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Cardiovascular Diagnosis Using Federated Learning

MAIN PROJECT REPORT

ANN MARIYA (JEC16CS026)

RAHUL M (JEC16CS092)

MANEESH MANOJ (JEC17CS063)

RASHI M (JEC17CS079)

in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY (B.Tech)

in

COMPUTER SCIENCE & ENGINEERING

of

A P J ABDUL KALAM TECHNOLOGICAL UNIVERSITY

Under the guidance of

Mrs. NAMITHA T N

CREATING TECHNOLOGY LEADERS OF TOMORROW

JANUARY 2021

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THRISSUR 679 531

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BONAFIDE CERTIFICATE

This is to certify that the main project report entitled **Cardiovascular Diagnosis Using Federated Learning** submitted by **Maneesh Manoj (JEC17CS063), Rashi M (JEC-17CS079), Ann Mariya (JEC16CS026), and Rahul M (JEC16CS092)** in partial fulfillment of the requirements for the award of **Bachelor of Technology** degree in **Computer Science and Engineering** of **A P J Abdul Kalam Technological University** is the bonafide work carried out by them under our supervision and guidance.

Mrs. Namitha T N	**Dr. Swapna B Sasi**	**Dr. Vinith R**
Project Guide	Project Coordinator	Head of The Dept
Assistant Professor	Associate Professor	Associate Professor
Dept. of CSE	Dept. of CSE	Dept. of CSE

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1. **Engineering Knowledge**: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

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11. **Project Management and Finance**: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

12. **Life-Long Learning**: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

PROGRAMME EDUCATIONAL OBJECTIVES (PEOs)

1. The graduates shall have sound knowledge of Mathematics, Science, Engineering and Management to be able to offer practical software and hardware solutions for the problems of industry and society at large.

2. The graduates shall be able to establish themselves as practising professionals, researchers or Entrepreneurs in computer science or allied areas and shall also be able to pursue higher education in reputed institutes.

3. The graduates shall be able to communicate effectively and work in multidisciplinary teams with team spirit demonstrating value driven and ethical leadership.

PROGRAMME SPECIFIC OUTCOMES (PSOs)

1. An ability to apply knowledge of data structures and algorithms appropriate to computational problems.

2. An ability to apply knowledge of operating systems, programming languages, data management, or networking principles to computational assignments.

3. An ability to apply design, development, maintenance or evaluation of software engineering principles in the construction of computer and software systems of varying complexity and quality.

4. An ability to understand concepts involved in modeling and design of computer science applications in a way that demonstrates comprehension of the fundamentals and tradeoffs involved in design choices.

COURSE OUTCOMES (COs)

C410.1 The students will be able to analyse a current topic of professional interest and present it before an audience.

C410.2 Students will be able to identify an engineering problem, analyse it and propose a work plan to solve it.

C410.3 Students will have gained thorough knowledge in design, implementations and execution of Computer science related projects.

C410.4 Students will have attained the practical knowledge of what they learned in theory subjects.

C410.5 Students will become familiar with usage of modern tools.

C410.6 Students will have ability to plan and work in a team.

ACKNOWLEDGEMENT

We take this opportunity to express our heartfelt gratitude to all respected personalities who had guided, inspired and helped us in the successful completion of this interim project work. First and foremost, we express our thanks to **The Lord Almighty** for guiding us in this endeavour and making it a success.

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Last but not least, we extend our gratefulness to all teaching and non-teaching staff who directly or indirectly involved in the successful completion of this interim project work and to all friends who have patiently extended all sorts of help for accomplishing this undertaking.

ABSTRACT

Cardiovascular diseases are the number one cause of deaths globally as per WHO. The first step of diagnosing such diseases is to auscultate or to listen for any abnormal sound, usually done by a medical practitioner. The effective diagnosis of any such condition depends upon the skill and experience of the physician. The usage of Machine Learning based as a solution for the above problem is hindered due to data privacy restrictions and confidential nature of medical data. This project investigates the employment of a privacy preserving Machine Learning paradigm known as Federated Learning as a solution to the aforementioned problem.

Keywords: Machine Learning, Federated learning, Sequence Neural Network, Cardiovascular disease diagnosis, Spectrogram.

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List of Abbreviations

CNN	: *Convolutional Neural Network*
FL	: *Federated Learning*
ESC	: *Environmental Sound Classification*
FTL	: *Federated Transfer Learning*
SDLC	: *Software Development Life Cycle*
CVD	: *Cardiovascular Disease*
SNR	: *Signalto Noise Ratio*
TF	: *TensorFlow*
TFF	: *TensorFlow Federated*

CHAPTER 1
INTRODUCTION

1.1 Overview

Our project is based on the papers Federated Learning for Healthcare Informatics[8] which discusses about how federated learning technologies can improve the machine learning practice especially in the field of healthcare and medicine and create a global improvement; by utilizing the data collected in distributed hospitals without compromising data privacy of its patients by sharing only the inferences of local model training or optimization; not the entire local data. The best part is that this collection of local improvements will, in turn, produce a much efficient global model respecting all the data privacy laws. In this project we try to use Federated Learning technology in Health Analytic purpose, to diagnose cardiovascular conditions. The main constraint while creating Machine Learning model in Health Sector are respectable privacy policies. By Federated Learning, we can perform machine learning on decentralized server or devices (here on local server of the respective hospital) preserving privacy constraints. Then we pass only the learned inference of the respective model trained on the local server to a central server. Similarly, the inferences of multiple servers from different hospitals contribute their inferences and these are aggregated to form a globally improved model. This model is then shared with all the participants, and they can attain a globalized improvised performance.

1.2 Objectives

The main objective of this project is to diagnose cardiovascular conditions using a Federated Learning based system. The usage of FL in this project work improves the accuracy of the classifier due to access to much more data, overcoming privacy restrictions when compared with conventional ML.

1.3 Data Description

The data for this project is taken from an open source challenge dataset known as "The PhysioNet Computing in Cardiology Challenge 2016". The dataset is publicly available at https://physionet.org/content/challenge-2016/1.0.0/. The dataset is divided into normal and abnormal heartbeat sounds, and combined the dataset has 3216 recordings taken using an electronic stethoscope. As is the case with a usual deep learning problem, we would be training the model using training dataset and evaluating the performance with the valuation dataset.

1.4 Organization of the project

The report is organised as follow:

- **Chapter 1:Introduction** Gives an introduction to the work "Cardiovascular Diagnosis using Federated Learning".
- **Chapter 2:Literature Survey** Summarizes the various existing techniques that helps in achieving the desired result.
- **Chapter 3: Problem Statement** Discuses about the need for the proposed system
- **Chapter 4:Project Management** Contains the effective project management model to be used for the project.
- **Chapter 5:Proposed System** Describes the various steps involved to produce this project.
- **Chapter 5:System Requirements & Specification**Describes the various technologies needed for implementation.
- **Chapter 6:Conclusion** Concludes with the future scope of implementation.
- **References** Includes the references for the project.

CHAPTER 2
LITERATURE SURVEY

2.1 Federated Machine Learning: Concept and Applications

Federated learning is a Machine Learning technique that trains algorithms across multiple decentralized edge devices or services holding data samples, without exchanging them. Federated learning enables multiple actors to build a common, robust machine learning model without sharing data, thus allowing to address critical issues such as data privacy, data security, data access rights and access to heterogeneous data [2].

The concept of Federated Learning was proposed by Google in 2016 as an idea to build machine-learning models based on datasets that are distributed across multiple devices while preventing data leakage.

Federated learning is essentially a training methodology with participating devices holding data without exposing them, collaboratively train a model $\mathbf{M_{FED}}$ with accuracy $\mathbf{V_{FED}}$, as opposed to conventional machine learning training methods producing a model $\mathbf{M_{SUM}}$ with accuracy $\mathbf{V_{SUM}}$ such that the absolute difference is less than δ[9].

$$|\mathbf{V_{FED}} - \mathbf{V_{SUM}}| < \delta \tag{2.1}$$

2.1.1 Categorization of Federated Learning

- Horizontal FL

  Horizontal federated learning, or sample-based federated learning, is introduced in the scenarios in which datasets share the same feature space but different space in samples. This essentially means that Client A and Client B has the same set of features. This version of FL is the most widely used in usecases in the current scenario. A horizontal federated learning system typically assumes honest participants and security against an honest-but-curious server. That is, only the server can compromise the privacy of data participants. At the end of the training, the universal model and all of the model parameters are exposed to all participants.

