of the border in order to enable visual impaired persons guide themselves better. However, this research assumes that users can interact with a smartphone without extra assistance.

2.5.5 Big data challenges of context-aware system

Context-aware systems have sensors generating a huge amount of data, requiring large and efficient storage space and analytics algorithms to gain knowledge. This poses several challenges during development. Big data is a huge unstructured data which, when analyzed; can reveal new and vital hidden information[66]. This section discusses some of the challenges of developing context-aware systems with respect to big data.

- Energy consumption: In order to monitor patients, mobile and wearable sensors generating a huge amount of data need to run continuously. This imposes a heavy drain on the mobile device battery.

- Embedded sensor diversity: Due to the diversity of sensors used in context-aware system, when a context-aware application is developed targeting a specific device, the application may not function properly in another device with the same sensor but different characteristics. This issue is also know as interoperability [67].

- Unreliable or redundant data or loss of data: Storing sensor data from different devices in the same domain requires sophisticated algorithms to detect redundancies and discard them. The algorithm should be able to detect when data is coming from unreliable sources or hackers and exclude them in further analysis. Data loss could also impose challenges, as insufficient data could mislead the decision-making process. This could be handle by data augumentation in order to improve the performance of the learning algorithms.

- Efficient communication infrastructure: Network infrastructure should be designed in a sophisticated manner in order to share big data-related contextual information across networks for processing, inferences, and recommendations.

- Scalable context inference algorithms: A context-aware application requires supervised or unsupervised algorithms to train a large amount of context data. Supervised algorithms require data labeling; however, labeling a huge amount of context data could be tedious and time-consuming, often requiring an expert. Some existing work manually labels their data; however, it becomes difficult to label such a huge amount of context data as the scale increases.

2.5.6 Context-Awareness in Healthcare

Contextual information could be used to enhance the quality of services in healthcare delivery, and to utilize human and healthcare resources efficiently during health monitoring [124]. Context-awareness is an important part of systems implemented in areas such as Intelligent Environment, Ambient Intelligence, Pervasive and Ubiquitous Computing [123]. The fundamental idea behind context-awareness in healthcare is to develop a proactive and efficient system that can adapt to the changes in the patient's condition and environment [124]. This system uses contextual information to provide useful services to the physicians for better patient monitoring.

A context-aware system in healthcare could be regarded as a system that uses contextual information to provide helpful information or services to clinicians, patients, or relatives. Context-awareness has been successfully applied for healthcare in areas such as patient monitoring, elderly monitoring, disease diagnosis, and treatment, and accident and emergencies [133],[102],[103],[104]. Several authors in the literature have also proposed context-aware systems in the healthcare domain. Examples of these systems are a context-aware system (MobileWard) aimed to support nurses in conducting morning procedures in the hospital ward [133] and an intelligent context-aware system (OcarePlatform) developed to support independent living [135]. Fallahzadeh et al.[106], also proposed a low-power context-aware system for continuous assessment of Edema patients in a remote environment. This application keeps track of changes around the patient ankle as well as the body posture. Kramer et al.[136], in their project- POSEIDON, proposed a context-aware system to assist people with Down's syndrome to navigate their routes without relatives or carer support. The project aims to support people with Down's syndrome to be more engaged in society through education, work, and socialization.

Due to the importance of security and privacy in context-aware systems, Motta et al. [107] proposed a contextual role-based access control authorization model to enhance patient privacy and data protection. The platform controls the user's access to electronic patient records based on the role set by the organization. It uses context data such as environmental information, and user/patient relationship to decide whether to authorize a user to access patient records. Quinde et al. [146] proposed a personalized context-aware solution for asthma disease management. Due to different triggers and symptoms experienced by asthma patients as result of the high heterogeneity level of the disease, this approach allows users to set the indicators they want to track based on the characteristics of their asthma. Personalization aims to present the right treatments and services to the considered patient [86].

2.5.7 Existing context-aware solutions for cardiac condition monitoring

Recently, some authors proposed context-aware systems for cardiac patient monitoring; however, research in this area requires significant improvements. Li et al. [137] developed a system that records the biosignal of patient and requests context information when there is an abnormality. As the patient has to input information about their daily life activities. This system is not fully automatic since it requires user intervention. The focus of Forkan and Hu [140] was on the older adult; they developed a cloud-based system that extracts health parameters from Fitbit devices and ECG sensors. The context information of the patient is sent via social media to the patient's doctor, relative, or friends when there are abnormal changes. They used the Fitbit device to collect the activity details from the user. However, this device could only recognize the steps of the subject and could not show the specific activities performed such as walking, running, or sitting.

Sannino et al. [141] introduced an "intelligent mobile system based on rule decision support system for cardiac patients". This system correlates data from the ECG sensor with physical activities such as walking, running, and body posture. They used the threshold rule to determine the patient's activity and argued that testing the system with fifteen healthy people proved the effectiveness of the proposed approach. Kunnath et al. [142] also used the threshold approach to detect four different activities (lying down, standing, walking, jogging) for cardiac disease monitoring and claimed a classification accuracy of 94%. Though the method is shown to be effective, using a threshold rule to determine the user's activity may not be the best option due to the wide range of physical activities, coupled with the disparity in how a specific activity can be performed.

Another similar solution was presented by [143], who combined ECG signals with physical activities for cardiac disease diagnosis. Miao et al. [143] applied a machine learning technique to recognize human activities. They recruited seven healthy people who wore ECG sensors on their chests and carried smartphones in their pockets to collect sensor data. Each subject was asked to perform three different activities (running, rest and walking). The sensor data from the seven participants was aggregated, processed, and used to train J48 decision tree algorithms to predict the users' activity when new data without ground truth was fed into the model. This approach proved to be effective; however, a centralized machine learning approach that does not maintain users' privacy was used to develop the model.

2.6 Discussion of the Existing Systems

This section explores some of the methods and technologies used for cardiac condition monitoring and highlights areas for improvement. This will serve as a guide for future research regarding cardiac condition monitoring. The discussion is based on the following areas:

Parameters for cardiac health monitoring: There are different parameters such as heart rate, activity data, blood pressure, and ECG signals which can be considered when monitoring a patient. These parameters can assist

Table 2.1: Different parameters used for context-aware cardiac disease monitoring (HR=Heart Rate, Temp= Temperature, AD=Activity Data, PS=body posture, Cal=calories)

Reference	HR	ECG	Temp	PS	AD	Cal
Li et al.[137]	✓	✓	x	x	✓	x
Kunnath et al. [142]	x	✓	x	x	✓	x
Forkan and Hu [140]	x	✓	✓	x	✓	✓
Sannino et al. [141]	✓	x	✓	✓	✓	x
Maio et al.[143]	x	✓	x	x	✓	x

physicians in decision-making and create avenues for effective monitoring and recommendations. Due to many symptoms of cardiac diseases, there is no consensus on the parameters used to monitor cardiac conditions. As indicated in Table 2.1, researchers used different parameters for cardiac condition monitoring. Only in [141], which involved cardiologists, were the reasons behind choosing the stated parameters. Considering the limited battery capacity of mobile devices, and given that patient monitoring involves continuous context acquisition from sensors, a context-aware system for cardiac monitoring should consider a minimal number of possible parameters without putting the subject in danger. Furthermore, it is essential to note that different patients might suffer different kinds of cardiac conditions; it is worth considering personalizing a context-aware system for patient monitoring in order to effectively monitor the subject based on their symptoms. For instance, a cardiac patient with high blood pressure might require that the blood pressure be monitored alongside other parameters, while the elderly patient might require that a fall event be considered when choosing parameters. Table 2.1 presents different research on context-aware systems and parameters used for cardiac condition monitoring.

Activity recognition: Recognizing human activities such as walking and running or human-related actions aims to observe and understand what type of activities or routines are performed by the subject at time-intervals [132]. From table 2.1, all the researchers adopted physical activity recognition as part of the parameters for developing a context-aware system for cardiac patient monitoring. This indicates the importance of physical activity data during cardiac monitoring and disease management. Due to the significance of this parameter, serious attention should be given to the process of acquiring, processing, and classifying of different activities when monitoring cardiac patients.

Forkan and Hu [140] used the Fitbit device to collect activity details from the user for cardiac condition monitoring. However, this device could only recognize the steps of the subject and could not show specific activities performed such as walking, running, and sitting. There was an improvement in Sannino et al. [141] as the system was intended to recognize the specific activity; however, applying the threshold method to detect activities might impose serious issues, as there are wide-range of physical activities, coupled with the disparity in how a particular activity can be carried out. To complement this approach, Miao et al.[143] applied machine learning techniques to recognize human activities. Machine learning provides computational methods and a learning mechanism for developing a model to make a prediction based on the ground truth. Miao et al. [143] recruited seven healthy people who wore ECG sensors on their chests and carried smartphones in their pockets to collect sensor data. Each subject was asked to perform three different activities (running, rest and walking). The sensor data from the seven participants were aggregated, processed, and used to train J48 decision tree algorithms to predict the users' activity when new data without ground truth was fed into the model. The machine learning algorithms were used with the default values set by WEKA software; other software such as Python and MATLAB, which allow the developer to adjust hyper-parameter values, could be used to have more effective results.

Energy efficiency: Due to the limited battery capacity of mobile devices, energy management is a serious issue that needs to be considered when developing a context-aware system. From the existing systems, an approach that could handle this challenge is the context-aware system presented by [137]. This system only requests for the patient's activity when an abnormality is detected in the patient's biosiginals. For instance, if the heart rate of the cardiac patient is above the average normal heart rate, the system should request for the activity of the patient at that time; if the activity is a vigorous activity such as running, the system might choose not to send alarm, but will record such an incident. However, when the heart rate is below average, and the patient's activity is running, then sending an alarm becomes necessary. Though this system is effective and energy-efficient, the patient has to input information about their daily life activities. So this system is not fully automatic as it requires user intervention. This approach can be improved by automatically collecting the physical activity of the patient using sensors attached to the person or the environment. Kramer et al. [136] in their research argued that another means of preserving the power of the monitoring device is by creating a system that is self-aware and adaptive. Yu¨ru¨r et al. [132] also pointed out that reducing the amount of data to be processed or transferred by applying adaptive sampling, data compression, and network coding could discard unnecessary information during sensing, hence minimizing the energy consumption of the device.

Health Monitoring Devices: As technology advances, modern smartphones and wearable devices are contributing immensely to the healthcare delivery process by enabling doctors and healthcare professionals to monitor patients at distance. Sensors embedded in these devices can be used to collect and aggregate a large amount of data from patients' biosignals and analyze them in order to assist doctors in decision-making. Several devices such as Fitbit, Mio Alpha 2, and Lifecard CF are available for health monitoring. These gadgets range from portable and wearable to implantable tools. The most regularly used tool for cardiac condition monitoring is the Holter monitor. Holter monitor is a portable and continuous monitoring device used to generate and record ECG signals [181]. Some of the modern Holter monitors allow users to wear the device while doing their normal activities and can transmit users' details to the physicians through mobile phones.

Forkan and Hu [140] proposed context-aware architecture that uses ECG sensor and FitBit to generate parameters to monitor an older adult living alone and suffering from cardiac disease. Sannino and De Pietro [141] used an Alive Heart Monitor(KardiaMobile), ECG sensor, and accelerometer sen-

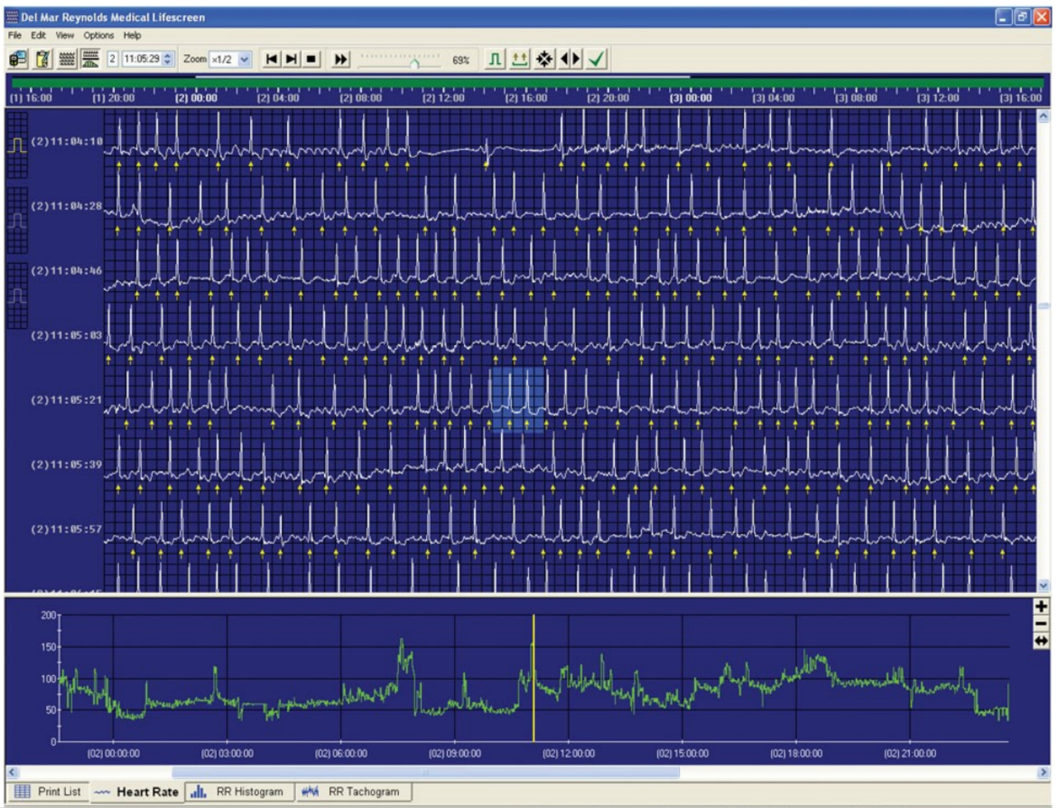
Table 2.2: Features of Health Monitoring tools

Device	Features
LifeCard CF	- Built in ECG display for monitoring ECG data. - Ability to mark when it detects Atrial and ventricular pacing spike. - Built in voice recording feature which can be used to identify patient. - Ability to diagnose complex arrhythmias.
KardiaMobile	- Captures a medical-grade ECG in just 30-seconds. - Detect Atrial Fibrillation, Bradycardia or Tachycardia. - Can record weight and blood pressure of the user.
Apple Watch	- Ability to detect atrial fibrillation and send a notification to the user. - Activity tracking and built in GPS for location tracking.
FitBit	- Ability to detect heart rate, record steps, calories, and distance. - Sleep tracking feature.
QardioCore	- Continuous Wireless ECG recording. - Monitors heart rate and heart rate variability, - Record skin temperature, respiratory rate and, activity tracking.
Mio Alpha 2	- Ability to monitor heart rate, - Record activities including steps, calories, and distance.

sor to collect and aggregate different parameters for heart disease monitoring. Frederix et al. [34] in their research used Mio Alpha 2 to collect user's details in order to monitor and support ischemic patients during rehabilitation. Some researchers, such as [143], and [142], used smartphones to collect accelerometer data for activity recognition during the monitoring process. The raw accelerometer data was processed and used to train machine learning algorithms for human activity detection. Table 2.2 summarized different features of the available devices in the market for health monitoring. Among the monitoring devices listed in table 2.2, Lifecard CF offers the advantage that it is capable of detecting atrial fibrillation, heart attack, and heart disease while recording the ECG signals. However, none of these gadgets could provide a platform that generates contextual information, process, analyze and offer a personalized recommendation to a cardiac patient during rehabilitation. Figure 2.2 shows (a) a picture of Lifecard CF, (b) a usages of Lifecard CF and (c) a graphical representation of the ECG signals from the device.

