Project Final Report

Date	11 October 2022
Team ID	PNT2022TMID42525
Project Name	Classification of Arrhythmia by Using Deep Learning with 2D ECG Spectral Image Representation

INDEX

1.INTRODUCTION

1.1 Project Overview:

Cardiovascular diseases (CVDs) are the leading cause of human death, with over 17 million people known to lose their lives annually due to CVDs . According to the World Heart Federation, three-fourths of the total CVD deaths are among the middle and low-income segments of the society . A classification model to identify CVDs at their early stage could effectively reduce the mortality rate by providing a timely treatment]. One of the common sources of CVDs is cardiac arrhythmia, where heartbeats are known to deviate from their regular beating pattern. A normal heartbeat varies with age, body size, activity, and emotions. In cases where the heartbeat feels too fast or slow, the condition is known as palpitations. An arrhythmia does not necessarily mean that the heart is beating too fast or slow, it indicates that the heart is following an irregular beating pattern. It could mean that the heart is beating too fast—tachycardia (more than 100 beats per minute (bpm)), or slow—bradycardia (less than 60 bpm), skipping a beat, or in extreme cases,cardiac arrest. Someother common types of abnormalheart rhythms includeatrial fibrillation,atrial flutter, and ventricular fibrillation. These deviations could be classified into various subclasses and represent different types of cardiac arrhythmia. An accurate classification of these types could help in diagnosing and treatment of heart diseasepatients. Arrhythmia could either mean a slow or fast beating of heart, or patterns that are not attributed to a normal heartbeat. An automated detection of such patterns is of great significance in clinical practice. There are certain known characteristics of cardiac arrhythmia, where the detectionrequires expert clinical knowledge.The electrocardiogram (ECG) recordings are widely used for diagnosing and predicting cardiac arrhythmia for diagnosing heart diseases. Towards this end, clinical experts might need to look at ECG recordings over a longer period of time for detecting cardiac arrhythmia. The ECG is a one-dimensional (1-D) signal representing a time series, which can be analyzed using machine learning techniques for automateddetection of certainabnormalities. Recently, deep learning techniques have been developed, which provide significant performance in radiological image analysis . Convolutional neural networks (CNNs) have recently been shown to work for multi-dimensional (1-D, 2-D, and in certain cases, 3-D) inputs but were initially developed for problems dealing with images represented as two-dimensional inputs . For time series data, 1-D CNNs are proposed but are less versatile when compared to 2-D CNNs. Hence, representing the time series data in a 2-D format could benefit certain machine learning tasks. Hence, for ECG signals, a 2-D transformation has to be applied to make the time series suitable for deep learning methods that require 2-D images as input. The short-time Fourier transform (STFT) can convert a 1-D signal into a 2-D spectrogram and encapsulate the time and frequency information within a single matrix.

1.2 Purpose:

In the model which assembled information is taken from MIT-BIH dataset. The first step is to pre-process the signs to expel the gauge, power line, low recurrence and high recurrence commotions present in the dataset. At that point the divisionof signs into heart pulsatesis finished by distinguishing the QRS top and the R-R interim.QRS complex is the most striking waveforminside the ECG. Since it mirrors the electrical movement inside the heart during the ventricular withdrawal, the hour of its event just as its shape give significant data about the current condition of the heart. A notable Pan- Tompkins calculation is applied to convey out the QRS recognition. The calculation incorporates aprogression of strategies that perform subordinate, figuring out, mix, versatile thresholding and look strategies for the recognition of R-pinnacles of the ECG signal. The pulses are changed over into pictures utilizing OpenCV and Matplotlib libraries of python language. The component extraction isfinished by the convolutional neural system which follows the VGG Net engineering.VGG networkmodel is similarto convolutional layers of 3×3 pile up over one another in increasing depth. Lowering volume size is dealt with by max pooling. Two associated layers, each with 4,096 hubs are at that point followedby a delicate max classifier. The arrangement is finished by utilizing extraordinary MLP Classifiers, LSTM, Faster RCNN andso forth.The input can be 1D,2D……. nD so any type of inputs can be giveninto the systemfor getting the outputs. Segmentation of heart beat in the proposedsystem i.e. segmentation is a way of arranging into distinct sub groups that typically have separate needs. Heart beats are converted into images and detect QRS peak and also R-R interval. System can have many numbers of clusterssuch that it can identifythe condition of the patientprecisely. If the accuracy is less, then the architecture is changed automatically and calculated again. This process is done until it get the better accuracy. Hence the proposed system has wide range of advantages while compared to the existingsystem.