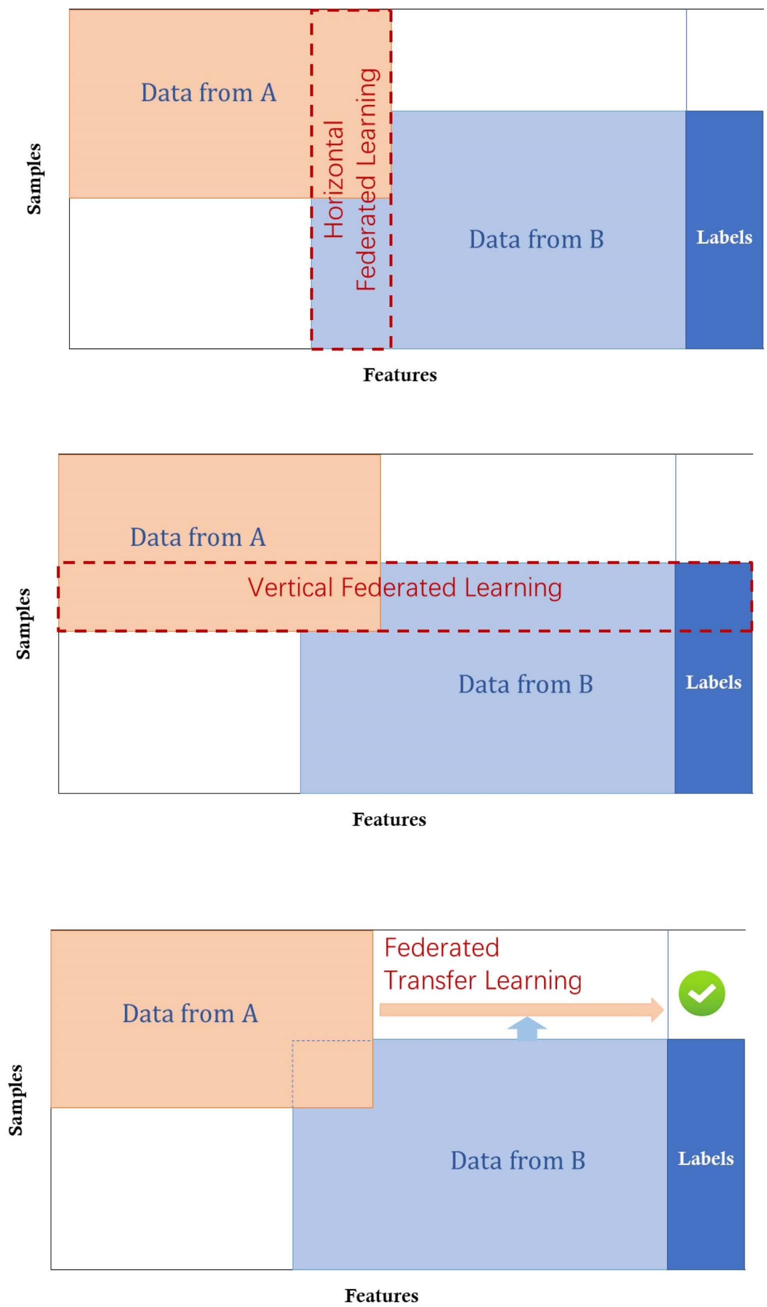


Figure 2.1: Horizontal, Vertical & Transfer FL

- Vertical FL

  Vertical federated learning uses different datasets of different feature space to jointly train a global model. Privacy-preserving machine-learning algorithms have been proposed for vertically partitioned data. Vertical federated learning or feature-based federated learning is applicable to the cases in which two datasets share the same sample ID space but differ in feature space. Vertically federated learning is the process of aggregating these different features and computing the training loss and gradients in a privacy-preserving manner to build a model with data from both parties collaboratively. A vertical federated-learning system typically assumes honest but curious participants.

- Federated Transfer Learning.

  Federated transfer learning is vertical federated learning utilized with a pre-trained model that is trained on a similar dataset for solving a different problem. One such example of Federated transfer learning is to train a personalised model e.g. Movie recommendation for the user's past browsing behavior. FTL is an important extension to the existing federated learning systems because it deals with problems exceeding the scope of existing federated learning algorithms.

2.1.2 Applications of FL

FL, being an innovative modeling mechanism that could train a collaborative model on data from multiple devices, without compromising privacy and security of those data, has a promising application in sales, financial, and many other industries in which data cannot be directly aggregated for training machine-learning models owing to factors such as intellectual property rights, privacy protection, and data security. Therefore, FL provides good technical support for us to build a cross-enterprise, cross-data, and cross-domain ecosphere for big data and AI. These are the main reason why FL is now well researched and applications are being developed in areas like:

- Personalised Ads and Commercials
- Healthcare Informatics and Smart Diagnose
- Smart Retail innovations

2.2 Spectral images based environmental sound classification using CNN

Convolutional Neural Networks (CNNs) are conventionally used to map image data to an output variable. Several other use cases of CNNs were discovered and utilized over time with the advent of proper data preprocessing and feature extraction methods. One such use of CNN is to classify audio data which are fed as spectrogram or any other graphical plotting of audio signals.

Environmental Sound Classification (ESC) refers to the common task of classifying audio signals based on the various component signals [4]. Most of the recent implementations of ESC uses CNN as a classifier due to the use of spectral images over audio clips. The spectral images can be viewed as a visible representation of the frequency spectrum for the audio signals. Audio signals are less periodic, weak ambiance, short interval, and the addition of noise on audio signals is much easy as compared with images.

The frequency spectrum of the audio signal is visually represented in the form of spectrogram images. It is a very rare approach to convert audio files into images for classification tasks. As discussed earlier, such conversion can provide a better classification accuracy and a less error rate. This study utilizes the following datasets for model training and validation purposes:

- ESC-10: This dataset consists of 400 short clips recordings with an average time span of 5s each. These small clips involve 10 different classes with a total time duration of 33 min
- ESC-50 The collection of this dataset is 2000 short recordings of 50 separate classes, which are grouped into 5 major categories
- Urbansound8k: The Urbansound8k (Us8k) includes 8732 sound clips. The average period of these short clips is up to four seconds each with a total of 10 classes of various indoor and outdoor environmental sounds.

2.2.1 Workflow of ESC procedure

- Data Preprocessing

  Audio recordings have background noises, very short intervals, and rapid changes in the clips. These noisy signals make it very hard for classification task. This study involves the classification of sounds from the environment after converting the audio clips into spectrogram images, which keeps the effects of noise in signals from affecting the classification procedure to a large extent.

- Classifier

  CNNs are presented in this study as a method of classifying audio signals by converting sound signals into spectrograms.

2.3 Classification of Heart Sounds Using Convolutional Neural Network

Heart sound play an important role in the diagnosis of cardiac conditions but it is problematic and time-consuming even for experts to discriminate different kinds of heart sounds due to the low signal-to-noise ratio(SNR) [3]. In this paper “Classification of Heart Sounds Using Convolutional Neural Network” a conventional feature engineering method is combined with deep learning algorithms to automatically classify normal and abnormal heart sounds.

Statistics show that cardiovascular disease (CVD) is one of the main reasons for mortality in the world. Heart sounds are a kind of mechanical vibration which is caused by the movement of blood in the cardiovascular system and they are considered to be an important indicator in the diagnosis of several CVDs. phonocardiogram (PCG) which is a graphical recording of heart sounds, can be used to diagnose deformation in heart organs and damage to heart valves. The common approaches to heart sound or PCG classification include three steps:

- Feature extraction
- Feature selection
- Classification by a classifier

2.3.1 Materials and Methods

- Dataset

  Dataset contains a total of 3153 PCG recordings and is composed of six subsets from different part of the world. Their sampling frequency is 2000Hz and length of recording varies from 5s to 120s. The dataset includes 2488 normal samples and 665 abnormal samples manually labelled with 1 and -1, respectively. The proposed method includes two major steps—feature extraction and feature selection and classification based on the designed CNN. First, the phonocardiogram (PCG) is preprocessed and segmented.

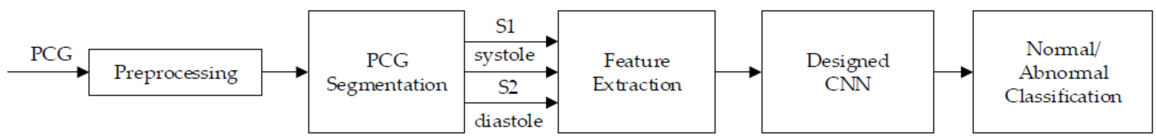


Figure 2.2: Block diagram of proposed method

After that, the four states of each PCG recording are used to extract multiple features.

Finally, the extracted features are fed into the designed convolutional neural network (CNN) model to classify normal and abnormal heart sound.

- Preprocessing

  Firstly, each PCG recording was filtered by a high-pass filter with a cut-off frequency of 10 Hz to remove baseline drift. Secondly, the spike removal algorithm was applied to the filtered recordings. Thirdly, the recordings were normalized to zero mean and unit standard deviation. Finally, the PCG recordings were segmented using the method of the hidden semi-Markov model (HSMM) segmentation method.

2.3.2 Heart Sound Classification Based on the Designed CNN

The proposed model in this paper [3] is composed of three Conv-blocks, a global average pooling (GAP) layer and a classification layer with the sigmoid function. Each Conv-block includes a convolutional1D (Conv-1D) layer and a maxpooling1D layer, followed by the strategy of dropout to prevent overfitting. The numbers of filters for the Conv1D layers were set to 32, 64 and 128, respectively and each filter had a kernel size of 3 and strides 3. The pooling size was 2 with two strides 2. Relu was adopted as the activation function in each convolution layer. Conv1D denotes a one-dimensional convolution layer. GAP denotes the global average pooling layer.

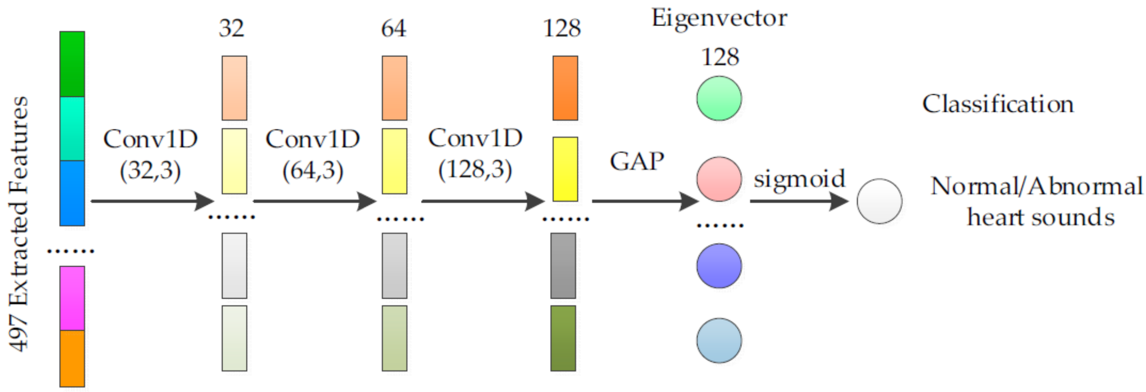


Figure 2.3: Structure of designed CNN

In this proposed classification method, as the input of the model comprises all of the extracted features, we assume that the designed model is used only to select features and classify normal and abnormal heart sounds. Therefore, the designed model is a shallow or compact model. Pooling layers is also used to reduce the feature dimensions. So, the dimensions of the input features gradually decreased from the bottom layers to the top layers of the Conv-blocks. This procedure reorganizes and reduces the dimensionality of the input (497 features in total), which can also be viewed as feature selection in signal processing.