(a) Lifecard CF

(b) Usage of Lifecard CF



(c) ECG signals from Lifecard CF

Figure 2.2: Lifecard CF gadget, usage and graphical representation of the ECG signals

Contextual information: To design a better health monitoring system that typically draws information from various sources, there is a need for a better understanding of the contextual properties that impact the design, development, and delivery of such services. Contextual information plays a significant role in patient monitoring by providing essential information to a patient or carer, thereby enhancing the quality of services offered. The understanding from previous research is that most researchers do not involve healthcare professionals during the development process. Some rely on what they read or perceive to be the most appropriate approach. The outcome of the system might have little or no impact as the main stakeholders that understand their need are not given the opportunity to be part of the system development. Feedback gathered from relevant professionals at earlier stages of this research shows that physical activity recognition is an essential part of cardiac condition monitoring. However, most of the existing technologies for cardiac health monitoring overlook the importance of this information in quality health service delivery. The activity information is integrated with the decision support system to enable the clinician to understand and consider the patient's activity when reading the ECG signals. Due to the importance of this component in cardiac health monitoring, an essential factor, which is the patient's privacy, was considered in the activity recognition process by adopting federated machine learning technique for model development.

2.7 Activity Recognition

Activity recognition is an important and challenging field that can support different areas of applications such as smart homes, healthcare, surveillance, gaming, and security. Recognizing human activities such as walking and running or human-related actions aims to observe and understand what type of activities or routines are performed by the subject at time-intervals [132].

In a smart home, an activity recognition system can track the users' activity for a long period of time to remind them about performing forgotten activities such as taking their medication or encouraging them to act more safely. In surveillance system, activity recognition system can be used to monitor the activity of people in order to predict their intent and motive as they interact with the environment. In a production environment, activity monitoring can ensure that production patterns are maintained. In hospital settings, such systems can remind a doctor or healthcare professional to carry out a particular test before an operation. Finally, these systems can also play a vital role in encouraging a healthy lifestyle among users by suggesting behavior changes to keep fit. For instance, people can be encouraged to use stairs instead of an elevator or walk around after a long period of sitting. Activity recognition can be achieved by using a vision-based approach or sensor-based approach.

Vision Based Approach: In vision-based activity recognition, the image/ video captured from different devices such as cameras, video recording devices, and surveillance cameras has been used as input data for activity recognition. This approach uses video processing techniques to analyze the visual observations detecting the subject's activity. The vision-based approach has proven effective in recognizing human physical activities; however, one of the significant challenge of using this method is privacy concerns as human image is involved. Moreover, vision-based devices such as cameras are costly and require experts in most cases to be installed.

Sensor Based Approach: The sensor-based approach makes use of sensor-based technology to generate time-series data. These sensors can be wearable devices attached to the subject's body or sensors installed in the user's environment.

Environmental sensor-based: Environmental-based sensors are used to monitor the interaction of the users and their environments. This can be achieved by installing many ambient sensors throughout the subject's living environment. These sensors monitor the occupant every day, thus requiring no action on the user's part. Ambient sensors, placed throughout the house, have fewer restrictions (size, weight, and power) than other types of sensors thus simplifying the overall system design. However, such systems are infrastructural based and cannot monitor a subject outside of the environment settings. Furthermore, they exhibit difficulties distinguishing between the monitored subject and other people in the home.

Wearable devices: Wearable sensor-based devices are designed to be worn by the user; hence the subject is not restricted to a particular environment.

Wearable sensors are well suited for collecting data on individual daily physical activities over a period of time. These sensors can be integrated into the subject's clothes, jewelry, or worn as wearable devices. Since the sensor is attached to the individual body, the device can measure the physiological parameters that may not be possible to track using environmental or video sensors. Moreover, such sensors are low-priced and are not considered a threat to people's privacy, unlike video sensors. A range of wearable sensors exists, such as accelerometers, gyroscopes, and pedometers are available for activity recognition.

The accelerometer sensor is the most widely used sensor for human activity recognition. It measures the acceleration of the subject along sensitive axes [148], and it has been proven to be effective in recognizing physical activities such as walking, standing, and running [176]. Besides having recorded significant accuracy in physical activity detection, they are small and cheap and require relatively little energy, memory, and processing power.

2.7.1 Applications areas of activity recognition

As research in the area of activity recognition continues to expand, it gives room for researchers to discover different areas where activity recognition can be utilized such as healthcare and assisted living, entertainments and games, industries, security and surveillance. This section briefly discuss some areas were activity recognition could be applied.

Elderly monitoring: There is increase in the ageing population that requires healthcare. This increase causes a lot of problems such as medical cost and demand for healthcare professionals [196]. Fortunately, with the advances in technology, remote monitoring of the elderly have become possible and easier. Human activity recognition has the potential to assist ageing population to live independently. It helps in early detection of diseases and assist healthcare professionals in decision-making for the patient. By remote monitoring of the elderly ones and reporting any abnormalities such as fall, activity recognition is helping to minimize medical expenses and avoid deaths.

Smart Environment: Human activity recognition is an important part of smart environments such as smart offices, smart health center and smart homes. With the help of human activity recognition, smart environments can understand the activity of its residents and adapt itself accordingly. For instance, if no one is present in a smart home or office, the light and heating systems in the smart environment will turn off. In order hands, if the system detects the presence of a resident, the appliances turns on to serve the resident.

Security and Surveillance: Human activity can be automatically detected for security in an environments where security is paramount and demand constant monitoring. Different techniques such as vision-based approaches and sensor-based exist for human activity recognition. For vision based techniques using camera, many solutions exists which can analyze the video or image from the camera and can detect the activities, hence can report suspicious activities. Also many systems exist which can analyze and process sensor data and report suspicious activity such as intrusion [196].

2.7.2 Health benefits of activity recognition

Participating in physical activities such as walking, cycling, running, and jogging is necessary for people of all ages. Physical inactivity, which can result in obesity and overweight, will affect the quality of life and also bring financial burden on the government. Chronic diseases such as obesity, diabetes, and cardiovascular disease could be managed by automatic recognition and monitoring of patients' daily activities by their physicians. These patients are usually required to follow a definite active exercise routine as part of their treatment. The manufacturers of mobile devices such as smartphones recently incorporated many sensors such as accelerometer, GPS, Gyroscope, temperature, and blood pressure sensors. Their high computational power, low cost, and small size make it possible for people to carry them always. Some of these sensors can be used to recognize human activities in real-time.

Providing an activity monitoring system will assist patients in managing their lifestyles and empowering their physicians to monitor them. Continuous activity monitoring of patients will definitely reduce the hospital stay, improve the reliability of diagnosis and equally enhance patients' quality of life [184]. Report from the World Health Organization (WHO) shows that the major cause of overweight and obesity is lack of physical exercise to balance energy between consumed calories and expended calories [186]. Despite the positive effect of regular physical activity, the majority of people, especially in developing countries, remain physically inactive [187], [185]. This is due to lack of awareness, motivating factors, and cultural constraints. Several studies such as [111]; [116]; [119], [188]; and [189] have been carried out on activity recognition using a smartphone. However, most of these studies are experimental-based and were not implemented and evaluated extensively on end-users.

2.7.3 Activity Recognition Process

The activity recognition process generally involves several steps,—from collecting information on human activity and behavior from raw sensor data to the prediction of the user's activity. The first phase of activity recognition is data collection. Secondly, the sensor data is processed and partitioned into equal groups at time-intervals for feature extraction. Finally, the extracted features are used to train machine learning algorithms in order to classify new data without ground truth. Figure 2.3 summarizes the process of physical activity recognition.

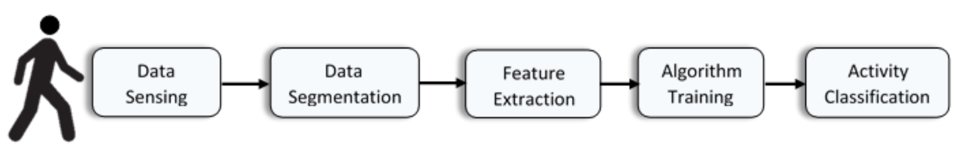


Figure 2.3: Activity Recognition Process

2.7.4 Data Sensing

The first step of activity recognition is data sensing using an activity recognition sensor. The data can be from one or more sensors placed in the subject body or installed in the subject environment. Bayat et al. [177] used a tri-axial accelerometer sensor in an android phone to collect data. Dataset from the accelerometer involves the acceleration along the x, y, and z axes. Four volunteers participated in the data collection, each carrying a cell phone, and performed six different activities. The data was collected at a sampling rate of 100Hz, that is a sample every 10ms. Kwapisz et al. [111] also collected accelerometer data at a sampling rate of 20Hz from 29 participants carrying android-based smartphones. During the exercise, the android phone was placed in their front pant leg pockets and performed six different activities. Khan et al. [112] collected accelerometer data from six volunteers, each person placing the phone in five different positions and performing five different activities. They used a sampling frequency of 45Hz and argued that it consumes less power. Kim et al.[113] used the UCI HAR dataset. The dataset comprises accelerometer and gyroscope sensor data collected from 30 individuals who performed six different activities (walking, sitting, standing, lying, walking_downstairs, walking_upstairs) using a Samsung Galaxy S2 smartphone. Zainudin et al. [114] also used a publicly available dataset from the WISDM website. The dataset was generated from 36 different participants who performed six different activities (walking, jogging, upstairs, downstairs, sitting, and standing) using an accelerometer sensor embedded in smartphones. The data was collected at a sampling rate of 20Hz. Kwon et al.[115] collected data at a frequency of 50Hz and recorded high recognition accuracy using artificial neural network as a training model.

2.7.5 Segmentation/Feature Extraction

A classification algorithm cannot be directly applied to raw time-series sensor data. Instead, the data needs to be transformed by partitioning the data by time or samples windows. Figure 2.4 illustrates the time and samples windows. In the time window, the sensor data is partitioned using a specific time interval, while in the samples windows, data is partitioned based on a number of samples. Then, the time and/or frequency domain features are extracted from the partitions. Examples of time-domain features are simple statistical features such as mean, variance, standard deviation, and root means square, while frequency domain features are energy, entropy, etc. Chawla and Wagner [116] used the fixed time window method to segment the sensor data into two-seconds windows each, and extracted time-domain features such as mean, standard deviation, maximum and minimum amplitude, root mean square, and inter-quartile range. Shoaib et al. [110] also segmented the data into sliding windows of two-seconds, with overlapping of 50%. To overcome the challenges of different phone orientations and positions, they computed the magnitude of the three-axis of each sensor data and extracted time-domain features from each segment of the windows. Ustev et al. [117]] in their research, segmented the sensor data into 2.56s windows length, each window containing 256 samples. Selecting appropriate features from the sensor data plays a vital role in the performance of the activity recognition system [117]; they extracted time domain features from the magnitude of the x, y, and z axes of the accelerometer components and the three-axis separately. Yin et al. [118] used fixed window sizes of 64 consecutive data points of 50% overlapping and computed both time and frequency domain features of each window; however, used only time-domain features, and argued that time-domain features are enough for satisfactory classification result.

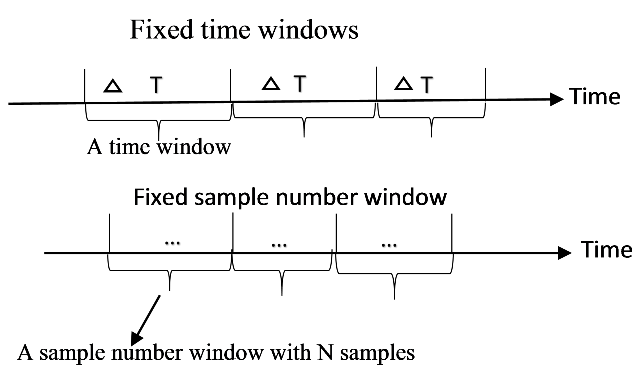


Figure 2.4: Fixed time and fixed sample number of windows for data segmentation

2.7.6 Algorithm Training and Classification

Algorithm training is an essential part of activity recognition; the process creates a model to predict the user's activity. Several researchers in the literature used different machine learning techniques to detect activity for patient monitoring. Chen and Lee [119], developed a cloud-based application that communicates with the mobile environment to sense and classify activities. In their experiment, they compared the classification accuracy of decision tree, MLP, random forest, and K-nearest neighbor and argued that K-Nearest neighbor achieved high accuracy in identifying most of the activities. Siirtola and Roning [120], in their research presented an online activity recognition system; all the classification processes apart from model training were carried out on the phone. The online recognition was tested with only one subject; therefore, it cannot justify the system's performance. They recommended sending the sensor data to a server and performing the classification to minimize the mobile phone workload. Support Vector Machine (SVM) model was developed to classify and identify different activities in [121]. They argued that the system's performance relies on the used features and the quality of the training model. The implemented system recorded a classification rate of 89.59%; however, the system was not evaluated on the targeted users. Huda et al. [122] implemented real-time activity recognition using smartphones and wearable devices. Using artificial neural network as the classification model, they recorded reasonable classification accuracy. However, the system demands wearing external devices, which can inconvenience users; moreover, the system was not evaluated on the targeted users.

2.7.7 Activity Recognition Challenges and Solutions

This section presents some issues of activity recognition, and explain how researchers attempted to address them.

Reading data from accelerometer sensor when the mobile phone is in the user's pocket is quite different from when the smartphone is in the subject's hand. Therefore, using a machine learning model trained with sensor data from the user's pocket to predict the user's activity when the phone is in hand might give deficient performance [115]. Researchers proposed different methods to address this challenge. Zhu et al [46], applied the concept of similarity to bridge the gap between different positions. They extracted and got the average features of different activities and locations and computed their similarity with the average features before applying classification algorithms.