2. LITERATURE SURVEY

2.1 Existing problem:

The ECG signal detects abnormal conditions and malfunctions by recording the potential bio-electric variation of the human heart. Accurately detecting the clinical condition presented by an ECG signal is a challenging task . Therefore, cardiologists need to accurately predict and identify the right kind of abnormal heartbeat ECG wave before recommending a particular treatment. This might require observing and analyzing ECG recordings that might continue for hours (patients in critical care). To overcome this challenge for the visualand physical explanation of the ECG signal, computer-aided diagnostic systems have been developed to automatically identify such signals automatically. Most of the research in this field has been conducted by incorporating different approaches of machinelearning (ML) techniques for the efficient identification and accurate examination of ECG signals . The ECG signal classification based on differentapproaches has been presented in the literature including frequency analysis, artificial neural networks (ANNs) , heuristic-based methods , statistical methods , support vector machines (SVMs) , wavelet transform , filter banks , hidden Markov models , and mixture-of-expert methods . An artificialneural network based method obtained an average accuracy of 90.6% for the classification of ECG wave into six classes .Machine learning is a subset of artificial intelligence used with high-end diagnostic tools for the prediction and diagnosis of different types of illnesses. Deep learning,as a subset of ML, has manyapplications in the prediction and prevention of fatal sicknesses, particularly CVDs. Different techniques of deep learning used for the analysis of bioinformatics signals have been presented in . A recurrent neural network (RNN) was used for featureextraction and achievedan average accuracyof 98.06% for detecting four types of arrhythmia. For the classification and extraction of features from a 1-D ECG signal, a 1-D convolutional neural network model was proposed and yielded a classification accuracyof 96.72%.

2.2 References:

1. Mc Namara,K.; Alzubaidi, H.; Jackson, J.K. Cardiovascular diseaseas a leading cause of death: How are pharmacists gettinginvolved? Integr. Pharm. Res. Pract. 2019, 8, 1.

2. Lackland, D.T.; Weber, M.A. Global burden of cardiovascular disease and stroke:hypertension at the core. Can. J.Cardiol. 2015, 31, 569–571.

3. Mustaqeem, A.; Anwar, S.M.; Majid, M. A modularcluster based collaborative recommender system for cardiac patients. Artif. Intell. Med. 2020, 102, 101761.

4. Irmakci, I.; Anwar, S.M.; Torigian,D.A.; Bagci, U. Deep Learning for Musculoskeletal Image Analysis. arXiv Prepr.

. 5. Anwar, S.M.; Majid, M.; Qayyum, A.; Awais, M.; Alnowami, M.; Khan, M.K. Medical image analysis using convolutional neural networks:A review. J. Med. Syst. 2018, 42, 226.

6. Gu, J.; Wang, Z.; Kuen, J.; Ma, L.; Shahroudy, A.; Shuai, B.; Liu, T.; Wang, X.; Wang, G.; Cai, J.; et al. Recent advances in convolutional neural networks. Pattern Recognit. 2018, 77, 354–377.

7. Wu, Y.; Yang, F.; Liu, Y.; Zha, X.; Yuan, S. A comparisonof 1-D and 2-D deep convolutional neural networks in ECG classification. arXiv Prepr. 2018, arXiv:1810.07088.

8.Zhao, J.; Mao, X.; Chen, L. Speech emotionrecognition using deep 1D &2-D CNN LSTM networks. B

9. Ortega, S.; Fabelo, H.; Iakovidis, D.K.; Koulaouzidis, A.; Callico, Gctral imagingin gastroenterology. Sh eddingsome–different–light into the dark. J. Clin. Med. 2019, 8, 36.

10. Feng, Y.-Z.; Sun, D.-W. Application of Hyperspectral Imaging in Food Safety Inspection and Control: A Review.
Crit. Rev. Food Sci. Nutr. 2012, 52, 1039–1058

11.Lorente, D.; Aleixos, N.; Gómez-Sanchis, J.; Cubero, S.; García-Navarrete, O.L.; Blasco, J. Recent Advances and Applications of Hyperspectral Imaging for Fruit and Vegetable Quality Assessment. Food

12. Pooja sharma, D.V Gupta, SurenderJangra, “ECG Signal Based Arrhythmia DetectionSystem Using Optimized Hybrid Classifier “(IJITEE) 2019.