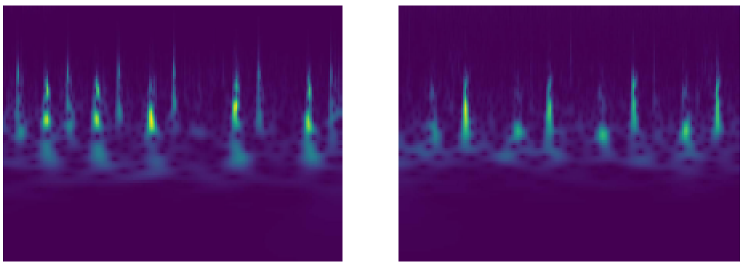
2.4 Learning Image-based Representations for Heart Sound Classification

Heart disease continues to be a leading worldwide health burden. Phonocardiograph is a method of recording the sounds and murmurs made by heartbeats, as well as the associated turbulent blood flow with a stethoscope, over various locations in the chest cavity. Phonocardiogram is widely used in the diagnose of heart disease.

In this paper [6] Image classification convolutional neural network is utilised to process scalogram images of PCG recording for abnormal heart sound detection. Instead of training CNNs from the scratch, the aforementioned pre-trained ImageNet is used to construct robust heart sound classification models.

2.4.1 Scalogram Representation

In this paper, to transform the PCG samples into images which can be processed by an ImageNet, the scalogram images are generated using the morse wavelet transformation with 2 kHz sampling frequency. While creating the images the frequency is represented in kHz on the vertical axis and time is represented in s on the horizontal axis. Viridis colour map, which varies from blue (low range) to green (mid-range) to red (upper range) is used to colour the wavelet coefficient values. Axes and margins are removed and finally, the scalogram images are scaled to 224 × 224 for compatibility with the VGG16 ImageNet.



(a) Normal (*a0007.wav*) (b) Abnormal (*a0001.wav*)

Figure 2.4: Scalogram images of a normal and an abnormal heartbeat

It can even be observed by human eyes that, there are some clear distinctions between the two classes in these images. The scalogram images are extracted from the first 4 s segments of normal/ abnormal heart sounds using the Viridis colour map.

2.4.2 Convolutional Neural Networks

In this paper, ImageNet is used to process the scalogram images for the heart sound classification. VGG16 is constructed from 13 ([2, 2, 3, 3, 3]) convolutional layers, five max-pooling layers, three fully connected layers fc6, fc7, fc and a soft-max layer for 1000 labels according to the image classification task in the ImageNet Challenge. The receptive field size of 3×3 is used in all of the convolutional layers.

2.4.3 Deep PCG Feature Representations

PCG Feature Extraction from ImageNet: The activations of the first fully connected layer fc6 of VGG16 are employed as the feature representations. Essentially, scalogram images are feed into VGG16 and then the deep PCG feature representations of 4096 attributes are extracted as the activations of all neurons in the first fully connected layer fc6.

PCG Feature Extraction from adapted ImageNet: Transfer learning methodology is used to adapt the parameters of VGG16 to better suit the task of abnormal heart sound detection. After the adaptation, the scalogram images are fed into the updated CNN model and a new set of deep representations are extracted from the first fully connected layer fc6.

2.4.4 End-to-end ImageNet based Classification

The parameter of VGG16 is adapted on the heart sound data by transfer learning. To construct a robust end-to-end heart sound CNN classifier, two different approaches are used.

- Learning Classifier of ImageNet ImageNet classifier is created by freezing the parameter of the convolutional layers and fc6, and updating the parameters of the final two fully connected layers and the soft-max layer for classification
- Learning ImageNet In this method, replace the last fully connected layer with a new one which has 2 neurons and a soft-max layer in order to achieve the 2-class classification task. Then update the entire network so that all VGG16 parameters are adapted to the heart sound data. This method represents a faster way to achieve a full CNN based classification than training an entire CNN from scratch with random initialisation of parameters.

2.5 The future of digital health with federated learning

Data-driven machine learning (ML) has emerged as a promising approach for building accurate and robust statistical models from medical data, which is collected in huge volumes by modern healthcare systems. Research on artificial intelligence (AI), and particularly the advances in machine learning (ML) and deep learning (DL) have led to disruptive innovations in radiology, pathology, genomics and other fields. Modern DL models feature millions of parameters that need to be learned from sufficiently large curated data sets in order to achieve clinical-grade accuracy, while being safe, fair, equitable and generalising well to unseen data [7].

Federated learning (FL) is a learning paradigm seeking to address the problem of data governance and privacy by training algorithms collaboratively without exchanging the data itself. Originally developed for different domains, such as mobile and edge device use cases, it recently gained traction for healthcare applications. Recent research has shown that models trained by FL can achieve performance levels comparable to ones trained on centrally hosted data sets and superior to models that only see isolated single-institutional data.

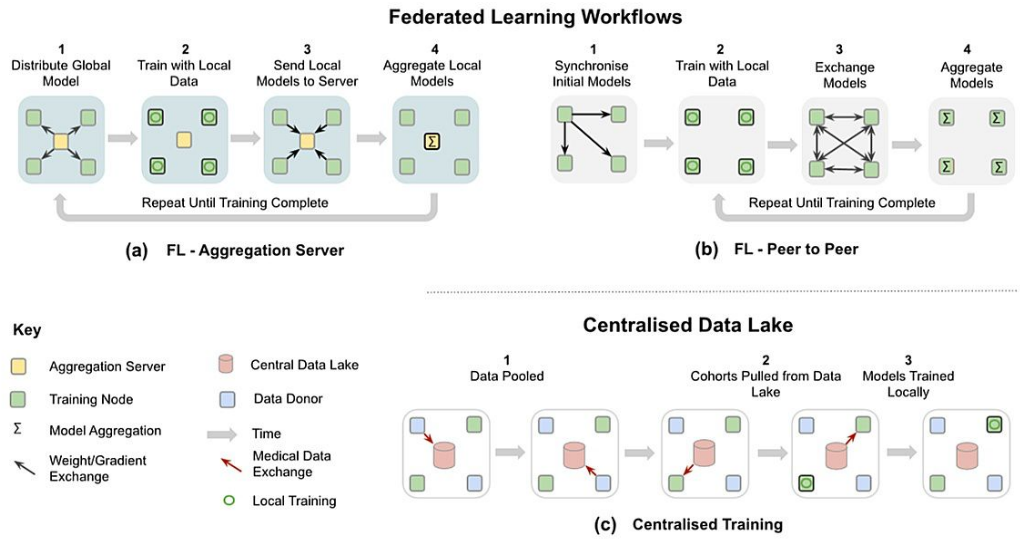


Figure 2.5: FL workflows and comparison with centralised architecture

2.5.1 The promise of Federated Efforts

The promise of FL is simple to address privacy and data governance challenges by enabling ML from non-co-located data. In a FL setting, each data controller not only defines its own governance processes and associated privacy policies, but also controls data access and has the ability to revoke it. This includes both the training, as well as the validation phase. FL implicitly offers a certain degree of privacy, as FL participants never directly access data from other institutions and only receive model parameters that are aggregated over several participants. In a FL workflow with aggregation server, the participating institutions can even remain unknown to each other.However,it has been shown that models.themselves can,under certain conditions, memorise information Therefore, mechanisms such as differential privacy or learning from encrypted data have been proposed to further enhance privacy in a FL setting.

2.5.2 Current FL efforts in Digital Health

Since FL is a general learning paradigm that removes the data pooling requirement for AI model development, the application range of FL spans the whole of AI for healthcare. By providing an opportunity to capture larger data variability and to analyse patients across different demographics, FL may enable disruptive innovations for the future but is also being employed right now.

The applicability and advantages of FL have also been demonstrated in the field of medical imaging, for whole-brain segmentation in MRI, as well as brain tumour segmentation. By linking healthcare institutions, not restricted to research centres, FL can have direct clinical impact.

2.5.3 Challenges and Considerations

A successful model training still depends on factors like data quality, bias and standardisation. These issues have to be solved for both federated and unfederated learning efforts via appropriate measures, such as careful study design, common protocols for data acquisition, structured reporting and sophisticated methodologies for discovering bias and hidden stratification.

- Data heterogeneity

  Medical data is particularly diverse not only because of the variety of modalities, dimensionality and characteristics in general, but even within a specific protocol due to factors such as acquisition differences, brand of the medical device or local demographics.

- Privacy and security

  Healthcare data is highly sensitive and must be protected accordingly, following appropriate confidentiality procedures. Therefore, some of the key considerations are the trade-offs, strategies and remaining risks regarding the privacy preserving potential of FL.

- Traceability and accountability

  As per all safety-critical applications, the reproducibility of a system is important for FL in healthcare. In contrast to centralised training, FL requires multiparty computations in environments that exhibit considerable variety in terms of hardware, software and networks. Traceability of all system assets including data access history, training configurations, and hyperparameter tuning throughout the training processes is thus mandatory.

2.5.4 System architecture

Healthcare institutional participants are equipped with relatively powerful computational resources and reliable, higher-throughput networks enabling training of larger models with many more local training steps, and sharing more model information between nodes.

The administration of such a federation can be realised in different ways. In situations requiring the most stringent data privacy between parties, training may operate via some sort of "honest broker" system, in which a trusted third party acts as the intermediary and facilitates access to data. This setup requires an independent entity controlling the overall system, which may not always be desirable, since it could involve additional cost and procedural viscosity. Additionally, in a trustless based architecture the platform operator may be cryptographically locked into being honest by means of a secure protocol, but this may introduce significant computational overheads.