Similarly, Fan et al. [191], collected data from different smartphone positions. To model position-independent recognition, they mixed all the collected data and studied three different kinds of modeling methods- vector (activity, position) based modeling, activity-based modeling, and position-based modeling. Khan et al [16], collected sensor data from five different body positions. They applied the kernel discriminate approach to extract important non-linear discriminating features, reduce the within-class variance, and increase between-class variance. Ustev et al. [117], used multiple sensors (Accelerometer, Gyroscope and Magnetic field sensor). A magnetic field sensor was introduced to remove the effect of gravity on the accelerometer readings and obtain absolute orientation independent by converting accelerometer readings to earth coordinates system. However, using multiple sensors can create a serious challenge due to mobile phone battery limitations and low battery capacity [192]. Activity recognition needs continuous sensing from the mobile phone [87]. To minimize the battery challenge, Liang et al. [192] proposed an energy-efficient method (hierarchical recognition scheme) of activity recognition using a single tri-axial accelerometer sensor in a smartphone. They developed the algorithm with a lower sampling frequency and argued that their method extends the battery time for activity recognition. Furthermore, an Adaptive Accelerometer-Based Activity Recognition (A3R) strategy was introduced by [193]. This strategy adaptively chooses the accelerometer sampling frequency and the classification features. They claimed that their strategy achieved 50% energy savings under normal conditions.

Most of the systems mentioned above are developed with pre-defined data sources and supervised machine learning techniques, which result in a static model. However, new data source might replace the initial data source. It is expected that a robust system adapts to this dynamism by automatically incorporating the available data source [194]. Wen and Wand [194] developed a model using ensemble classifiers that can automatically adapt and refine the recognition system at run-time to address this problem. They argued that ensemble classifiers, particularly Adaboost, can automatically discover and adapt to the differences between the original and new datasets.

Labels are required to train classifiers from sensor data, and obtaining them can be tedious, costly, and painstaking and require expertise. Unsupervised learning was applied by [195], [197], [198], and [200] to address this issue. Unsupervised learning is a machine learning method that does not require ground truth (class label), but aims to model the distribution in the data to learn more about the data and discover hidden patterns. Another challenge is when most of the sensor data are not labeled (semi-supervised). Guan et al. [199] proposed a semi-supervised algorithm called 'En-Co-training' to utilize the unlabelled sensor data sample.

Some authors recently proposed a deep learning approach to enhance activity recognition performance. For example, Chen and Xue [8] used Convolution Neural Network (CNN) in their research. They developed CNN model and improved the convolution kernel to adapt to the features of tri-axial acceleration signals. Their experimental result shows that the model reached a mean accuracy of 93.8% without applying any feature extraction technique. Zeng et al. [201], Ronao and Cho [202], and Lee et al. [119], also used Convolutional Neural networks. Lee et al. [119] compared the accuracy with random forest algorithms. The analysis shows that CNN outperformed random forest in terms of recognition accuracy.

All the experiments was carried out without adequate privacy consideration. The participants were required to send their dataset to a central server, where algorithms is developed and trained to generate a model for activity recognition. This approach does not maintain the subject's privacy. Hence, this research presents a federated model where an individual dataset is not required to be sent to a central server; instead, model generated from the participants are sent for aggregation and computation.

2.8 Privacy preservation in healthcare

Healthcare data contain sensitive information which needs to be protected to avoid breaking the law and regulations that guide the use of data. Privacy in healthcare means giving access to health information to only authorized persons and providing a policy in which data might be accessed, utilized, and disclosed to a third-party [77]. Privacy must be addressed at all levels, such as data aggregation, storage, retrieval, and analysis, in order to prevent abuse and disclosure of sensitive information of the patient. To protect patients' sensitive information from potential misuse or disclosure, healthcare providers and institutions should understand various data sources and privacy requirements that must be followed. Recent researches in the healthcare industry is moving healthcare data control from the organization's level to the patient level, thereby giving patients more control and authority over decision-making regarding their sensitive information.

Different privacy preservation techniques exist, such as cryptography, access control, pseudonymization, blockchain-based and federated learning techniques [78]. The cryptographic technique uses an encryption mechanism to maintain user's privacy. In pseudonymization, the idea is to exclude any information which could be used to identify the patient. The access control method aims to ensure that only authorized personnel's have access to the patients' information, while the blockchain technique allows users to control their data through private and public keys. Finally, the federated learning techniques allow users to train machine learning algorithms without sending their dataset to a central server. Some potential research in healthcare domain have been conducted that aims to maintain patients' privacy. Huang et al.[79] proposed secured Personal Health Records system to collect and share health information. They used biometric-based and attribute-based health record accessing approaches for privacy preservation. Aledhari et al. [80] designed a cryptography algorithm to secure the cloud-based services in the healthcare system. Kshetri et al.[81] described a blockchain role to ensure privacy from cybersecurity threats. In [82], the authors developed an anonymous National

Clinical Data Warehouse (NCDW) framework to support research and analysis; while Li et al. [83] developed deep compression learning techniques in privacy computing infrastructure for analyzing and training neural decoding models.

This research proposes a privacy-preserving context-aware framework for cardiac health monitoring. The framework considers the patient's privacy from the initial design by allowing the user to take control of the data generated from the sensors as information is stored in the user's device and not transferred to any server, thereby allowing the patient to determine who can access their private information. This minimizes the mishandling and the misuses of patients private data. Furthermore, the user's privacy is also considered at the algorithm training and model generation stage by adopting a federated machine learning approach.

2.9 Summary

This chapter presented the literature review of previous works on health monitoring, more specifically on cardiac condition monitoring, discussing different technologies and methods used to develop context-aware systems for cardiac health monitoring. Challenges of developing context-aware systems in the healthcare domain and possible areas for improvements are also discussed. The analysis of the existing systems indicates that the available solutions in the literature lack some important features and requires significant improvements. This research aims to improve the existing systems by providing a better framework for cardiac health monitoring using contextual information. The proposed framework makes use of a federated machine learning technique for model development and provides an opportunity for healthcare professionals to offer personalized recommendations following contextual analysis. Next chapter outline the methodology that guided the development of the proposed context-aware system. The features of the proposed framework are also discussed in section 3.2.

Chapter 3

Research Methodology

3.1 Background

This chapter discusses the methodology employed in this research that led to the development of the system prototype. The features of the proposed framework are also discussed. The first phase of this research was a review of the current methods and technologies used to develop context-aware systems for cardiac health monitoring [126]. The comprehensive survey necessitates adopting the User-Centred Intelligent Environments Development Process (U-CIEDP) for the research design, development, and evaluation.

3.1.1 U-CIEDP Model

The U-CIEDP methodology was proposed to guide system developers in implementing systems that are robust and meet stakeholders' expectations in an intelligent environment [145]. On the other hand, the U-CIEDP methodology is more tailored for the end-users. The U-CIEDP model has three primary loops: initial scoping, main development, and IE installation. System requirements are gathered at the initial scoping stage by engaging stakeholders through interviews. Then, at the main development stage, the system is designed and implemented, involving the stakeholders at every stage. Finally, in the installation stage, different hardware components such as sensors, actuators, and network interfaces are installed, then the software is installed on the infrastructure, and various stakeholders carry out functional testing to ensure compliance. The U-CIEDP model has been used to develop systems such as projects proposed to support people with Down's syndrome [145] and a context-aware system developed for asthma condition management [146].

Figure 3.1 shows how the U-CIEDP guided the development of the system. The *stakeholder Engagement* part of the diagram indicates that the healthcare professionals were interviewed at the early stage of the research and were also involved during the validation process. The *Initial Scoping* stage indicates the feedback gathered from the stakeholder (Health Professionals and Cardiac Patients) from the initial interview to the validation stage. The *Main Development* stage shows the components of the system that was implemented for cardiac health monitoring, which was presented in section 4.2. Finally, the installation stage shows the mCardiac prototype ready for testing and deployment. The process that led to the development of the system had the approval of the Computer Science Research Ethics Committee of Middlesex University. More details about the development process is explained below.

3.1.2 Research Development Process

The stakeholders are at the heart of the U-CIEDP methodology, making it crucial to involve the healthcare professionals at the initial stage of the research. The understanding from the previous studies is that most researchers do not involve healthcare professionals during the development process. Some rely on what they read or what they perceive to be the most appropriate approach; however, this can sometimes be misleading as the system's main users are not engaged.

As part of the process, an interview was conducted with a cardiologist and a cardiac rehabilitation nurse at the early stage of the research to gather user requirements. The outcome of the interview reveals that physical activity recognition is a key element of cardiac condition monitoring, especially during rehabilitation; this leads to the next stage, activity recognition. A

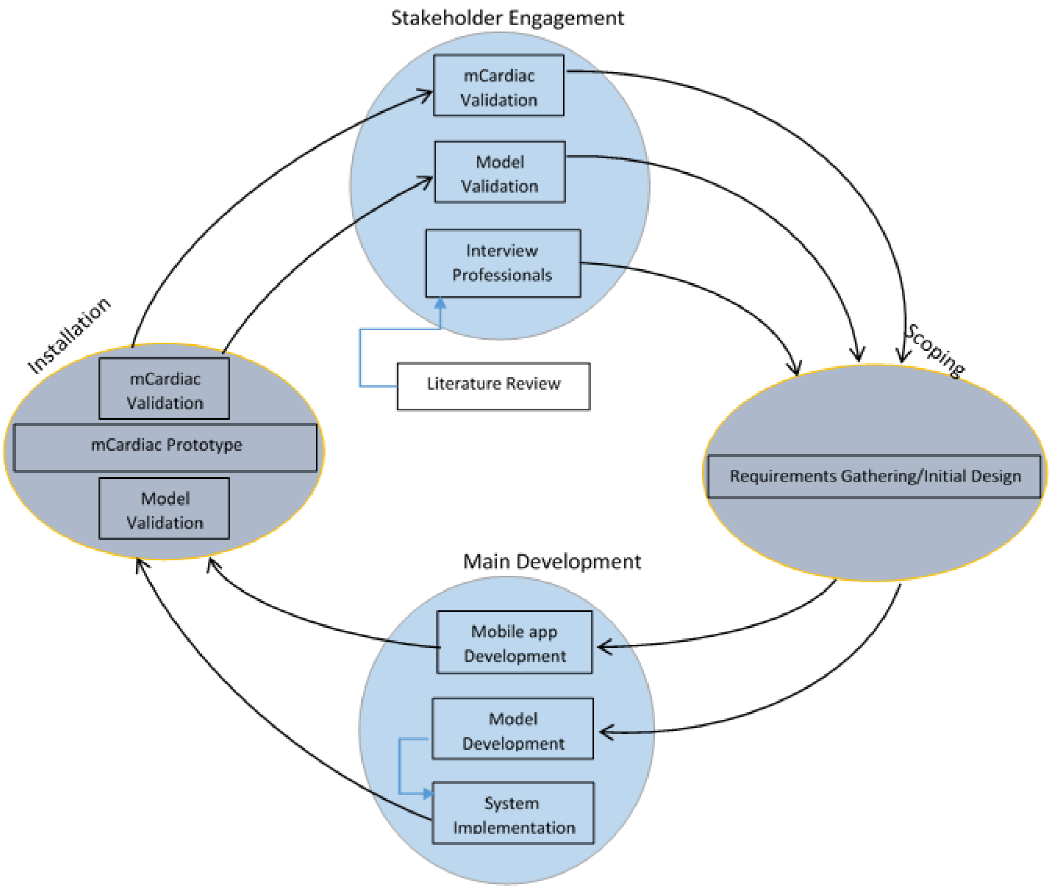


Figure 3.1: Research Methodology Guided by U-CIEDP model

mobile application was developed to collect accelerometer sensor data. The mobile app collects the x, y, z coordinates and the corresponding timestamp of the smartphone's accelerometer sensor. The x, y, and z coordinates indicate the direction and movement of the phone. The mobile app is supported on both Android and IOS based smartphones. Participants were recruited for the experiment, and the data collected from the volunteers was used to train machine learning algorithms for activity recognition. A federated machine learning technique was used to develop a model to predict the user's activity when sensor data without ground truth is fed into the model. A prototype was developed to enable healthcare professionals to visualize the patients' activity. To evaluate the system, cardiac patients were asked to wear the Holter monitor to record the ECG signals and smartphones running the mobile app. Finally, the system was presented to a group of healthcare professionals, which their feedback attest to the usefulness of the system.

3.2 Proposed Context-aware Framework

Context-awareness appears to be a promising field in the healthcare domain, particularly for cardiac patient monitoring as evidenced by the literature. However, a thorough foundation for developing such platform in an intelligent environment is lacking. This paper presents a paradigm for creating context-aware cardiac condition monitoring systems. The framework supports context acquisition, modeling and storage, context reasoning and visualization, and personalized recommendation. Furthermore, during the development process, the framework employs a federated machine learning technique to protect the user's privacy. It also address the issues of acquiring context by consulting stakeholders and tailoring the implementation strategy.

3.3 Proposed Framework Architecture

Context-aware system can significantly assist healthcare professionals in the patient monitoring process. However, existing context-aware solutions lack some important features and require significant improvement. For instance, existing context-aware architecture for cardiac condition monitoring does not consider the recommendation component, which our proposed approach incorporated in the design. It facilitates communication between healthcare professionals and patients under their care. This approach can also be used in other wellbeing and lifestyle improvement systems.

Figure 3.2 shows the high-level architecture of the proposed framework. The architecture is made up of the following features: (i) Context acquisition, (ii) Context modeling and storage (iii) Context reasoning and visualization, and (iv) Personalized recommendation. A brief explanation of each component is presented in this section.