13. S. Celin and K. Vasanth, “Survey on the methods for Detecting Arrhythmias using heart rate signals” (JPSR) 2017.

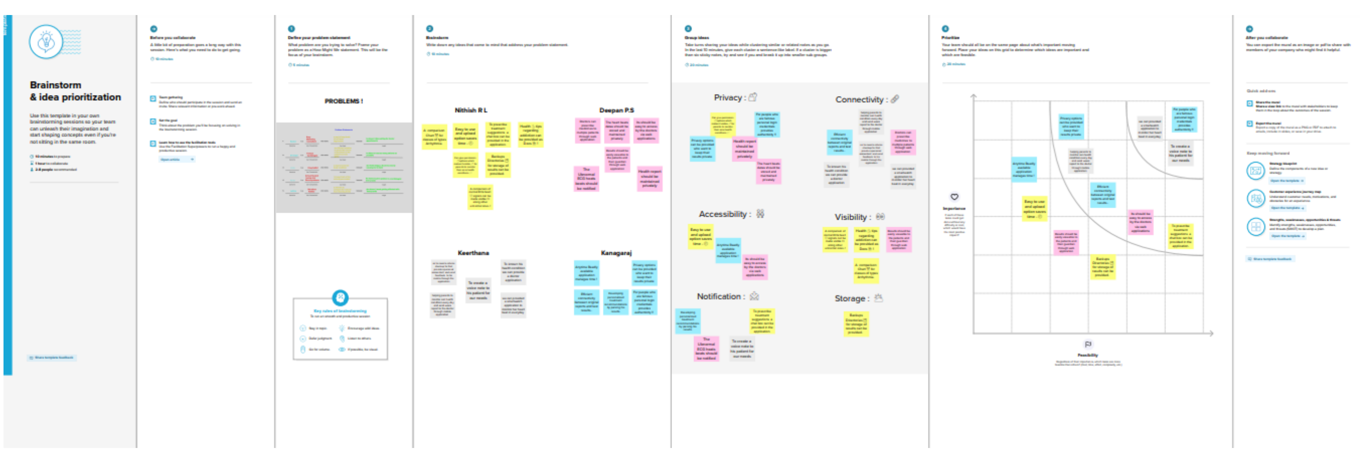
2.3 Problem Statement Definition :

In order to guide the customers throughout all the financial services provided by the hospitals, an intelligent systemhas to be introduced to provide people with the best solutionpossible. The users are health issue patients who need a service, available 24/7, to clear all their queries and guide them through the various health care processes. So, an enhanced and smarter way of interaction with the doctores has to be built to ensure efficient delivery of service. In order to overcome the user satisfaction issues associated with healthcare services, a webapplication will provide personal and efficient communication between the user and the patients.It is built to be the overall virtual assistant that can facilitate customers to ask Arrhythmia- related questions without visiting the bank or calling up patients service centres as well as providing them with relevant suggestions

3.IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas :

3.2 Ideation & Brainstorming:



3.3 Proposed Solution :

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	● ECG is aften used alongside other tests helpthe diagnose and monitor canditions affecting the heart ● Its used to investigate symptoms of a possible heart problems such as chest pain,palpitations andshortness of breath ● arrthmia is an abnormal of the heart'srytham ● So they needs to dependent on otherperson which makes them feel more reliable ● The web application can find the heartissues and show the result visualy
2.	Idea / Solution description	● It should provide quik result of theirproblems ● The electrocardiogram (ECG) is one of the most extensively employed signals used inthe diagnosis and prediction of cardiovascular diseases (CVDs). The ECG signals can capture the heart's rhythmic irregularities, commonly known as arrhythmias ● The 2-D CNN model consisting of four convolutional layers and four pooling layersis designed for extracting robust features from the input spectrograms ● machine learning and deep learning Commonly, if deep learning is adopted in physiological-based emotion recognition, there are no feature extraction and feature selection steps. ● If the deep learning architecture has a convolutional layer, it might somehow beconsidered as a

		dimensionality reduction stage.

3.	Novelty / Uniqueness	● This enables the elderly to keep track oftheirmeditation. ● Back up option is available,if the data orrecord is deleded accidently. ● The user receives the notification commandin the appropriate time. ● It’s a time saving application.