ML, and particularly DL, has led to a wide range of innovations in the area of digital healthcare. By enabling multiple parties to train collaboratively without the need to exchange or centralise data sets, FL neatly addresses issues related to egress of sensitive medical data. As a consequence, it may open novel research and business avenues and has the potential to improve patient care globally.

2.6 Lung and Heart Sounds Analysis: State-of-the-Art and Future Trends

In this paper [5], we explore a variety of techniques and open questions that address the challenge of analysing heart sound disease more efficiently and effectively. We are analyzing a global system in which smartphones are used for monitoring, diagnosis, and giving medical support and assistance which is based on a large database.The current technology in treatment has brought improvements in quality of life and survival to heart-failure patients. On the other hand, improved survival and is accompanied by some of the additional health problems. Recent studies show that a substantial number of heart-failure patients die from causes other than the cardiac disease.

2.6.1 Heart Sound Characteristics

Some of the mechanisms used by detecting the heart sounds are generated includes opening or closing heart valves, flow of blood through the valve orifice,flow of blood into the ventricular chambers, and rubbing of cardiac surfaces.

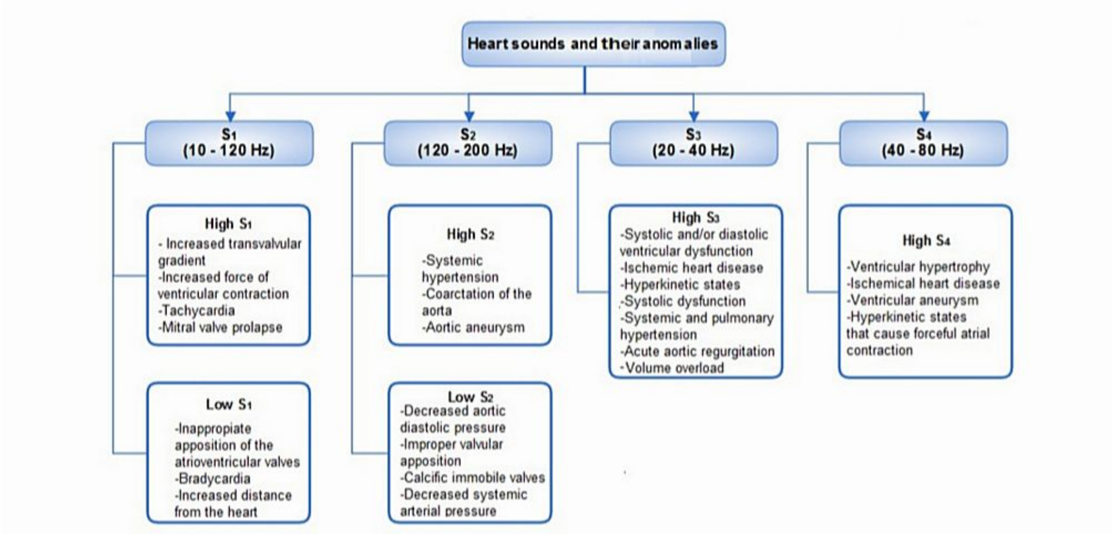


Figure 2.6: Heart Sound Characteristics

2.6.2 Auscultation

Auscultation is a rapid,easy, effective, and noninvasive technique and it is used by trained physicians to diagnose respiratory and cardiac diseases.In recent stethoscopes it can be recorded and send the recorded sounds to a personal computer for processing and analysis. Auscultation with a stethoscope is a highly subjective process and depends on several factors including experience and skill of healthcare professionals and their ability to recognize different sound patterns. Computerized analysing methods will enables a systematic approach to the diagnosis of different respiratory or cardiac diseases.The computerized heart sound analysis takes place in different stages.

2.6.3 Heart Sound Databases

The heart sound databases are developed for the learning tools and enhance problem-solving skills in the area of respiratory medicine. The effort which is needed to document data for storage and sharing in a semi permanent manner is rarely available at the close of a research project.During the past few years, some websites contain rich educational material on heart sound databases which have been developed and can be used to train health-care professionals. They incorporate user manuals, listening tips, respiratory and cardiac sound recordings, waveforms, exercises for diagnosis training, and quizzes. These include Easy Auscultation Training, Practical Clinical Skills, The Auscultation Assistant, and SoundCloud. In addition to the online repositories and several books for understanding heart sounds and murmurs are available. Computerized heart sound analysis represents the advance technologies in diagnosing, monitoring, treatment, and visualization signaling of respiratory and cardiac pathologies. However, due to a lack of published guidelines, significant differences exist among various laboratories, such as the use of different ways of sensors to acquire signals and signal-processing techniques.

2.7 Attack Detection using Federated Learning in medical cyber-physical systems

Cyber-Physical Systems (MCPS) are networked systems of medical devices that provide seamless integration of physical and computation components in healthcare environments to deliver high quality care by enabling continuous monitoring and treatment. As MCPS store sensitive medical data and personal health data, security breaches and unauthorized access to this information can lead to severe repercussions for both the patient and hospital in the form of loss of privacy, abuse, physical harm and liability. The heterogeneity of devices involved in these systems (such as body sensor nodes and mobile devices) introduce large attack surfaces and hence necessitate the design of effective security solutions for these environment.MCPS helps constantly monitor and analyze in- formation gathered from medical devices, infer the patient's health condition for diagnosis, and provides timely treatment either through direct feedback from healthcare providers or through automated treatments using medical actuators.

2.7.1 Network Architecture

The MCPS network consists of medical devices that are basically wireless body sensor nodes placed on the patient's body; mobile devices that acts as a local gateway to the medical devices and a back-end server at the hospital. The sensor nodes are used to collect patient vitals and administer drugs, such as insulin or anesthetics. The mobile device acts as a gateway for the medical devices. The sensor nodes communicate with the mobile device wirelessly using a short-range communication protocol, such as Bluetooth or Zigbee. The server is also connected to the Internet via a wired connection to the hospital's gateway.

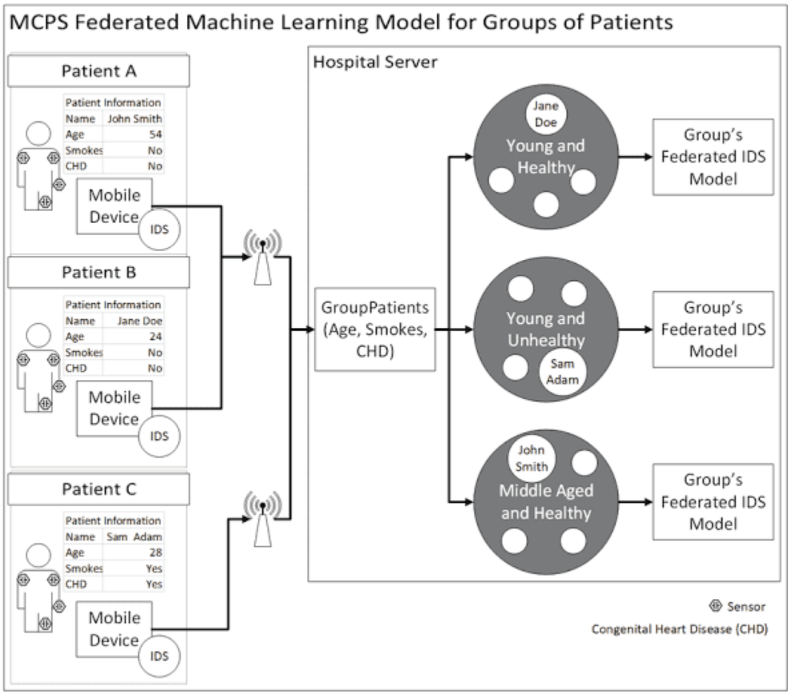


Figure 2.7: FL model for a group of patients

The server is responsible for handling messages transmitted from the mobile device as well as relaying messages back to patient's mobile devices. mobile device collects, aggregates, and keeps a history of node measurements, such as blood pressure.The system follows a client-server topology between patient's mobile devices and the hospital server. This ensures scalability as adding more or new mobile devices in the hospital network increases message traffic and logic at the server linearly.

2.7.2 Clustering of Patients

The clustering process occurs during registration of a mobile device with the hospital sever (Figure 2). After a mobile device has been assigned to a group, it only receives and contributes to that groups model.The attack detection process begins with a mobile device registering with the server. Devices are then clustered into different groups based on their patient history. Determining the correct number of clusters will depend on several factors including the number of mobile devices in network and the number of parameters used for clustering process. Each group has a federated model stored on the server. The mobile device then downloads the federated model from the server and continues to learn and update a new model using the patient's data.

2.7.3 Updating the Model

Federated Learning is a distributed machine learning algorithm that builds a global model by averaging weights w across many devices over several communication rounds t. Each neuron in the hidden layer has a transfer function, denoted by f, that takes each feature in a sample (In1...Ini) and multiplies it by its weight (IW1,1...IWi,1) plus a bias (B1). The weights are modified during training.when a patient registers with the server they are clustered into a group who share a single IDS model. After determining the number of patients to use, the server selects patients from the group at random and without replacement. The mobile devices of the subset are then sent a message by the server to send their model's weights to the server. The server keeps a record of each mobile device's weights and at an end of a communication round calculates the next federated model w t+1.

2.7.4 Experimental Setup

The MIMIC dataset from PhysioNet is used for evaluation of the proposed system. This dataset has six features, which are typically displayed on an ICU monitor, including elapsed time, arterial blood pressure, heart rate, pulse, respiratory rate, and blood oxygen concentration. The dataset has 121 records with each record having about 35-40 hours of monitored activity. The ma- chine learning was executed using Sci-kit Learn's Multi-Layer Perceptron running on Raspberry Pi's. Each Raspberry Pi is associated with a patient who is generating data for the device to train the IDS. All attack were simulated using new patient data; data the ML model has not been trained on. Half of the data samples are modified to simulate attacks and half remain unperturbed. We also simulated the system using MATLAB by following the same process as above, where the Raspberry Pi's were replaced with MATLAB objects to represent each device. As a result, we can conclude that a federated learning based IDS can train on more data, increasing accuracy and lowering FPR, while decreasing the amount of time and computation needed of an individual mobile device.