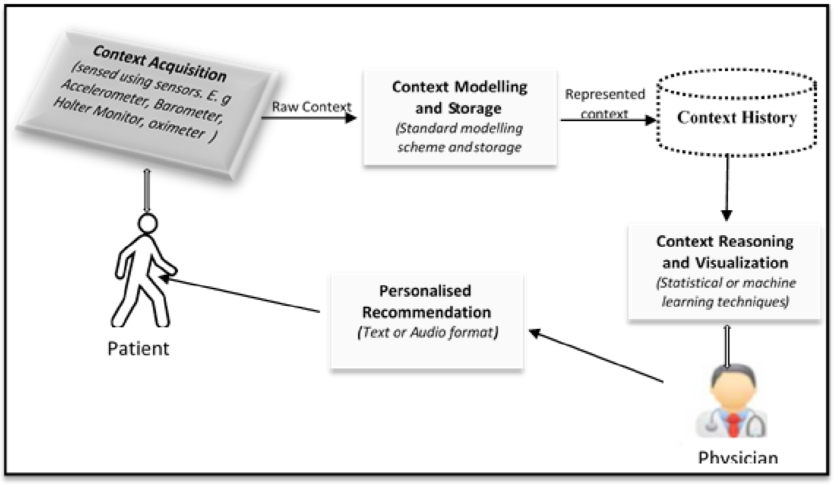


Figure 3.2: High level architecture of the context-aware framework

3.3.1 Context-Acquisition

Context acquisition is the process of obtaining contextual information. Perera et al. [129] presented three types of context acquisition process, which are sensed context, derived context, and context explicitly provided. Sensed context is acquired through physical or software sensors such as pressure, temperature, lighting, and noise level. Derived context can be computed from primary contexts such as distance, time, and date. An example of context explicitly provided is the user's preferences, "when explicitly communicated by the user to the requesting application" [129]. Regarding the way data is captured using sensors, it can be classified into three different groups: physical sensors, virtual sensors, and logical sensors [129].

Physical Sensors: This type of sensor generates sensor data by itself. These sensors are embedded in most of the devices we use today eg. accelerometer, temperature sensors, and blood pressure sensors. The raw data from physical sensors are called low-level contexts, which are less meaningful.

Virtual Sensors: The virtual sensors generate context data from software applications or services. For example, it is possible to track individual locations by the travel booking system, Facebook, or email. These sensors mainly use web services technology to send and receive data.

Logical Sensors: Logical sensors combine physical and virtual sensors to produce meaningful information. A web service used to get weather information could be regarded as a logical sensor. Weather stations make use of physical sensors to collect weather information. The stations also make use of virtual sensors such as map, calendar, and database data [129].

There is a lot of context information to consider when designing a context-aware system for health monitoring; however, only part of these contexts might be relevant. These contexts could be information from ECG signals, heart rate, blood pressure, temperature, medical profile, oxygen saturation, time of the day, and activity data. In health monitoring, healthcare professionals make decisions based on the derived knowledge from multiple sources of information such as physiological data, activity data, and medical history. A detailed understanding of the relevant contextual information is necessary to understand what the context-aware system should sense and adapt. System developers should only include entities and relationships that are relevant to a system task to prevent the system from becoming very complex [130]. This research addressed the challenge of context acquisition by consulting healthcare professionals to determine the necessary parameters for cardiac condition monitoring. Varshney [124] stated that health monitoring should be personalized and scalable. The personalization approach will improve the overall medical decisions, while the system's scalability will allow monitoring of more patients or frequent monitoring of the same number of patients. Due to different conditions and symptoms of cardiac diseases, the framework supports personalization in order to allow the healthcare professional to select the necessary contexts based on the needs, conditions, and preferences.

3.3.2 Context-Modelling and Storage:

Here, the sensed data is represented in an efficient and structured format for retrieval. Context modeling is defined by [66] as the "context representation that assists in the understanding of properties, relationship and details of context".

The goal of context modeling is to reduce the complexity of applications for robustness and usability and to improve the adaptability and maintainability for future development [132]. After data is sensed, it needs to be represented in meaningful values and formats for retrieval. There are different techniques for context modeling, such as key-value, mark-up scheme, graphical model, object-oriented, logic-based, and ontology-based.

Key-value: The key-value model is the simplest context modeling technique used for data representation. Here, a list of key-value pairs is used to define a set of attributes and values [131]. This method is easy to manage; however, it lacks the capability for sophisticated structuring for effective context retrieval algorithms.

Mark-up scheme: This model technique is an improvement of the key-value methods; It uses mark-up languages such as XML to define hierarchical data structures. The mark-up tag (attributes and content of attributes) is used to represent and format the data. "The use of the XML-based scheme was motivated by the ability to solve data heterogeneity and to represent, store and flexibly exchange data" [131].

Graphical model: This is a graphical representation of the contextual data using appropriate models such as Unified Modeling Language (UML) or Object-Role Modelling (ORM). This approach is applicable in Entity Relationship (ER) model, which is very useful for structuring relational database systems [147].

Object oriented model: Object-oriented modeling approach tends to employ the concept of encapsulation, reusability, and inheritance to represent context data. The details of the context processing are hidden from other components and encapsulated in the object level [147]. Mshali et al. [131] reported that the research by [8] proposed a context-aware system for smart homes using an object-oriented context model. Context data is structured around a set of entities in this model, and each entity describes a physical or contextual object such as a person or an activity. Contextual entities are connected to their attributes and other entities with defined relations.

Logic based model: In this model, facts, expressions, and rules are used to define the context model. The logic-based knowledge representation model is used to model the raw data and the logical rule then used to extract contextual information [131]. The model representation can be developed by employing an interactive graphical approach to allow non-technical users to add rules and logic to the system, hence making it flexible [148]. However, the drawback of this model is that it "lacks standards, specification, and validation and is strongly coupled with applications, which reduces its usability and applicability" [148].

Ontology based model: The ontology-based model is the most widely used modeling technique, hence adopted for this research. It uses semantic technologies to represent and organize context information into hierarchical structures based on their relationship. The major components of this modeling approach are concepts, instances, and relationships that can be used to form the context data. This model aims at providing simple and flexible well-designed objects; however, context reasoning could be computationally expensive with growing data size [132]. It has advantages over other models in that it allows the domain knowledge to be shared and reused, and they have a lot of development tools such as Web Ontology Language (OWL) and Resource Description Framework Schema (RDF) [148].

The proposed framework allows for representing and storing the contexts in different formats for extraction and reasoning. For this research, machine learning model was used to classify activities from the sensor-generated data to enable the abstraction of a high-level context from the low-level context, which is more meaningful than the sensor-generated data. Details about the use of the machine learning algorithms are presented in section 4.2.

3.3.3 Context-Reasoning and Visualization

This component aims to deduce knowledge from the context data [129]. The contexts data acquired from sensors does not make meaning unless it is processed, analyzed, and interpreted to gain knowledge. Therefore, a context-aware system needs to use appropriate reasoning methods to communicate the content of the sensor data. The task of context reasoning can be divided into three stages: Data pre-processing, data fusion, and context inference. The stage of data preprocesses aims to clean collected data, handle missing values, and remove unnecessary features. The data fusion stage aims to integrate data from different sources, while the context inference phase analyzes and interprets context data. Researchers applied different techniques such as supervised and unsupervised learning methods to discover hidden information from the represented contexts.

This research provides a pattern discovery approach with the corresponding time-of-the-day information that will enable the healthcare professional to read, understand and consider the subject's activity when reading the physiological data. The system will enable the clinician to reason about the patient's health condition and offer personalized recommendations. In addition, it will enable the physician to understand the time spent on each activity daily or weekly and the implications of this on the patient's health condition.

3.3.4 Personalized Recommendation

For effective cardiac rehabilitation monitoring, the finalized system will incorporate a personalized recommendation module to communicate to the monitored patient regarding their health status. Different recommendations exist, ranging from providing a simple user interface to using machine learning techniques. By providing a user interface, the healthcare professional studies the outcome of the analysis and offers personalized recommendations to the patient. At the same time, in the machine learning approach, the system learns from itself and provides the right advice to the subject. The recommendations could be in the form of text, or audio [149] and tailored to the patient's specific needs and conditions. The recommendation aims to continue engaging the patient to adjust or change behavior and maintain the change.

3.3.5 Summary

This chapter presented the methodology used for the system design, development and evaluation. The research adopted U-CIEDP methodology in order to present a context-aware system that meets stakeholders' expectations in an intelligent environment. Next chapter of this thesis explores the impact of machine learning on health monitoring. Various machine learning approaches and algorithms are explained. Federated machine learning techniques are also discussed, including their ability to maintain users' privacy.

Chapter 4

Health Monitoring using Machine Learning

A context-aware system is made up of heterogeneous sensors and devices generating numerous amounts of data regularly. However, converting this large amount of data into a knowledge base requires machine learning technique [150]. Machine learning provides computational methods and learning mechanisms that help us induce knowledge from sensor data. Most machine learning methods fall into one of two learning tasks: supervised and unsupervised learning. The major aim of supervised learning is to develop a model to predict an output based on the class label; while in unsupervised learning, there is no class label; the goal is to model the distribution in the data to learn more about the data [162]. This work is about supervised learning, where machine learning algorithms are trained on labeled data (the training set) to build predictive models which will enable us to predict the output of new unseen observations. Supervised learning task the machine to learn from data when we specify the ground truth [162]. The processed data is fed into algorithms; the algorithms learn from observations and make a prediction based on the class label. Such data could be sensor, image, or historical information. Examples of supervised learning algorithms are support vector machine, k-nearest neighbor (KNN), random forest, artificial neural networks (ANN), decision tree, and logistic regression.

4.0.1 Random Forest

Random forest is an ensemble machine learning approach that works by averaging several predictions of independent base models [165]. It is developed by combining the prediction of different trees, each of which is trained individually. It can be used for both classification and regression tasks, and is capable of handling noise data and can prevent data overfitting.

4.0.2 Support Vector Machine

Support vector machine is a supervised machine learning technique that discriminates between two classes by generating a hyperplane that optimally separates the classes. It uses machine learning techniques to maximize classification accuracy while automatically avoiding model overfitting [166]. The algorithm makes use of nonlinear functions known as kernels to transform the input data into a multidimensional space [167]. On the other hand, the kernel is responsible for transforming the given dataset to another dimension space to linearly separate the classes. For this research, the experimental analysis is based on learner SVM which is parametric.

4.0.3 Artificial Neural Network

ANN is a biologically inspired algorithm used to model a very complex nonlinear dataset [66]. "The purpose of the neural network is to create a model that correctly maps the input to the output data so that the model can be used to produce the output when the desired output is unknown" [91]. Multi-Layer Perceptron (MLP) is the most widely used ANN and is considered to be a great model for classification and prediction tasks. It is made up of the input layer, hidden layer, and output layer. The input layer represents the input variables, while the hidden layer, of which there can be one or more, performs computations on weighted input to produce the output. Finally, the output layer is the class label of the dataset. The neurons in the input layer receive the input variables and pass them to the hidden layer. The data is processed mathematically and brings out the result which is the output layer.

4.0.4 K-nearest Neighbor

KNN is a supervised machine learning technique that stores the training dataset and makes use of distance metrics such as Euclidean distance, Manhattan distance, or Hamming distance to classify new data points based on the k-nearest category. The objective is to classify a new data point by searching through the K given points in the training dataset that are nearest to it in the input or feature space [90]. It is a non-parametric algorithm because it does not make assumptions about the underlying data. One major challenge of using KNN is that it requires storing the training dataset, which can be computationally expensive given a large dataset.

4.0.5 Decision Tree

Decision Tree is a classification algorithm that can be used for solving regression and classification problems [162]. The goal of using Decision Tree is to create a training model that can be used to predict the class or value of the target variable by learning simple decision rules inferred from training data. To predict a class label for a record, the algorithm starts from the root of the tree, then compare the values of the root attribute with the record's attribute. On the basis of comparison, follow the branch corresponding to that value and move to the next node.

The challenge of the decision tree algorithm is the identification of the attribute for the root node in each level. This process is known as attribute selection.

4.0.6 Naive Bayes

Naive Bayes is a probabilistic machine learning algorithm based on the Bayes Theorem [162]. Bayes' Theorem aims to calculate the probability of a piece of data belonging to a given class, given prior information about the data. Bayes' Theorem is stated as

$P(class|data) = (P(data|class) * P(class))/P(data)$

where $P(class|data)$ is the probability of class given the provided data. Naïve Bayes classifier is a popular classifier which has been employed in many tasks. It assumes that all attributes (i.e. features) of the samples are independent of each other given the context of the class. The Naive Bayes model is easy to build and particularly useful for very large data sets. Along with its simplicity, it is known to outperform even highly sophisticated classification methods.

4.0.7 Logistic Regression

Logistic regression is a classification algorithm that helps to estimate categorical results with the help of a group of variables [92]. The model makes use of the black-box function known as the softmax function to understand the relationship between the categorical dependent and independent variables. In machine learning classification, the dependent variable is the target class to predict, while the attributes or features used to predict the target class is regarded as the independent variables. Logistic regression is a parametric algorithm in that it summarizes data with a set of parameters of fixed sizes independent of the number of training datasets. This implies that no matter the amount of dataset used to learn the model, it will not change the number of parameters the algorithm needs.

4.0.8 Application of machine learning in healthcare

Machine learning models have been largely developed to facilitate the diagnosis, prediction, and treatment of different diseases such as brain disease [93], kidney disease [159] and diabetic disease [95]. A couple of researchers such as [96], and [98] used ANN for heart disease diagnosis. A support vector machine classifier was also used to diagnose diabetes disease in [97]. In [128], random forest classifier was used to classify sensor data for cardiac condition monitoring. These machine learning models have proven to be effective in healthcare services. However, the centralized approach of training the machine learning algorithms poses privacy infringements as the approach requires gathering datasets on a single server. This research proposes federated learning approach that does not require gathering datasets from different clients on a central server.

4.1 Federated machine learning

Health care data contains sensitive information that different clients may not be happy to share with anyone. Moreover, various policies and regulations, such as the General Data Protection Regulation (GDPR) which was enforced in 2018 by the European Union, have been developed to regulate the sharing and analysis of such sensitive data. These create a huge problem when exploring the potential of machine learning techniques in the healthcare domain, which typically requires a large amount of training dataset [99]. "Privacy is also a key value of the Montreal Declaration for a Responsible Development of Artificial Intelligence 2018" [173].

Federated learning is a new paradigm in the field of machine learning, which allows different clients in different locations to collaboratively learn a machine learning model without transferring datasets that may contain private information to a central server [138]. It allows knowledge sharing without compromising user privacy and minimizes model overfitting, which is prevalent in the centralized approach. Federated learning has been applied in different domains ranging from healthcare; to IoT, transportation, mobile apps, and defense [163]. The difference between the centralized approach and the federated approach is that in the centralized approach, the individual dataset is sent to the server, where the machine learning model is developed. The aggregated data is used to train the machine learning model, and each user can access the model by connecting to the server. Meanwhile, in the federated learning approach, each client trains the model using their private data, and the parameters are sent to the server for aggregation. Data is kept in each client domain, and knowledge is shared through aggregated models [43]. Figure 4.1 shows the architecture of the federated learning technique, while figure 4.2 shows the architecture of the centralized learning technique. The local model represents the model at the client's level, while the global model summarizes the aggregated local models.