4.	Social Impact/ Customer Satisfaction	• It will also serve to assist the elderly in a more effective manner and will be used to improve their daily life in terms of arrthmia consumption. • Our system promotes safe and independent living which makes them more self-reliable and healthier cared-for individuals. • It is time saveingapplication • From anywhere in the world, family members may check on a loved one's wellbeing. • This web application efficient to use docter and patient
5.	Business Model(Revenue Model)	• Our proposed web application will be a subscriber servicewhich is very affordable. • Proper updates in the application according to trends and customer convenience which makes high customer retention. • Proper upkeep of privacy policies that enhances customer's trust.

3.4 Problem Solution fit :

Define CS, fit into CL

1. CUSTOMER SEGMENT(S) CS

- Patients looking forward to know about their class of arrhythmia.
- For users who want to be self-reliant without any medical equipment.
- Also Doctors / clinical experts who want automated methods to improve the clinical diagnosis and treatment of some of the major CVDs.

6. CUSTOMER LIMITATIONS EG. BUDGET, DEVICES CL

- have to know basic image uploading skills.
- have a cell phone / laptop.
- have a Gmail / Google Account.
- have proper images and medical records.

5. AVAILABLE SOLUTIONS PLUSES & MINUSES AS

- wearing a small portable ECG recording device for 24 hours or longer is usual of detection which is considered to be time consuming by users.
- Timely treatment is not possible with using only ECG.
- Traditional Clinical lab testing but does not use any automated systems related to CVDs.

Explore AS, differentiate

Focus on PR, tap into BE, understand RC

2. PROBLEMS / PAINS + ITS FREQUENCY PR

- People want to know about their results of classification even though they don't have any knowledge for taking timely treatments as quick as possible.
- People / users / patients want to share their reports with clinical experts and their prescribed doctors for further course of action that is need to be taken.
- People are also afraid that if their results are accurate and how proper classification is being done with automated systems being used and also privacy of personal reports being shared through websites.
- People want do quick conformation anywhere anytime with just having only the images they have from tests.

9. PROBLEM ROOT / CAUSE RC

- They need use multiple ECG tests which could not be even accurate under traditional methods.
- Have to wait for long hours for the test results done in Clinical labs by experts were there are proven to be human errors in classification.
- No proper maintenance of patient records in hospitals and labs and leading to privacy issues of patient documents being made publically available under health organizations.
- Clinical experts might need to look at ECG recordings over a longer period of time for detecting cardiac arrhythmia.

7. BEHAVIOR + ITS INTENSITY BE

- People use different methods of classification techniques under the guidance of doctors and clinical experts for arrhythmia but there no automated systems being used mostly in daily life.
- Some even stop taking tests as they cost high and also takes lots of time under experimentation leading to poor test results making early treatment not possible in some cases.

Focus on PR, tap into BE, understand RC

Identify strong TR & EM

3. TRIGGERS TO ACT TR

- People want to make their life easier, feel safe and connected anytime, anywhere.
- Have a proper web application to make things automated and easy to detect their health with accuracy.

4. EMOTIONS BEFORE / AFTER EM

- People / patients / users did feel reliable and efficient with traditional ECG methods so automated systems and the web application goal is to change it!
- People with be having result classified quickly with more accuracy without taking longer periods of time waiting for treatments.

10. YOUR SOLUTION SL

- to propose a 2-D CNN-based classification model for automatic classification of cardiac arrhythmias using ECG signals.
- to make a web application as reliable as possible for the user/patient to fed his image into the model that is trained and the cited class is displayed on the webpage.
- to help experts diagnose CVDs by referring to the automated classification of ECG signals.
- to further improve experimental cases.
- enhancing the accuracy of diagnosis algorithms in the fusion of medicine and modern machine. learning technologies.

8. CHANNELS of BEHAVIOR CH

ONLINE

- Social media results regarding automated web application create awareness for other users on the efficiency and reliability about the automated classification of cardiac arrhythmias and also Expert advertise online test proofs.

OFFLINE

- Word of mouth among users, clinical experts, patients and people in the society.

Extract online & offline CH of BE

4. REQUIREMENT ANALYSIS

4.1 Functional requirement:

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Uploads	Interacts with User interface to upload image
FR-2	User Selection	Knowledge about ECG images Select the imageto be classified
FR-3	User Input	No input (For Training) images need to be given.. (All normal and the other six being different types ofarrhythmia ECG imagesare already fed)
FR-4	User Output	Cited class will be displayed on the webpage (UI).
FR-5	User Storage	Cloud Storage Services via GoogleDrive.