2.8 An open access database for the evaluation of heart sound algorithms

Cardiovascular diseases (CVDs) continue to be the leading cause of morbidity and mortality worldwide. One of the first steps in evaluating the cardiovascular system in clinical practice is physical examination. Auscultation of the heart sounds is an essential part of the physical examination and may reveal many pathologic cardiac conditions such as arrhythmias, valve disease, heart failure, and more. Heart sounds provide important initial clues in disease evaluation, serve as a guide for further diagnostic examination, and thus play an important role

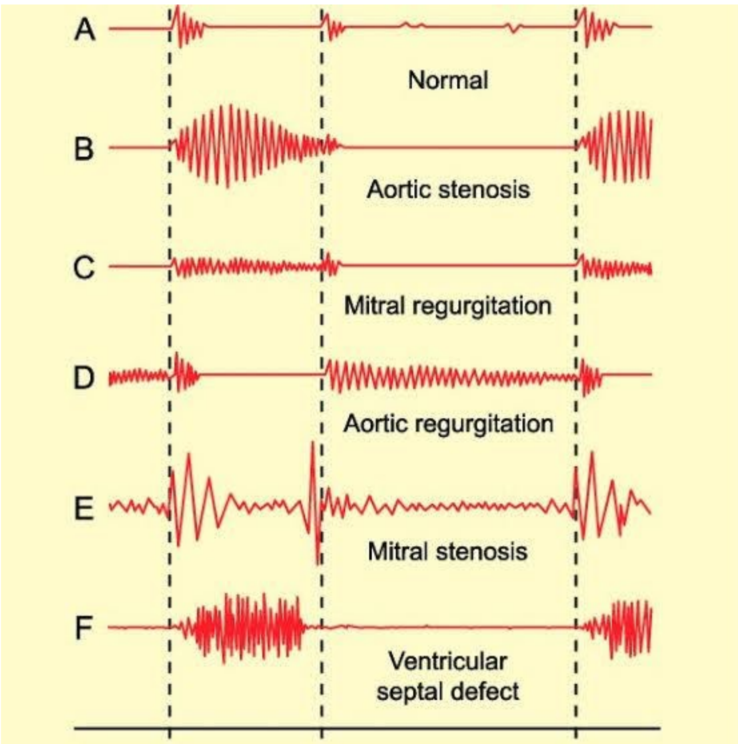


Figure 2.8: Normal vs Abnormal PCGs

in the early detection for CVDs. During the cardiac cycle, the heart first experiences electrical activation, which then leads to mechanical activity in the form of atrial and ventricular in which the valves can be best heard in the following locations:

- Aortic area—centred at the second right intercostal space.
- Pulmonic area—in the second intercostal space along the left sternal border.
- Tricuspid area—in the fourth intercostal space along the left sternal edge.
- Mitral area—at the cardiac apex, in the fifth intercostal space on the midclavicular line.

Fundamental heart sounds (FHSs) usually include the first (S1) and second (S2) heart sounds. S1 occurs at the beginning of isovolumetric ventricular contraction, when already closed mitral and tricuspid valves suddenly reach their elastic limit due to the rapid increase in pressure within the ventricles. S2 occurs at the beginning of diastole with the closure of the aortic and pulmonic valves. While the FHSs are the most recognizable sounds of the heart cycle, the mechanical activity of the heart may also cause other audible sounds, such as the third heart sound (S3), the fourth heart sound (S4), systolic ejection, mid-systolic click (MC), the diastolic sound or opening snap (OS), as well as heart murmurs caused by turbulent, high-velocity flow of blood.

2.8.1 Classification procedure of heart sounds

2.8.2 Step 1 Pre-processing

- To assess the signal quality
- To filter out baseline changes and high frequency noises
- To extract relevant features

Step 2 Segmentation

- To delineate the start and end of each phase of the heart beat (S1, systolic, S2, diastolic, etc.)

Step 3 Classification then Clinical

- To map the features for each segmented phase of the beat to a known phase or sound, or the entire recording to a pathology. Sometimes quality classifications are made on sections or entire recordings.

These typical three steps for automated analysis of heart sound in clinical applications.

2.8.3 Potential benefits of Public Heart sound data

The public release of the heart sound database has many potential benefits to a wide range of users. First, those who lack access to well-characterized real clinical signals may benefit from access to these data for developing prototype algorithms. The availability of these data can encourage researchers from a variety of backgrounds to develop innovative methods to tackle problems in heart sound signal processing that they might not otherwise have attempted. An additional benefit is that the data can be re-evaluated with new advances in machine learning and signal processing as they become available.These databases have value in medical and biomedical engineering education by providing well-documented heart sound recordings from both healthy subjects and patients with a variety of clinically significant diseases.

CHAPTER 3

PROBLEM STATEMENT

This Project aims to implement a privacy preserving distributed Machine Learning paradigm Federated Learning which enable collaborative learning among entities containing confidential and/or private data to diagnose heart conditions of a person. This paradigm can improve the efficiency of prediction keeping the data secured at respective entities.

CHAPTER 4
PROJECT MANAGEMENT

4.1 Introduction

Project management is the discipline of planning, organizing, securing, managing, leading, and controlling resources to achieve specific goals. A project is a temporary endeavor with a defined beginning and end (usually time-constrained, and often constrained by funding or deliverables), undertaken to meet unique goals and objectives, typically to bring about beneficial change or added value. The temporary nature of projects stands in contrast with business as usual (or operations), which are repetitive, permanent, or semi-permanent functional activities to produce products or services. In practice, the management of these two systems is often quite different, and as such requires the development of distinct technical skills and management strategies.

In our project we are following the typical development phases of an engineering project

1. Initiation
2. Planning and Design
3. Execution and Construction
4. Monitoring and Controlling Systems
5. Completion

4.1.1 Initiation

The initiating processes determine the nature and scope of the project. The initiating stage should include a plan that encompasses the following areas :

1. Analysing the business needs/requirements in measurable goals
2. Reviewing of the current operations
3. Financial analysis of the costs and benefits including a budget
4. Stakeholder analysis, including users, and support personal for the project

5. Project charter including costs, tasks, deliverables, and schedule

4.1.2 Planing and design

After the initiation stage, the project is planned to an appropriate level of detail (see example of a flow-chart). The main purpose is to plan time, cost and resources adequately to estimate the work needed and to effectively manage risk during project execution. As with the initiation process, a failure to adequately plan greatly reduces the project's chances of successfully accomplishing its goals.

- Determining how to plan
- Developing the scope statement
- Selecting the planning team
- Identifying deliverables and creating the work breakdown structure
- Identifying the activities needed to complete those deliverables
- Developing the schedule
- Risk planning

4.1.3 Execution

Executing consists of the processes used to complete the work defined in the project plan to accomplish the project's requirements. The execution process involves coordinating people and resources, as well as integrating and performing the activities of the project in accordance with the project management plan. The deliverables are produced as outputs from the processes performed as defined in the project management plan and other frameworks that might be applicable to the type of project at hand.

4.1.4 Monitoring & controlling

Monitoring and controlling consists of those processes performed to observe project execution so that potential problems can be identified in a timely manner and corrective action can be taken, when necessary, to control the execution of the project. The key benefit is that project performance is observed and measured regularly to identify variances from the project management plan.

4.2 System Development Life Cycle

The Systems development life cycle (SDLC), or Software development process in systems engineering, information systems, and software engineering, is a process of creating or altering information systems, and the models and methodologies that people use to develop these systems. In software engineering, the SDLC concept underpins many kinds of software development methodologies. These methodologies form the framework for planning and controlling the creation of an information system.

The SDLC phases serve as a programmatic guide to project activity and provide a flexible but consistent way to conduct projects to a depth matching the scope of the project. Each of the SDLC phase objectives is described in this section with key deliverables, a description of recommended tasks, and a summary of related control objectives for effective management. The project manager must establish and monitor control objectives during each SDLC phase while executing projects. Control objectives help to provide a clear statement of the desired result or purpose and should be used throughout the entire SDLC process.

4.2.1 Spiral Model

We have used the Spiral model in our project. The Spiral model incorporates the best characteristics of both- waterfall and prototyping model. In addition, the Spiral model also contains a new component called Risk Analysis, which is not there in the waterfall and prototype model. In the Spiral model, the basic structure of the software product is developed first. After the basic structure is developed, new features such as user interface and data administration are added to the existing software product. This functionality of the Spiral model is similar to a spiral where the circles of the spiral increase in diameter. Each circle represents a more complete version of the software product. The spiral is a risk-reduction oriented model that breaks a software project up into main projects, each addressing one or major risks. After major risks have been addressed the spiral model terminates as a waterfall model. Spiral iteration involves six steps:

1. Determine objectives, alternatives and constraints.
2. Identify and resolve risks.
3. Evaluate alternatives.
4. Develop the deliverables for the iteration and verify that they are correct.
5. Plan the next iteration.

6. Commit to an approach for the next iteration.

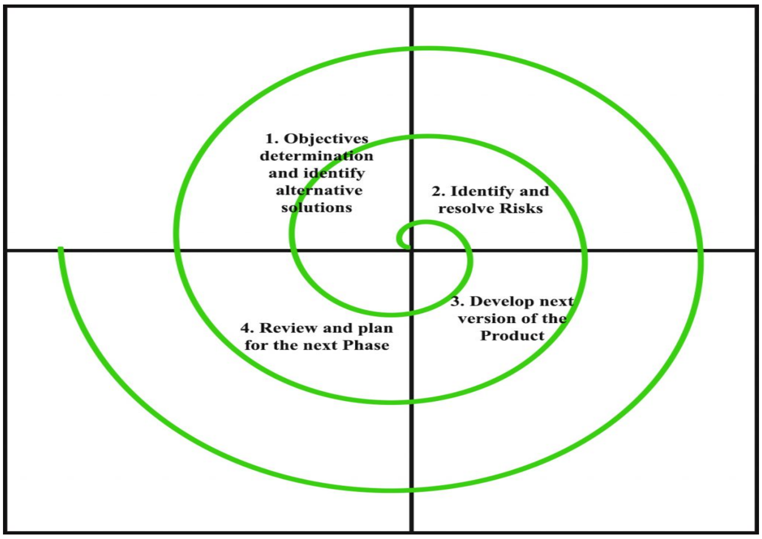


Figure 4.1: Spiral Model

CHAPTER 5
METHODOLOGY

5.1 System Requirements & Specifications

5.1.1 Introduction

This document describes the functionality and basic idea behind the project “Cardiovascular diagnosis using Federated Learning”.