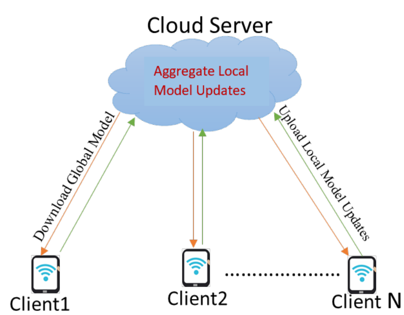


Figure 4.1: Federated Architecture

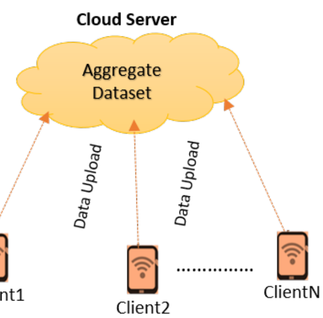


Figure 4.2: Central Architecture

Local Models: The local model is the representation of the knowledge from the client's dataset. Each client trains the local model with their dataset. Finally, the learning parameters from the local model are sent to the server for aggregation and computations.

Global Model: The global model is a collection of the local models from different clients. If the local models are a good representation of the underlying data structure, then an aggregation will create a stronger and better global model.

There are four steps in the development of a federated learning model [163]. (1) Develop and train the model using a publicly available dataset. It is assumed the dataset can be used without privacy concerns (2) A copy of the global model is sent to different clients, and they train the copy of their model using their private dataset (3) Then, each client sent the updated model to the server without sharing their dataset(only parameters are shared) (4) The server aggregates the parameters from different clients and generates a new model. The new model is then distributed to the participating clients.

4.1.1 Model Aggregation Algorithms

Model aggregation is a way of combining trained models from different clients in order to have one global model that is more robust and generalized to the population. Carlsson [171] presented three approaches for model aggregation in a federated manner: FederatedAveraging, FederatedHighest and FederatedRandom. In FederatedAveraging, each model's weight (learning parameters) is added together and then divided by the total number of clients involved in the federation. In FederatedHighest, the aim is to find the highest-scoring local model and adopt it as the new global model. This will be distributed to the other clients, while in the FederatedRandom; the algorithms try to remove some models from the aggregated model and then calculate the average of the remaining models' weights, taking this as the new global model. The most widely used algorithm for federated learning is federated averaging [172]. In this approach, the weights(learning parameters) of the models from the clients are averaged to provide a new weight leading to a new model.

4.1.2 Application of federated learning in healthcare

This section presents some potential research in healthcare that utilizes a federated learning approach to maintain privacy. Lee et al. [175], presented a privacy-preserving platform using federated approach for patient similarity learning across different healthcare institutions. They argued that their model has the capacity to find similar patients from one hospital to another without sharing patients' sensitive information. Silva et al. [168], proposed a federated learning framework to access and analyze any biomedical data without sharing patients' information. They demonstrated the feasibility of the framework by investigating brain structure relationships across different diseases and clinical records. The framework was tested on different datasets to show the potential of the proposed approach. Brisimi et al. [169], also proposed to solve a binary classification problem in predicting cardiac hospitalization events using distributed algorithms. Pfohl et al, [170], studied the efficacy of centralized versus federated learning approaches using healthcare data in both private and public settings. They considered the prediction of prolonged length of stay and in-hospital mortality across 31 hospitals.

Sharma et al.[173], also applied the federated learning technique for the prediction of in-hospital mortality amongst patients admitted to the intensive care unit (ICU). They trained a global machine learning model using vital signs of data across different hospitals without sharing datasets. They argued that the federated learning framework provides a solution to issues related to privacy and ownership of healthcare data. Choudhury et al. [174], proposed a federated learning framework for distributed health data held in different locations. The framework has the advantage of maintaining the privacy of the clients involved in the learning process and also makes use of differential privacy mechanisms to further protect the model from potential privacy attacks. Chen et al. [100] proposed a federated transfer learning framework for wearable healthcare. The framework was evaluated using activity data and argued that it achieved high accuracy without compromising the privacy of the individuals.

Most of these research used deep learning technique for the federated approach and had reasonable classification accuracy . However, deep learning algorithms are computational demanding and may not be suitable for some devices for the algorithm training. This research investigates the potential of traditional machine learning algorithms for the federated learning. Using federated learning approach for the algorithm training aims to maintain user's privacy.

4.1.3 Challenges of Federated Learning

The federated learning technique has the potential to maintain the privacy of users; however, the application of the approach has its drawbacks, such as imbalanced datasets, model attack, and communication cost.

Imbalanced datasets: When training algorithms using the federated approach, there is the possibility that the data may be imbalanced, which can affect the performance of the algorithms [172]. Imbalanced data occurs when one or more clients have more datasets than other clients in the federation.

Communication cost: Communication cost is one of the major bottlenecks of the federated learning process, during the training process. Due to differences in download and upload speed, communication between server and clients should be minimal to reduce upload times [108]. Previous research attempted to solve this challenge through data compression or sending only relevant weight (learning parameters) back to the central server for aggregation [109].

Model attack: Malicious personnel, could modify the training model by tampering with its parameters before sending the model to a central server for aggregation. This can lead to the model being poisoned with invalid parameters during the aggregation process, hence can affect the performance of the global model[109].

4.2 Experimental Analysis using Federated Approach

The built-in accelerometer sensor in modern Smartphones has made it possible to detect the user's activity dynamically. To recognize user's activity, the subject needs to carry the mobile phone while doing daily activities. The first phase of the activity recognition is data collection using a mobile app. Smartphone was selected for the research because of its convenience and a large proportion of the population has a smartphone with an accelerometer sensor. The mobile app collects the A_x, A_y, A_z axis data, and the corresponding timestamps. Secondly, the sensor data is processed and partitioned into equal groups at time-interval representing the segmentation stage. In the third stage, features are extracted from each group. Finally, the extracted features are used to train machine learning algorithms in order to classify new data without ground truth. Algorithm 1 shows the process of activity recognition using a centralized approach. The process starts by aggregating data from different clients $K = k_1, k_2, ...k_n$. The aggregated data is partitioned into windows w and features F_i extracted. The extracted features are used to train machine learning algorithms using the training dataset, $Ftrain$. Finally, the model evaluated using the test dataset, $Ftest$, and the accuracy returned.

Algorithm 1 Activity Recognition Process for Centralized Learning

Input: $D = A_x, A_y, A_z, M_g$
Output: Predicted Activities
Aggregate data D_k from clients $(k_1, k_2, \ldots\ldots\ldots k_n)$
Partition D_K into sliding windows (w)
for each w in D_K **do**
    Extract features $F_i = f_1, f_2 \ldots\ldots\ldots\ldots f_j$
Split F_i into Train($Ftrain$) and Test($Ftest$) sets
Train algorithm with $Ftrain$
Predict activity with $Ftest$
$results$ = accuracy(Predicted activities)
Return $results$

Feedback gathered from relevant professionals at earlier stages of the project indicates that physical activity recognition is an essential part of cardiac condition monitoring. However, the traditional machine learning method of developing a model for activity recognition suffers privacy infringements. Our initial approach to handle the privacy challenge was by personalizing the activity recognition process [128]. In this approach, each user generates a model which is used to recognize the subject's activities. This proved to be effective; however, each participant might not generate enough data for algorithms training which might result in model overfitting. Hence, this research adopted a federated machine learning approach, allowing different clients in different locations to train a copy of their model and send it to a central server for aggregation and knowledge sharing without compromising users' privacy.

4.2.1 Dataset Description

Samples of accelerometer data from 13 volunteers [178] were used to demonstrate the federated learning approach. Dataset from 12 volunteers was used for the algorithm training, while dataset from one participant was used for testing. The participants were asked to put the mobile phone running our data collector app in their pocket and perform four activities: sitting, walking, jogging, and standing. However, five of the participant could perform only three activities; Sitting, Standing and Walking. The participants whose dataset was used for testing performed the four activities. The mobile app collects the A_x, A_y, and A_z axis data along with the timestamps at a frequency of 50Hz. The x-axis captures the horizontal movement of the smartphone; the y-axis indicates the upward/downward movement of the phone; while the z-axis shows the forward/backward movement of the mobile device [177]. The dataset is available at [178].

4.2.2 Preprocessing and Feature Extraction

The magnitude of the three axes was computed to handle the orientation problem of the smartphones making it four features; A_x, A_y, and A_z and magnitude. The magnitude (m_g) of the total acceleration is computed by the square root of the sum of the squared acceleration of three axes in equation (4.1).

$$M_g = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2} \tag{4.1}$$

Sliding window techniques were used to partition the sensor data into four-second equal windows and extracted time-domain features from each segment. For a given time series $[x_1, x_2, x_3, ..., x_n]$, n represents the total number of samples in each window segment, then features were extracted from each window. Table 4.1 presents the extracted features for the analysis. Each feature represents an input vector used for the algorithm training.

The experimental analysis is based on two different use cases. In the first scenario, we consider a client to be a hospital, institution, or station; while in the second scenario, a participant is considered as a client.

Table 4.1: Extracted features for algorithm training

Feature	**Equation**
Mean	$mean = \frac{1}{n}\sum_{i=1}^{n} x_i$
Variance	$var = \frac{1}{n}\sum_{i=1}^{n}(x_i - mean)^2$
Standard Deviation	$std = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - mean)^2}$
Minimum Value	$min = MIN(x_i)$
Maximum Value	$max = MAX(x_i)$
Median value	$median = \frac{n+1}{2}$
Standard Error of the Mean(sem)	$sem = \frac{std}{\sqrt{n}}$
Kurtosis Value	$n * \sum_{i}^{n}(x_i - \overline{x})^4 / (\sum_{i}^{n}(x_i - \overline{x})^2)^2$
Skewness Value	$\sum_{i}^{n}(x_i - \overline{x})^3 / (n-1) * std^3$

4.2.3 Baseline model

Global models was developed using the default parameters provided by Sklearn library in python and dataset from the first four clients in table 4.4 . It is assumed that the dataset from the four participants could be used without privacy concerns. The four participants performed the four activities. The dataset were aggregated, processed and used to train different machine learning algorithms. Table 4.2 shows the performance of each of the machine learning algorithms. Random forest and K-nearest neighbour had the highest classification accuracy. However, these algorithms are not suitable for federated learning because they are non-parametric. Logistic regression and linear SVM which are parametric algorithms was selected for the experiment. Logistic Regression and linear SVM are parametric algorithms in that they summarizes data with a set of parameters of fixed sizes independent of the number of training datasets. The code for this experiment is available at [179].

4.2.4 Case Study One

In this case study, we grouped the participants into four groups and assumed each group to be a clinical center (client); hence, we had four clients for the

Table 4.2: Comparison of different models

SN	**Algorithms**	**Accuracy** (%)
1	Random Forest	92
3	Naïve Baye	86
4	Logistic Regression	77
5	Decision Tree	91
6	K-Nearest Neighbour	92
7	Linear SVM	81

experiment. A client could be a mobile phone, a wearable device, or a hospital data warehouse [99]. Five of the participants were able to perform only three activities: sitting, standing, and walking; while eight participants performed four activities: sitting, standing, walking, and jogging. Therefore, each group contains data sets from two participants who performed the four activities and one participant who performed only three activities, except group one with one participant who completed the four activities and two participants who performed the three activities. The distribution of samples collected from the groups is presented in table 4.3. Due to the imbalanced distribution of the dataset as shown in the table, the class weight was set to "balanced" in the Sklearn python library. The code for this experiment is available at [179].

Table 4.3: Distribution of samples from the users for case study one

Activities	Client1	Client2	Client3	Client4	TestData
Sitting	21649	32045	19192	14411	19905
Standing	16203	28028	20184	11262	9970
Walking	20470	33160	13821	16200	12228
Jogging	5320	6253	6363	15868	11851

Model Development and Aggregation: Two machine learning algorithms (Support Vector Machine and Logistic Regression) were used in demonstrating the federated learning approach. The regularization parameter in Support Vector Machine (SVM) and the inverse of the regularization parameter in Logistic Regression (LR) were used as the learning parameters for the experiment. The regularization parameter shows how much the algorithm will focus to minimize misclassification.

Federated Logistic Regression: The global model from logistic regression was used as the baseline model and assumed to be distributed to the clients. With the help of the Gridsearchcv library in python, the optimal parameter was retrieved from each client. Figure 4.3 shows the results of the parameter turning for the four clients. The solid line shows the training score, while the dotted line indicates the cross-validation scores using 10-fold cross-validation. The optimal parameter for client1 was found at $P_l = 0.004$, client2 at $P_l = 0.004$, client3 at $P_l = 0.001$ and client4 at $P_l = 0.001$. Different values of the learning parameter were tested to determine the optimal parameter, see Figure 4.3. The parameters were aggregated, and the average was computed and the result used to update the global model. The updated model gave a classification accuracy of 80% using the testing dataset which indicates improvement compared to baseline model.