5.1.2 Purpose

Cardiovascular diseases (CVDs) continue to be the leading cause of morbidity and mortality worldwide according to WHO. Automated classification of cardiovascular sounds has the potential to detect abnormalities in the early stages of a cardiovascular dysfunction and thus enhance the effectiveness of decision making. One of the first steps in evaluating the cardiovascular system in clinical practice is physical examination, which is dependant on the level of expertise of the physician. Also, because of data-privacy restrictions, conventional Machine Learning based technologies are not able to achieve the level of accuracy, comparable to a human counterpart. Our system, which uses Federated Learning methodology proves to be a solution to most of the currently prevailing restrictions.

5.1.3 Description

An Electronic stethoscope is used to auscultate a patients heartbeat sound and obtain the recorded sample of the same. This recorded sample is passed to our system to obtain a diagnosis of the patient’s heart condition. Federated Learning training methodology is utilized to obtain inferences from many such implementations of the system to improve the overall efficiency of the system over time without sharing private patient data.

5.1.4 Functional requirements

1. Detect abnormal heart sound using heart sound recording of patient

2. Produce a diagnosis within a 60s time

5.1.5 Non Functional Requirements

1. Privacy The system should respect the confidentiality of medical data and should maintain privacy
2. Security

   The system should maintain the security of data used.

5.1.6 Technical requirements

- TensorFlow

  TensorFlow is a free and open-source software library for machine learning. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks..

- TensorFlow Federated (TFF)

  TensorFlow Federated (TFF) is an open-source framework for machine learning and other computations on decentralized data. TFF has been developed to facilitate open research and experimentation with Federated Learning, an approach to machine learning where a shared global model is trained across many participating clients that keep their training data locally.

- Python3

  Python is an interpreted, high-level and general-purpose programming language used worldwide. Python's design philosophy emphasizes code readability with its notable use of significant whitespace.

- Google Colaboratory (Colab)

  Colaboratory, or "Colab" for short, is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis and education.

5.1.7 Design Constraints

- Limited number of data samples in publicly available datasets.

5.2 Proposed System

Modules

5.2.1 Data Acquisition Module

Deep Learning is known for the amount of data required for training and validating the model. Our work makes use of publicly available datasets [1] that is currently the benchmark dataset in the field of Heart sound classification. More than 3,126 heart sound recordings, lasting from 5 seconds to just over 120 seconds were collected and used in this work. The dataset is organised into classes of normal and abnormal heartbeat sounds.

The dataset acquired is a real-life dataset that contains various forms of noises and other components associated with hospitals, that is prevailing in the conditions where our work could be implemented.

In order to evaluate the effect of different methodological choices, we prepared three standard data sets for training and prediction:
D1: The standard training gives the model an insight into the classes of heartbeat sounds. Different set of heartbeat sounds have been grouped for the purpose
D2:The prediction set or validation set includes the rest 30 % of the training set.
The forecasts will be evaluated on future data (D3 - test set).

5.2.2 Data Preprocessing Module

Deep learning is quickly becoming a powerful tool for solving complex modeling problems across a broad range of industries. An efficient model is developed through intensive training by providing a large number of datasets. These datasets contain a significant proportion of unwanted data (also called noise) in it. These data, if not removed leads to tremendous misclassification of the input data. This will ultimately degrade the performance and efficiency of the classifier. Thus, it is very important to remove unwanted noise from the dataset to improve efficiency. Therefore, the step of data preprocessing plays a very important role in contributing to the accuracy of any training model. In this project, we mainly perform three steps in the preprocessing stage. They are Filtering, Audio to Spectrogram conversion and Reshaping

1. **Filtering:**

   This refers to the process of removing unwanted data from the input and extracting only the required signal/data from the mixture. This forms one of the most important steps in preprocessing.

2. **Audio to Spectrogram conversion:**

   The input provided to the Neural Network (NN) is in the form of images. So in order to transform audio signals into Spectrogram, which is a graphical representation of sound signals, we need to pass them through a Audio to Spectrogram converter.

3. **Reshaping**

   In this process we convert all spectrograms into a uniform shape that can be used as an input to the model.

5.2.3 Identification and Classification Module

This module identifies and classifies the data given. The classifier that we use is a Deep Learning module that takes spectrogram as input and produces a corresponding classified label of it.

5.2.4 Federated Learning Module

This module take care of federated operations namely Federated Aggregation and Federated Optimization.

NEURAL NETWORK IDENTIFIED

Neural network identified for classification is Sequential Neural Network.

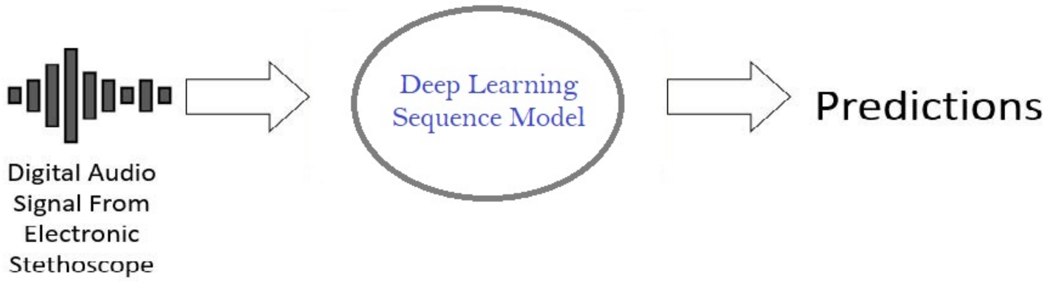


Figure 5.1: Sequence Model

ALGORITHM USED: Sequence Models

Sequence models are the machine learning models that input or output sequences of data. Sequential data includes text streams, audio clips, video clips, time-series data and etc.

Types of layers in Sequential Neural Network:

Consider a spectrogram image of dimension 32 x 32 x 3.

1. **Input Layer**: This layer holds the raw input of image with width 32, height 32 and depth 3.

2. **Convolution Layer**: This layer computes the output volume by computing dot product between all filters and image patch. Suppose we use total 12 filters for this layer we'll get output volume of dimension 32 x 32 x 12.

3. **Activation Function Layer**: This layer will apply element wise activation function to the output of convolution layer. Some common activation functions are RELU: max(0, x), Sigmoid: $1/(1+e^{-x})$, Tanh, etc.

4. **Pool Layer**: This layer is periodically inserted in the covnets and its main function is to reduce the size of volume which makes the computation fast reduces memory and also prevents from overfitting. Two common types of pooling layers are max pooling and average pooling. If we use a max pool with 2 x 2 filters and stride 2, the resultant volume will be of dimension 16x16x12.

5. **Fully-Connected Layer**: This layer is regular neural network layer which takes input from the previous layer and computes the class scores and outputs the 1-D array of size equal to the number of classes.

5.3 Data Flow Diagrams

5.3.1 Data Flow Diagram- Level 0

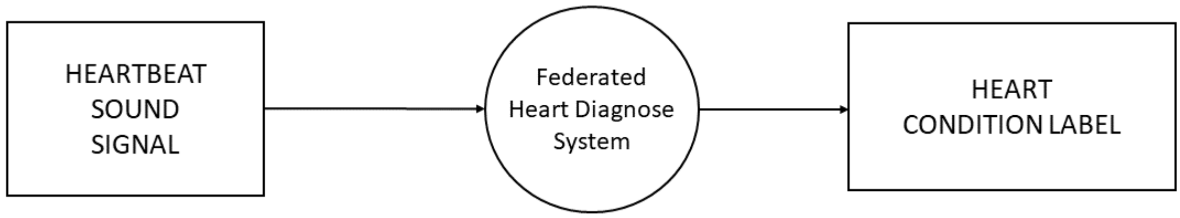


Figure 5.2: DFD- Level 0

5.3.2 Data Flow Diagram- Level 1

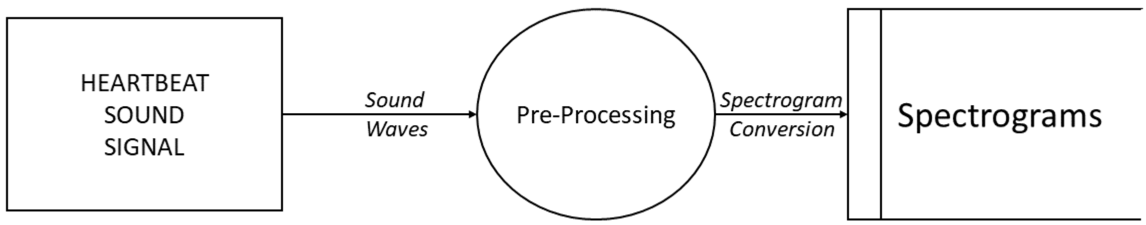


Figure 5.3: DFD- Level 1: Pre-Processing

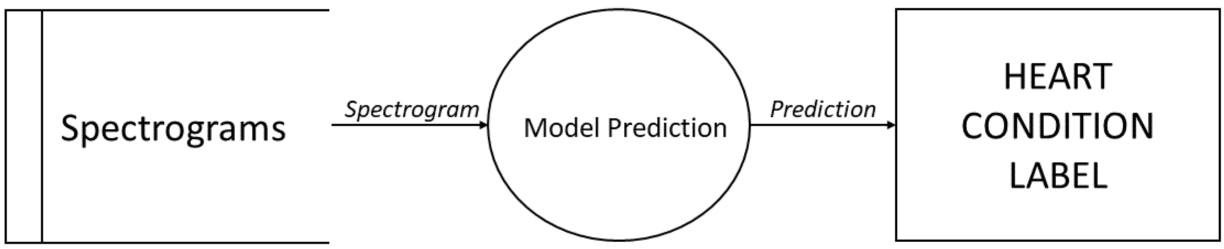


Figure 5.4: DFD- Level 1: Prediction

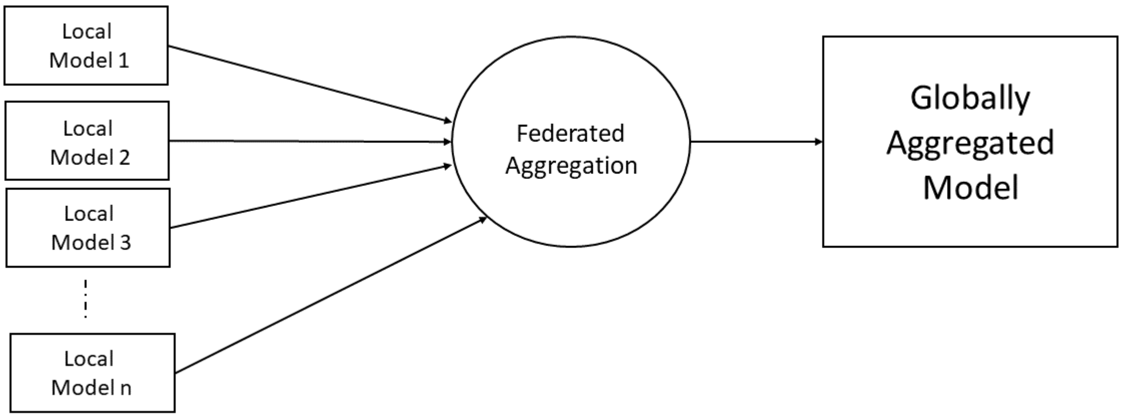


Figure 5.5: DFD- Level 1: Federated Aggregation

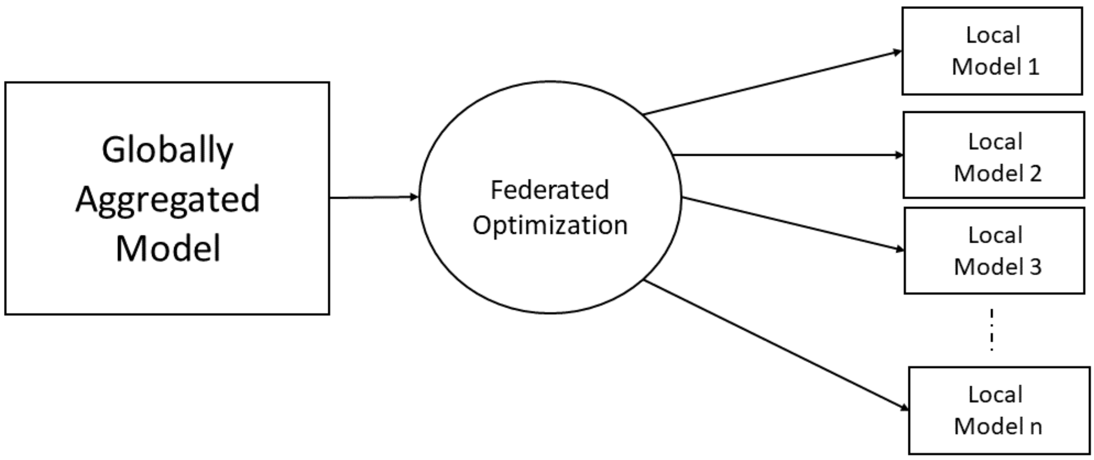


Figure 5.6: DFD- Level 1: Federated Optimization

5.3.3 Data Flow Diagram- Level 2

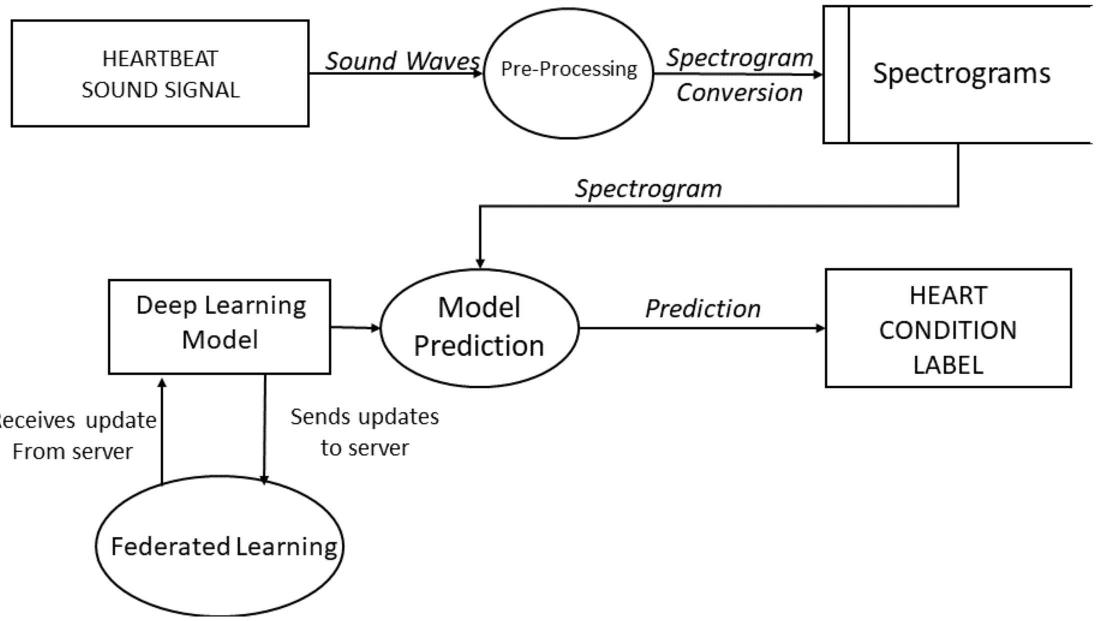


Figure 5.7: DFD- Level 2: System

5.4 Use Case Diagram

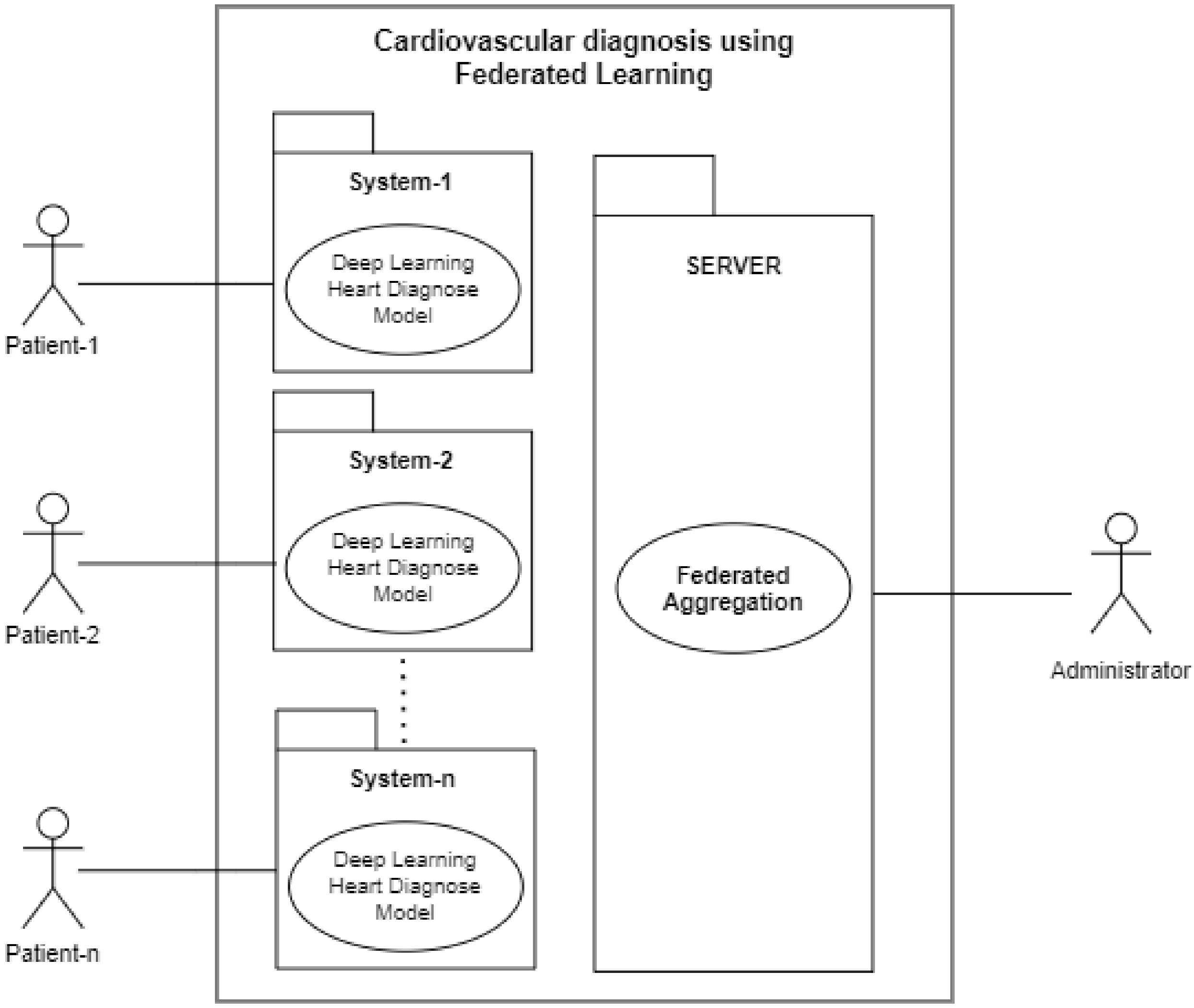


Figure 5.8: Use Case Diagram

5.5 Architecture

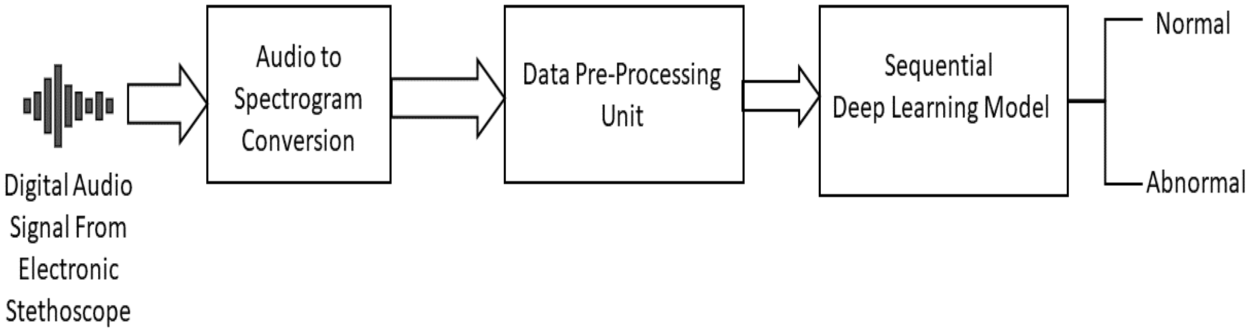


Figure 5.9: Distributed Device Architecture

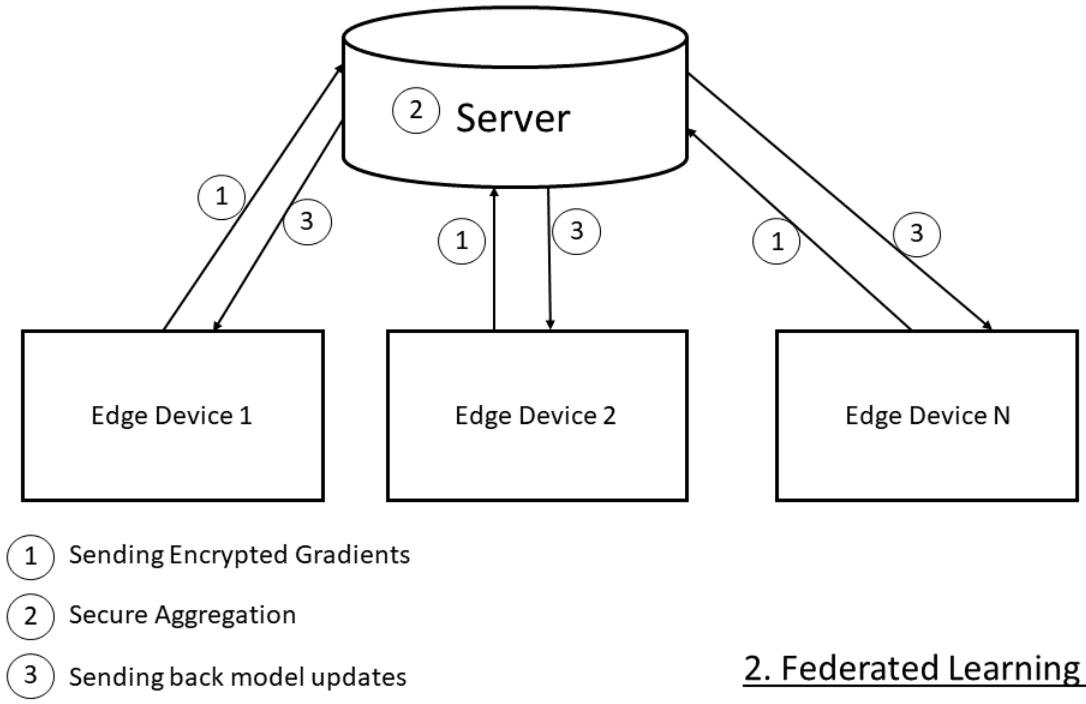


Figure 5.10: Federated Learning Architecture

CHAPTER 6

RESULTS

In the first experiment, a basic Machine Learning model detecting heartbeat sound abnormalities is developed based on the earlier mentioned dataset. The model effectively discriminates between normal and abnormal heartbeat sounds. TensorFlow library was used to design and train the model, along with Google Colab being the hardware for training purpose. The model was evaluated based on the accuracy of classifications and it produced accurate classifications.

CHAPTER 7

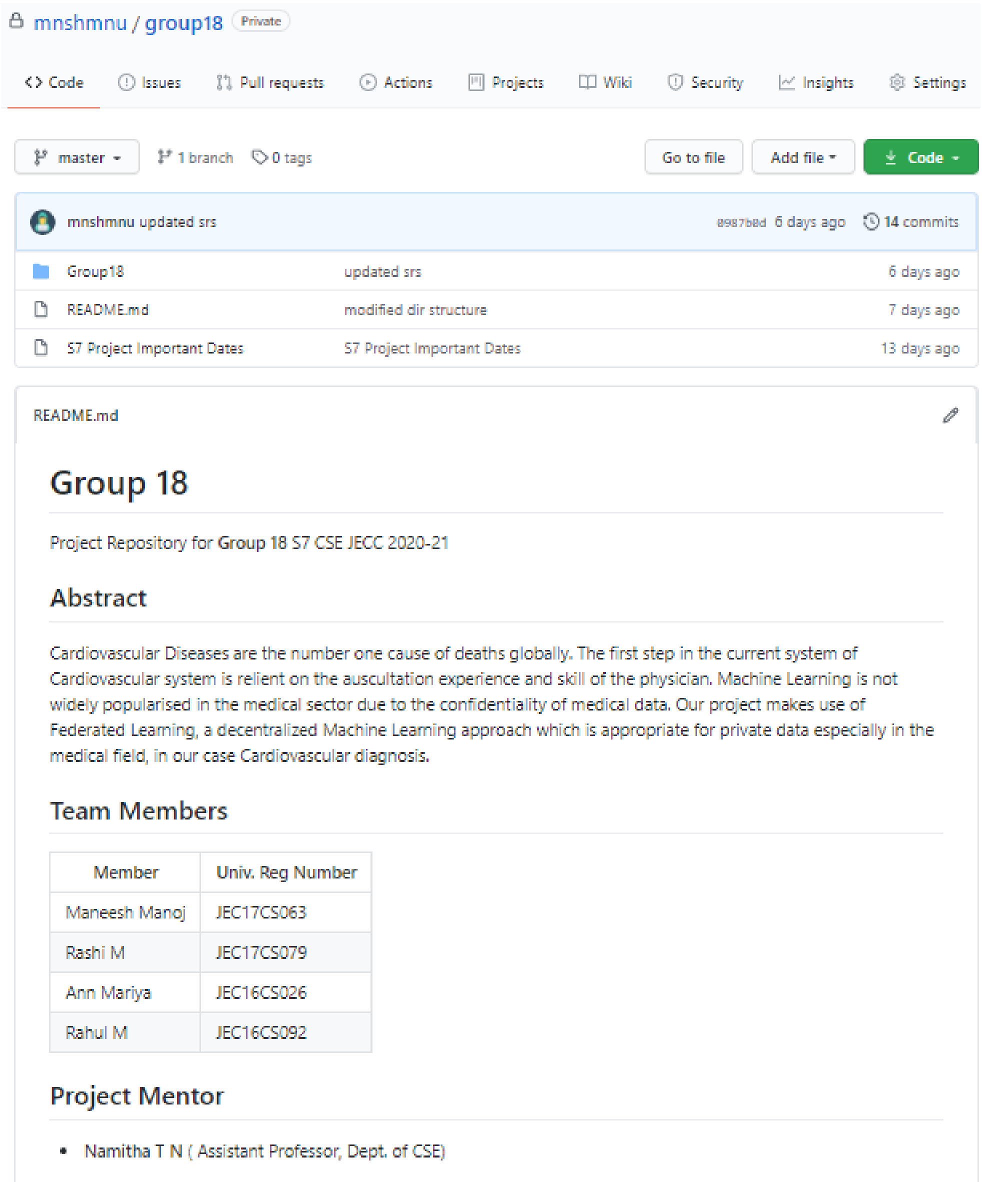
CONCLUSION AND FUTURE WORKS