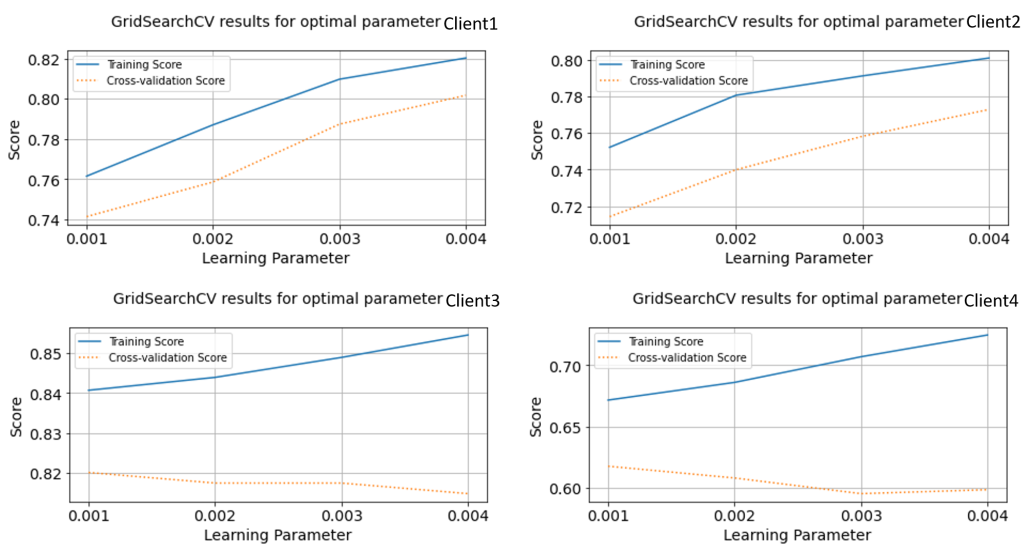


Figure 4.3: Results of the learning parameter search using logistic regression

Federated Support Vector Machine: The global model from linear SVM was used as the baseline model and assumed to be distributed to the clients. With the help of the Gridsearchcv library in python, the optimal parameter was retrieved from each client. Figure 4.4 shows the results of the parameter turning

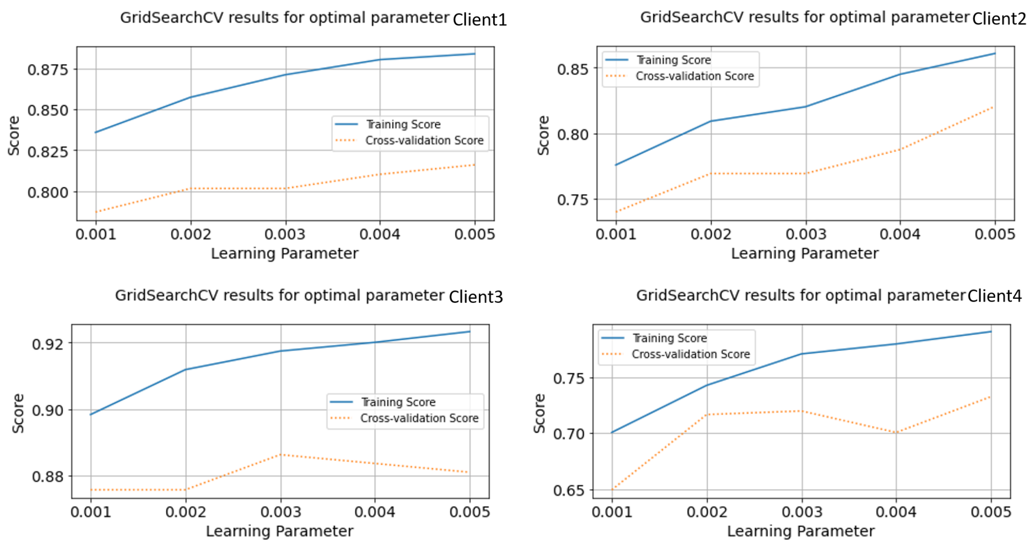


Figure 4.4: Results of the learning parameter search using support vector machine

for the four clients. The solid line shows the training score, while the dotted line indicates the cross-validation scores using 10-fold cross-validation. The optimal parameter for client1 was found at $P_l = 0.005$, client2 at $P_l = 0.005$, client3 at $P_l = 0.003$ and client4 at $P_l = 0.005$. The optimal parameters were aggregated, the average computed, and the result used to update the global model. Different values of the learning parameter were tested to determine the optimal parameter, see Figure 4.4. Evaluating the model using the testing dataset gave a classification accuracy of 76%. This is relatively lower than the performance of LR which recorded accuracy of 80% accuracy. The code for this experiment is available at [179]

4.2.5 Case Study Two

In this case study, we assume each participant to be a client. The accelerometer sensor data from the eight participants that performed the four activities (sitting, standing, walking, and jogging) were used for the federated analysis in this case study. The distribution of the samples is presented in table 4.4. Due to the imbalanced distribution of the dataset, as shown in the table, the class weight was set to "balanced" using the Sklearn python library. The code for this experiment is available at [179].

Table 4.4: Distribution of samples from the users for case study two

Activity	Client1	Client2	Client3	Client4	Client5	Client6	Client7	Test
Sitting	9767	4919	10415	5066	5169	4105	4472	19905
Standing	8037	4102	11978	6259	4396	5622	3378	9970
Walking	6859	5515	5857	8472	4608	3771	3574	12228
Jogging	5320	4581	2323	14314	4040	1554	1672	11851

Federated Logistic Regression: The LR global model in case study one was used as the baseline model in this case study. The optimal value of the learning parameter using each client's dataset was searched. With the help of the Gridsearchcv library in python, the optimal parameter was retrieved from each client. Figure 4.5 shows the results of the parameter turning for the seven clients. The solid line shows the training score, while the dotted line indicates the cross-validation scores using 10-fold cross-validation. The optimal parameter for client1 was found at $P_l = 0.001$, client2 at $P_l = 0.005$, client3 at $P_l = 0.001$ client4 at $P_l = 0.004$, client5 at $P_l = 0.003$, client6 at $P_l = 0.003$ and client7 at $P_l = 0.005$. The optimal parameters were aggregated, the average computed and used to update the global model. Evaluation of the model using the test dataset gave a classification accuracy of 80% which shows improvement compared to the baseline model.

Federated Support Vector Machine: The SVM global model in case study one was used as the baseline model in this case study. The optimal value of the learning parameter was also searched using each client's dataset. With the help of the Gridsearchcv library in python, the optimal parameter was obtained from each client. Figure 4.6 shows the results of the parameter turning for the seven clients. The solid line shows the training score, while the dotted line indicates the cross-validation scores using 10-fold cross-validation. The optimal parameter for client1 was found at $P_l = 0.001$, client2 at $P_l = 0.003$, client3 at $P_l = 0.001$ client4 at $P_l = 0.003$, client5 at $P_l = 0.001$, client6 at $P_l = 0.005$ and client7 at $P_l = 0.005$. The optimal parameters were aggregated,

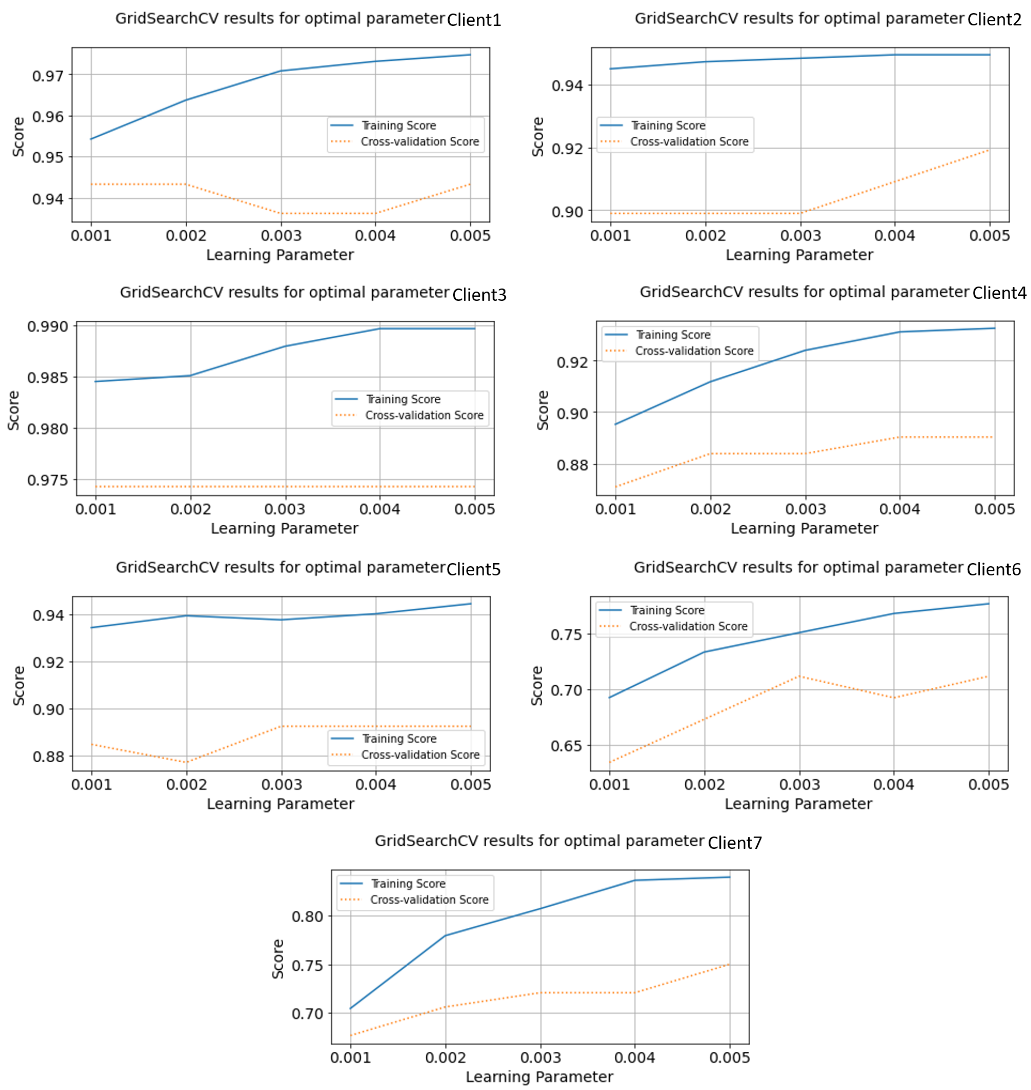


Figure 4.5: Results of the learning parameter search using Logistic Regression

the average computed, and the result used to update the global model. Different values for the learning parameter were tested to determine the optimal parameter, see Figure 4.6. Evaluating the new model using the testing dataset gave classification accuracy of 76%. This is also lower than the performance of the LR in this case study. It was also observed that the baseline model performed better than the federated model using SVM in both case studies. However, the FL model may result in lower accuracy for gaining higher data privacy as a trade-off [164].

4.2.6 Federated Algorithm for the Activity Recognition

The algorithm 2 shows the federated machine learning process for the activity recognition. The algorithms start by developing a global model m. Then the model distributed to different clients $k = k_1, k_2, ...k_n$. Each client extract features $F_i = f_1, f_2...f_j$ from their dataset. The extracted features were used to obtain the optimal learning parameter P_l using GridSearchCV library. The values of P_l are aggregated from different clients, and the average is computed and used to update the global model.

Algorithm 2 FederatedAveraging for activity recognition. The K is the number of clients and P_l is the learning parameter

Input $D = A_x, A_z, A_y, M_g$
Develop global model m
Distribute m to clients K
for each client in $K = k_1, k_2, \ldots\ldots\ldots k_n$ **do**
    Partition D_K into sliding windows (w)
    for each w in D_K **do**
        Extract features $F_i = f_1, f_2 \ldots\ldots\ldots\ldots f_j$
    Search for optimal P_l
Aggregate P_l and compute average $avg(P_l)$
Update model m

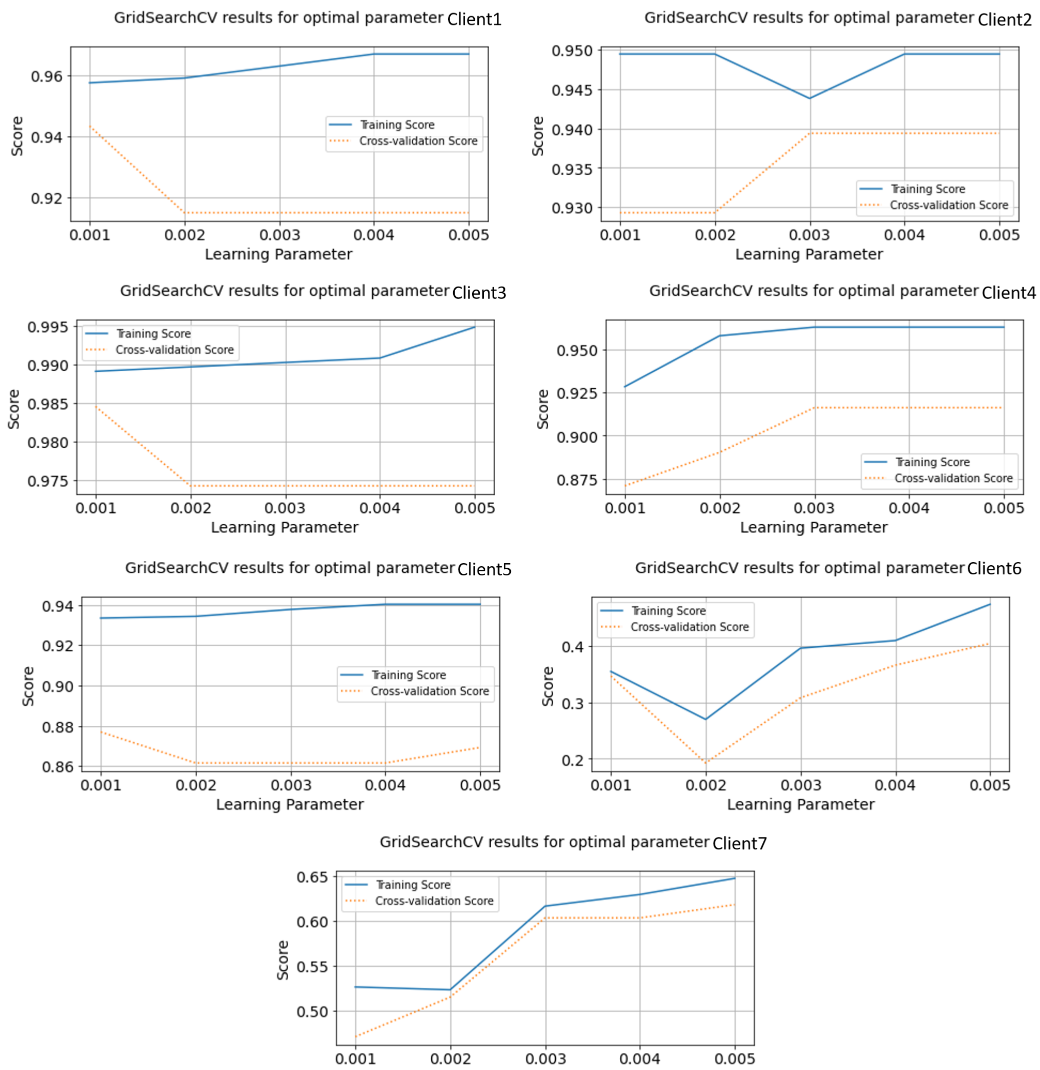


Figure 4.6: Results of the learning parameter search using SVM

4.3 Summary

Machine learning is on the edge of transforming productivity, working habits, and our overall way of living. Improving the quality of life and reducing medical costs are the key benefits of machine learning in the healthcare domain. Commonly known for its capacity to perform complex tasks such as activity recognition, pattern recognition, and disease diagnosis, machine learning has the potential to simplify the life of patients and healthcare professionals by performing a task in a shorter time and at a reduced cost. This chapter discussed different machine learning techniques for health monitoring, such as naive Bayes, linear SVM, logic regression, k-nearest neighbor, and decision tree. Logistic regression and linear SVM were selected for the experimental analysis due to their parametric nature.

Despite its drawback, federated learning has become a hot topic in research areas related to machine learning. It has proved to increase the confidence of the society participating in model training. This machine learning approach (federated learning) was used to develop a model for activity recognition in section 4.2.