The applications of Machine Learning and various other paradigms of ML in the field of Healthcare and Informatics is ever increasing and a wide range of innovations are showcased in recent years. The approach discussed in this work, Federated Learning is a recent research area, and applications based on the same is being developed for active use. Federated Learning is to be used in the future upgrades of this project work to implement Federated learning based diagnose of cardiovascular abnormalities. The design and the requirements for the project has been outlined the direction of work to be followed has been set.

CHAPTER 8

Appendix

The resources used and designed for this project is available in the Github repository *https://github.com/mnshmnu/group18*



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Code Issues Pull requests Actions Projects Wiki Security Insights Settings

master 1 branch 0 tags Go to file Add file Code

mnshmnu updated srs 8987b8d 6 days ago 14 commits

Group18	updated srs	6 days ago
README.md	modified dir structure	7 days ago
S7 Project Important Dates	S7 Project Important Dates	13 days ago

README.md

Group 18

Project Repository for Group 18 S7 CSE JECC 2020-21

Abstract

Cardiovascular Diseases are the number one cause of deaths globally. The first step in the current system of Cardiovascular system is relient on the auscultation experience and skill of the physician. Machine Learning is not widely popularised in the medical sector due to the confidentiality of medical data. Our project makes use of Federated Learning, a decentralized Machine Learning approach which is appropriate for private data especially in the medical field, in our case Cardiovascular diagnosis.

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Project Mentor

- Namitha T N (Assistant Professor, Dept. of CSE)

Figure 8.1: Screenshot of Project Github Repository

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