The main difference between centralized and federated learning is that the centralized learning approach requires aggregating datasets from different locations into a central server. In contrast, federated learning involves aggregating model parameters from different clients. In centralized learning, each client is required to transfer their dataset to a central server. However, some clients might not be happy to send their datasets due to privacy concerns. This usually results in developing a model that overfits; hence, it does not generalize to the population due to insufficient training datasets. Generalization is the ability of a machine learning model to classify data not in the training dataset correctly. This is not the case with federated learning, as the dataset is not required to be transferred to a central server; only trained models are sent to the server for aggregation. The federated approach allows individual clients to use their dataset to train a copy of the global model. Then, the models from each client are sent to a central server for aggregation and averaging, which is used to update the global model.

Another advantage of federated learning over centralized learning is that the centralized approach entails that a huge amount of storage capacity is required as well as sophisticated security protocols to avoid violation of the right to data. While in federated learning, only the trained model is sent to the server, which is not heavy compared to the dataset. The security required to protect the model is not as demanding as for datasets.

To demonstrate the federated approach, we collected accelerometer sensor data from 13 participants to train machine learning algorithms. We study two different scenarios where federated learning can be applied. In the first use case, we partitioned the dataset into four groups and assumed each group to be a client, while in the second use case, we considered each participant to be a client. Then, we compared two machine learning algorithms: logistic regression and linear support vector machine. The overall results indicate that logistic regression performed better than linear SVM in terms of classification accuracy; hence adopted for the rest of the work.

Chapter 5

Decision Support System (DSS)

Interactions between humans and machines characterize many activities of healthcare professionals. Away from the traditional manual approach, computerized systems are now moving toward complex analysis, making use of artificial intelligence to assist humans in the decision-making process [151]. A computerized decision support system may be required in an organization or industry for various reasons, such as fast computation, improved communication, increased productivity, technical support, and data warehouse access.

Most of the decision support methods provide an opportunity for quick data queries and models to convert the data into usable information for further investigation by humans. For instance, data can be fed into a forecasting model where it is converted to information that could be helpful for decision-making resulting in better and higher-quality services. A computer-based DSS involves the combination of computer hardware and software that is designed to complement the cognitive processes of humans in their decision-making process [151]. There are different areas of DSS applications such as Agriculture [152],[153]; Marketing [154], and Manufacturing Industries [155]. However, this research focuses on healthcare, more specifically for cardiac health monitoring.

5.1 Context-Aware Decision Support for Cardiac Monitoring

The importance of context-aware DSS is revealed by the knowledge gained by combining multiple sources of information to provide better insight and understanding of the situation under consideration. It helps in establishing a diagnosis and provides reminders and alerts to clinicians when new patterns in a patient's data are discovered [46]. The most promising applications of this technology in healthcare are for the diagnosis of chronic and cardiovascular diseases such as heart disease [47]; [48], brain disease [93], kidney disease [159] and diabetic disease [95], as well as monitoring of activity in elderly people using intelligent home monitoring devices [49]. It uses context data in combination with learning algorithms to provide proactive services, and a highly adaptable context-aware system [50].

This research presents a context-aware decision support system (mCardiac) for cardiac condition monitoring and management during rehabilitation. The system will utilize the patient's contextual information from activity data to provide a useful tool to physicians. This will enable the healthcare professional to make better decisions and recommend appropriate treatment mechanisms to avoid cardiac readmission or perhaps even death.

This research considers ECG signals from Holter monitor, activity data from smartphones and time of the day as essential sources of information to provide an effective and efficient system for cardiac rehabilitation monitoring. These sources of information were selected based on interviews with the stakeholders (Health professionals). The system involves data collection from Holter monitor and smartphone sensors, machine learning algorithm training for activity recognition and pattern discovery, and finally, implementation of a decision support tool. Figure 5.1 shows the architecture of the context-aware decision support system. During the monitoring process, the subject will be required to carry a smartphone running the mobile app to collect accelerometer sensor data and a Holter monitor to record ECG signals, this forms the context acquisition unit. Then, at the modeling and storage stage, the acquired contexts will be presented in an efficient and structured format and stored in a database for retrieval; while at the context reasoning and visualization stage, relevant features will be extracted from the context data and analyzed for knowledge discovery. Also at this stage, the outcome of the analysis will be presented as a decision support tool. Finally, healthcare professionals will be able to offer personalized recommendations to the patient based on the contextual analysis. These recommendations could be in the form of text or auditory format regarding the health condition.

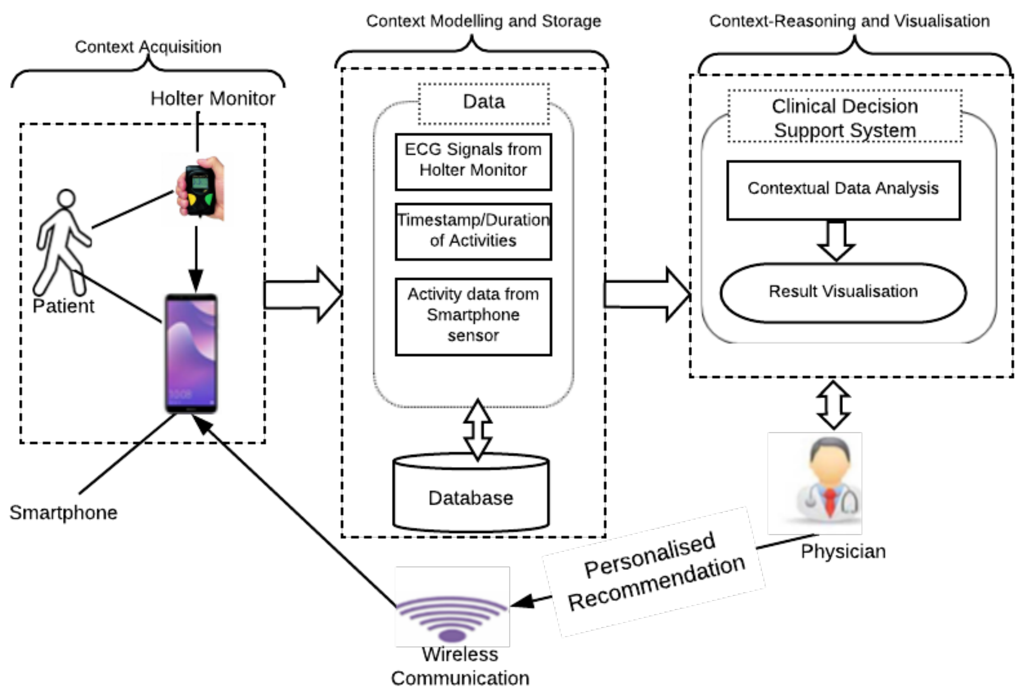


Figure 5.1: Context-aware decision support architecture

5.2 System Prototype

Modern smartphones and wearable devices are contributing immensely to the healthcare delivery process by assisting doctors and healthcare professionals in monitoring patients at a distance. Sensors embedded in these devices could be used to collect and aggregate a large amount of data from patients' biosignals and analyze them to assist doctors in the decision-making process. The most regularly used tool for cardiac condition monitoring is the Holter monitor. A Holter monitor is a portable and continuous monitoring device used to generate and record ECG signals [181]. Some modern Holter monitors allow users to wear the device while doing their normal activities and can transmit users' details to physicians through mobile phones.

For this research, Lifecard FC was used for recording the ECG signals. It has 3-channel 3-electrode hook up designed to keep patient comfort [160]. The device even has an integrated feature even to mark when it has detected each atrial and ventricular pacing spike. Lifecard CF can record up to seven days of continuous ECG using one AAA battery and one memory card, thus requiring no patient interaction.

A smartphone is equipped with an accelerometer sensor that generates data about the user's movement. The sensing technique is known for its high accuracy, stability, and low power dissipation [161]. The generated raw sensor data is processed and used to train machine learning algorithms for activity detection.

5.2.1 User Interface

Figures 5.2 and 5.3 show the picture of the Holter monitor and the screenshot of the mobile app used for the research respectively. The Holter monitor generates time series data which is analyzed to show the wave of the signals. The mobile app collects the x, y, z coordinates and the corresponding timestamp of the smartphone's accelerometer sensor. The x, y, and z coordinates indicate the direction and movement of the phone. The generated sensor data is saved as a csv file in the user's phone download folder. To train algorithms, the user is required to select the activity to perform and the position of the mobile phone. Selecting the activity and position of the phone is not necessary when the aim is to collect data without ground truth for activity detection. The aggregation of the information from these gadgets could assist physicians in decision-making.

Figure 5.2: Lifecard fc Monitor

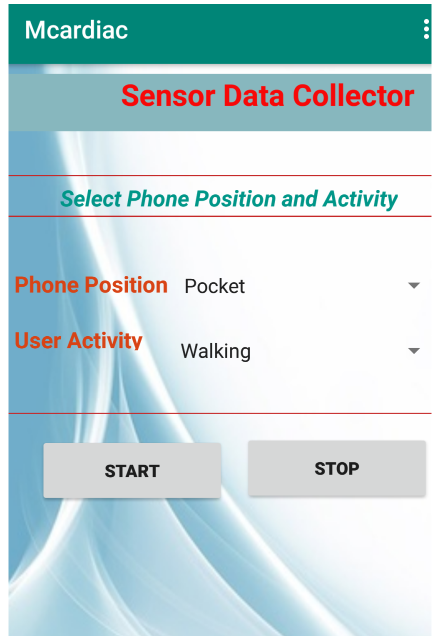


Figure 5.3: Data Collector App

After data collection from the patient, the federated model generated from the experimental analysis is used to recognize the patient's activity. Federated logistic regression model was selected for the activity detection due to better performance in terms of classification accuracy. The model processes the data and display the activities of the patient as shown in figure 5.4.

Figures 5.6, provide a prototype showing the graphical representation of (a) the activity information from the smartphone and (b) ECG signals from the Holter monitor respectively. The information from the Holter monitor represents the heartbeat at time intervals, while the information from smartphone shows the user's activity at a time interval.

Finally, the healthcare professionals will be able to offer personalized recommendations to the patient following contextual analysis. Figure 5.5 shows the interface for enabling the healthcare professionals to offer personalized recommendations to the patient. The physician needs to enter the patient's email address and the information in order communicate with the patient.

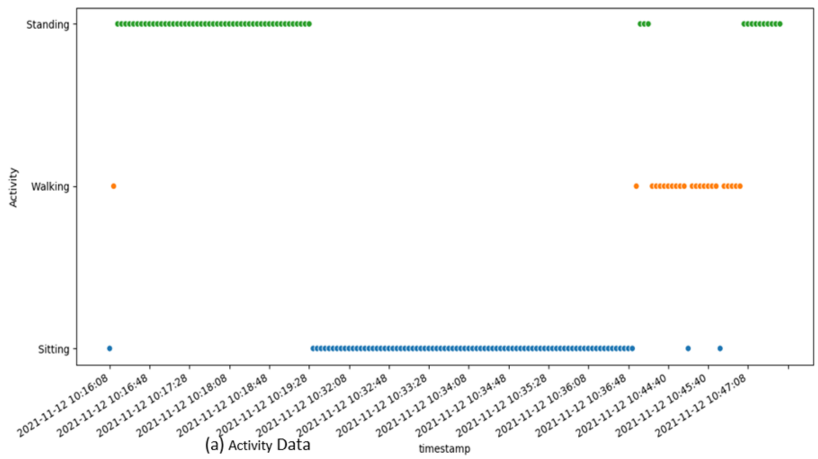


Figure 5.4: System output showing the activity details

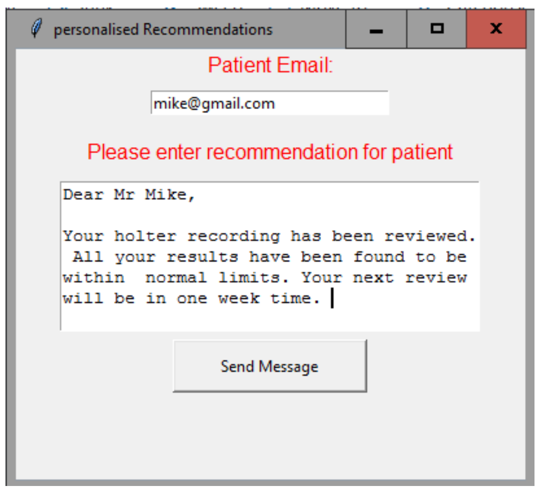


Figure 5.5: Interface for personalized recommendation

5.3 System Evaluation

System evaluation is key for ensuring that the system meets defined requirements. In addition, it offers an insight into how the system is received and accepted by the target users. To evaluate the system, cardiac patients and healthcare professionals were recruited in collaboration with the Health Department of Middlesex University, London, which assisted in recruiting the participants. The process that led to the system's development had the approval of the Computer Science Research Ethics Committee of Middlesex University. The details of the evaluation are presented in this section.

5.3.1 Evaluation with Cardiac Patients

Four cardiac patients and one healthy person participated in the system evaluation. The goal of the research and the working principles of the system were explained to the participants through a record video. After accepting to participate in the study, they were required to use Holter monitors and smartphones running the mobile app for data collection. The Holter monitor used is "Lifecard CF" and the mobile app is available for Android and IOS platforms. The generated raw sensor data was processed, and the federated logistic regression model was used to predict the activities of the users.

Figure 5.6, shows the graphical representation of (a) the activity information from smartphones and (b) the ECG signals from the Holter monitor generated by one of the cardiac patients. The system will enable the clinician to understand and consider the contextual information (patient activity) when reading the ECG signals. The change in the wave of the ECG signals when the subject moved from the sitting activity to the walking activity shows the system's effectiveness in predicting the activity of the subject. The analysis shows a long R-R interval when the subject is seated and a short R-R interval when the subject takes a walk. The R-R interval is the time elapsed between two successive R-waves of the QRS signal on the electrocardiogram [182]. If the patient had an increase in the R-R rate without any activity changes, this could be of concern and can be queried by the physician. If this happens often, then it will be necessary to investigate further. The system will enable the physician to understand the daily activity pattern of the patient, the change in daily behavior, the change in physiological information, and its effects on the recovery process. It will also allow the physician to offer the right advice to the patient instead of prescribing unnecessary medications.

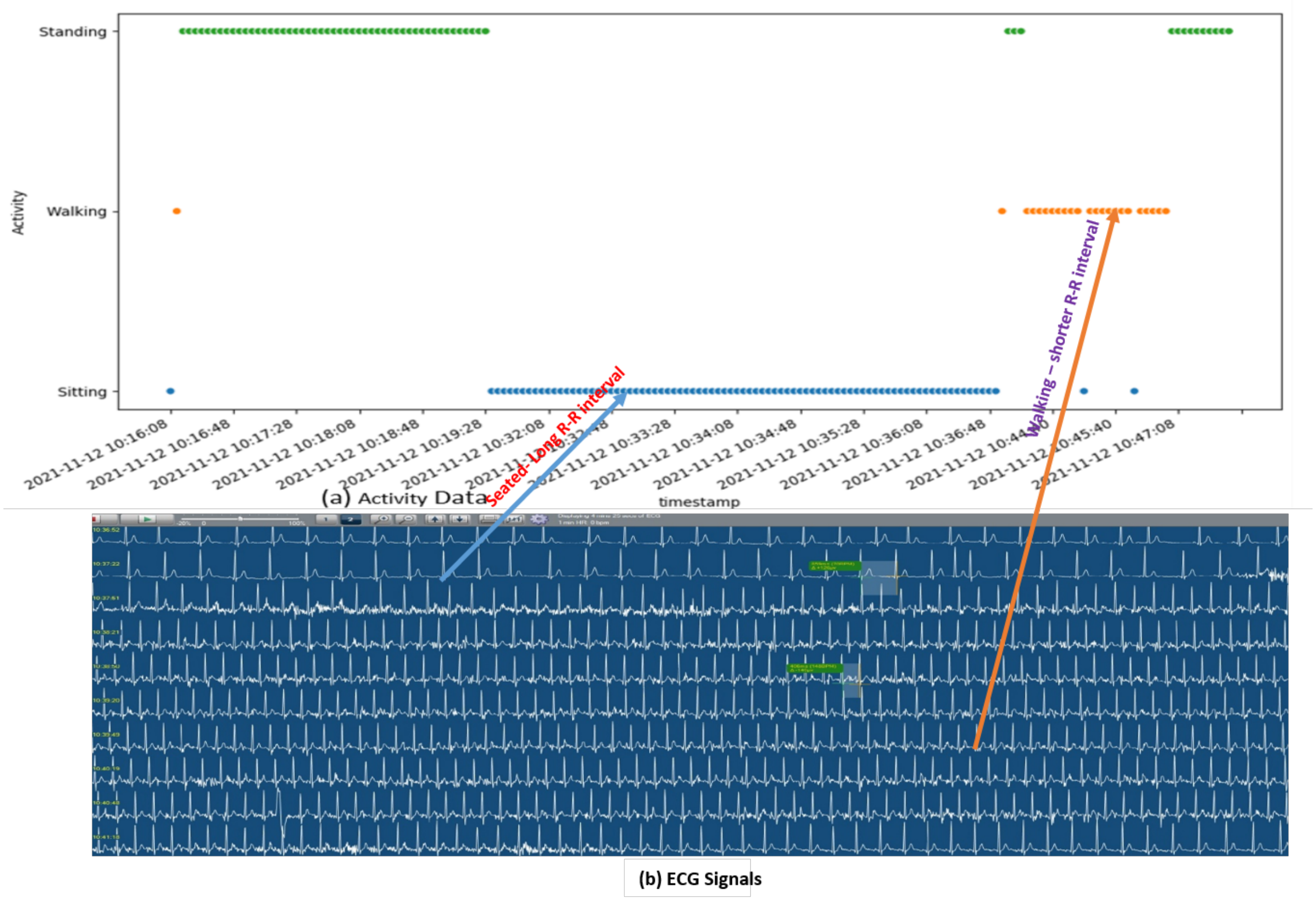


Figure 5.6: System output showing the activity details and the ECG signals

5.3.2 Presentation to Healthcare Professionals

The context-aware system was presented to a group of healthcare professionals to evaluate its usefulness. The participants were professionals with a wide knowledge of cardiac health monitoring. The working principles of the system were demonstrated to the participants. Firstly, we explained what context-awareness represents in the technology-based system, given that the audience may not have been conversant with some of the technical terms. Secondly, the research goal was also explained to them; the aim is to develop and evaluate an intelligent and privacy-focused context-aware decision support system for cardiac condition monitoring. Finally, the role of machine learning in the system, as well as an interactive interface of the system, were also explained to the participants. After the presentation, they were asked to provide their views through a questionnaire [180] about the usefulness of the system. The demonstration was done remotely, and four participants responded to the questionnaire.

The results of the exercise indicate that the healthcare professionals were happy with the system. They indicated that using mobile phones to detect the activities of cardiac patients will improve the monitoring process as the existing approach is paper-based diaries requiring patients to record their activities manually.

The questions were designed to understand the importance of health monitoring parameters with regards to physiological information (PI), physical Activity(PA) data, and lifestyle information(LI). The lifestyle information, which is not part of the proposed system was included in the questionnaire for future research purposes. The questionnaire also allowed participants to mention any other parameters that were not listed. For PI, three participants indicated that ECG signals and heart rate are important in their decision making. The four participants indicated that blood pressure is important for cardiac health monitoring. This will be considered in future research as one of the parameters for cardiac rehabilitation monitoring as it was not included in the proposed system. Body temperature information was not important to any of the participants.

Walking and jogging were judged to be most important activity to the participants for physical activity data, while standing activity was the least important. For the LI, medical adherence was essential to all the participants. One of the participants stated that nutrient intake (diet) is another vital lifestyle to consider. Based on the analysis, it will be necessary to consider nutrient intake as a contextual information in future research.

5.4 Discussion

As technology advances, modern smartphones and wearable devices contribute immensely to the healthcare delivery process by assisting doctors and healthcare professionals in monitoring patients at a distance. Sensors embedded in these devices could be used to collect and aggregate a huge amount of data from patients' biosignals and analyze them to assist doctors in decision-making. This research aims to improve the existing systems by providing a better framework for cardiac health monitoring using contextual information. In addition, it provides an opportunity for healthcare professionals to offer personalized recommendations following contextual analysis.

To design a better health monitoring system that typically draws information from various sources, there is a need for a better understanding of the contextual properties that impact the design, development, and delivery of such services. Contextual information plays a significant role in patient monitoring by providing essential information to a patient or carer, thereby enhancing the quality of services offered. The understanding from previous research is that most researchers do not involve healthcare professionals during the development process. Some rely on what they read or perceive to be the most appropriate approach. The outcome of the system might have little or no impact as the main stakeholders that understand their need are not given the opportunity to be part of the system development.

Feedback gathered from relevant professionals at earlier stages of this research shows that physical activity recognition is a key elements of cardiac condition monitoring. However, most of the existing technologies for cardiac health monitoring overlook the importance of this information in quality health delivery services. In this research, the activity information is integrated with the decision support system to enable the clinician to understand and consider the patient's activity when reading the ECG signals. Due to the importance of this component in cardiac health monitoring, an essential factor, which is the patient's privacy, was considered in the development process by allowing the user to take control of the data generated from the sensors as information is stored in the user's device and not transferred to any server, thereby allowing the patient to determine who can access their private information. This minimizes the mishandling and the misuses of patients private data. Furthermore, the user's privacy is also considered at the algorithm training and model generation stage by adopting a federated machine learning approach.

Machine learning is on the edge of transforming productivity, working habits, and our overall way of living. Improving the quality of life and reducing medical costs are the key benefits of machine learning in the healthcare domain. Commonly known for its capacity to perform complex tasks such as activity recognition, pattern recognition, and disease diagnosis, machine learning has the potential to simplify the life of patients and healthcare professionals by performing a task in a shorter time and at a reduced cost.

The use of machine learning techniques have increased substantially in healthcare services to extract valuable insights from healthcare data. The machine learning model development involves data acquisition from reliable sources, data processing to make it suitable for building the model, choosing an algorithm to build the model, and evaluating the model. The user's privacy is an important factor considered from the early stages of this research. Our initial model development approach was to personalize the activity recognition process by generating a model for each user using their personal dataset. In the personalized approach, the user generates a model, which is used to recognize the subject's activities. One major challenge of this approach is the chances of model overfitting as the user might not generate enough dataset for algorithm training. After thorough investigation, the research adopted a federated machine learning approach for activity recognition. In the federated approach, the machine learning model learns from large and diverse data sets without compromising users' privacy, resulting in a better model. Despite its drawback, federated learning has become a hot topic in research areas related to machine learning. Details about the federated machine learning approach were discussed extensively in section 4.1.

This thesis discussed different machine learning techniques for health monitoring, such as naive Bayes, linear SVM, logic regression, k-nearest neighbor, and decision tree. However, logistic regression and linear SVM were selected for the experimental analysis due to their parametric nature. They are parametric algorithms in that they summarizes data with a set of parameters of fixed sizes independent of the number of training datasets.

To demonstrate the federated approach, we collected accelerometer sensor data from 13 participants to train machine learning algorithms. We study two different scenarios where federated learning can be applied. In the first use case, we partitioned the dataset into four groups and assumed each group to be a client, while in the second use case, we considered each participant to be a client. Then, we compared two machine learning algorithms: logistic regression and linear support vector machine. The overall results indicate that logistic regression performed better than linear SVM in terms of classification accuracy. Hence, the logistic regression federated model generated from the experimental analysis was used to implement a prototype tagged "mCardiac which aims to facilitate physician's decision-making using contextual information from activity data.

Decision support systems have been a key element of systems' approaches to improving the quality of care in the healthcare domain. The process involves collecting a huge amount of patient data from sensors. The data need to be processed, analyzed, and presented to the clinician in the form of alerts, recommendations, or suggestions. The system prototype involves data collection from Holter monitor and smartphone sensors, machine learning algorithm training for activity recognition and pattern discovery, and finally, implementation of a decision support tool. The developed context-aware system was evaluated with cardiac patients and presented to healthcare professionals. The cardiac patients were required to put on the Holter monitor and carry smartphones that ran the mobile app to collect data concurrently. The federated logistic regression model generated in section 4.2.4 was used to predict the activity of the patients. As indicated in Figure 5.6, the change in the wave of the ECG signals when the subject moved from the sitting activity to the walking activity shows the system's effectiveness in predicting the activity of the subject. The working principles of the system was also presented to the healthcare professionals whose assessments of the system were gathered through a questionnaire. The results of the exercise shows that the healthcare professionals were happy with the system.

The next chapter of this thesis presents the conclusions relating to the contributions to knowledge and proffers possible areas of future work for further contribution in areas involving cardiac health monitoring.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

Context-awareness facilitates a better understanding of the health condition of a patient by identifying information required to enhance the quality of services offered by the system and making more precise inferences about the patient's health condition. In order for patient monitoring system to help individual in terms of the required assistance and services, there is a need for understanding of the contextual information which can actualize such services. The success of these systems lies in their capacity to collect, aggregate and process data to better understand the subject's health condition and deliver contextual services.

In order to answer the research questions posed in section 1.1, this research proposed, developed, and evaluated a context-aware framework for cardiac health monitoring. The system involves data collection from Holter monitor and smartphone sensors, machine learning algorithm training for activity recognition and pattern discovery, and implementation of a decision support tool. In addition, it provides an interface that enables healthcare professionals to offer personalized recommendations following contextual analysis. Feedback from relevant professionals at earlier stages of this research shows that physical activity recognition is a key element of cardiac condition monitoring.

Hence was considered as the key information necessary to enhance the quality of the cardiac health monitoring system. Considering the contextual information in decision-making enables the health professional to understand the activity of the patient when reading the ECG signals and offer personalized recommendations.

Furthermore, the system considered patient's privacy at every stage of development by allowing the user to take control of the data generated from the sensors as information is stored in the user's device and not transferred to any server. The user's privacy was also considered at the algorithm training and model generation stage by adopting a federated machine learning approach that allows different clients in different locations to train a global model without sending their dataset to a central server. Hence, this results in a better model that maintains users' privacy. The results of the evaluation of the system with cardiac patients and presentation to healthcare professionals shows its usefulness and effectiveness.

6.2 Future Research

Context-awareness plays a vital role in cardiac health monitoring by providing information required to enhance the quality of healthcare delivery services. This research proposed, designed, and developed a context-aware system for cardiac health monitoring whose major strength lies in the ability to ensure that patent's privacy is not compromised. The implementation and evaluation with the stakeholders show the effectiveness and usefulness of the system; however, some areas require further research.

Based on the experimental analysis and system implementation, there is a need for further research to improve the system's performance by exploring more sophisticated machine learning techniques and transforming the prototype into a more interactive and user-friendly system. Enhancing the activity recognition performance will be a future task in order to have a better, higher-performing system. This could possibly be achieved by exploring the potential of deep learning techniques or considering frequency domain features for algorithm training. Several approaches will be implemented and compared in order to define the best solution to increase the performance of mCardiac. The experimental analysis was done on a single computer which is not the case in real-life scenarios; hence future work will conduct the experiments using different devices in different locations that can interact during the algorithm training process.

The federated learning technique has the potential to maintain the privacy of the users; however, the application of the approach has its drawbacks which need to investigate in future research. For instance, malicious personnel could modify the training model by tampering with its parameters before sending the model to a central server for aggregation. Therefore, in order to avoid this issue, there is a need to further protect the system from malicious attack. This research collected data for four activities (sitting, standing, walking and jogging) which are basically necessary for health monitoring; however future research could consider other activities such as walking downstairs, walking upstairs and lying down.

Future work will need to include nutrient intake as contextual information, which the healthcare professionals indicated as an essential element for cardiac condition monitoring. Furthermore, we aim to integrate more intelligent features such as the system assessing the patient's health condition and providing feedback to the patient as mCardiac only provides contextual information enabling the clinician to reason about the patient's health condition and offer personalized recommendations. Also involvement of patients in the experiments were affected by Covid so presentations to them were by video which they can consume separately before the gathering of data. Future work will need to have more interaction with the patients to understand their needs.

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Appendix: Publications

Research publications

1. Ogbuabor, G. O., Augusto, J. C., Moseley, R., & van Wyk, A., (2020). Context-aware system for cardiac condition monitoring and management: a survey. Behaviour & Information Technology, 1-18.

2. Ogbuabor, G. O., Augusto, J. C., Moseley, R., & van Wyk, A. 2021. Context-Aware Support for Cardiac Health Monitoring Using Federated Machine Learning. In Artificial Intelligence XXXVIII: 41st SGAI International Conference on Artificial Intelligence, AI 2021, Cambridge, UK, December 14–16, 2021, Proceedings (p. 267). Springer Nature.

3. Ogbuabor, G. O., Augusto, J. C., Moseley, R., & van Wyk, A. (2020). Context-Aware Approach for Cardiac Rehabilitation Monitoring. In Intelligent Environments 2020: Workshop Proceedings of the 16th International Conference on Intelligent Environments (Vol. 28, p. 167) Spain. IOS Press.