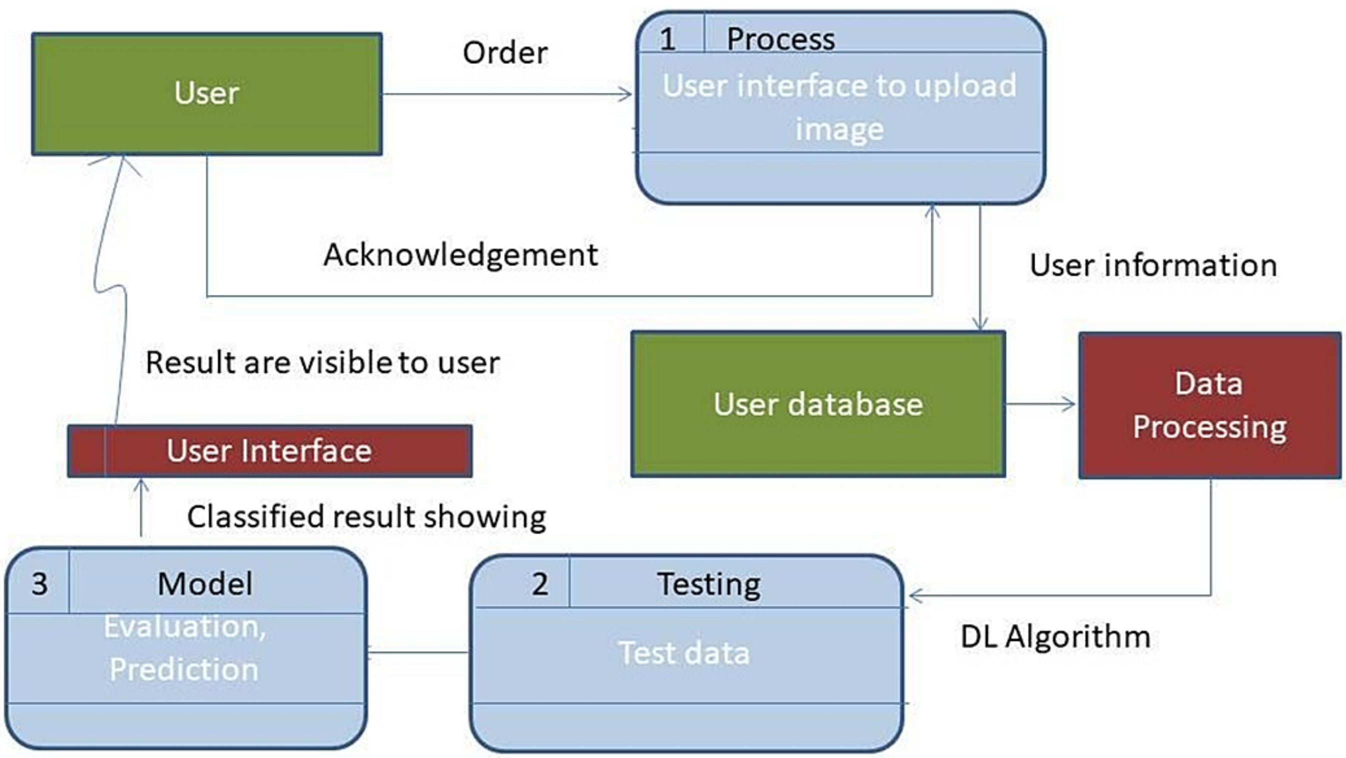
4.2 Non-Functional requirements :

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	An user friendly and simple UI web application.Easydrag and dropuploading options. No input, can select between pre-defined images made available in the UI web application by just selecting the type of image.
NFR-2	**Security**	Only user uploaded images / images selected by user are cited and classified by the model and displayed. No third party web and UI is used for prediction of data. Details about user interaction with the web application are protected by Advanced Security System.
NFR-3	**Reliability**	Defect free. Higher accuracy rate. Performs correctly in every scenario. The website's load time is not more than one second for users.

NFR-4	**Performance**	Fast and quick classification of the required class is done as the GPU used for the model is 10% more fast in analysing and uploading the user uploaded images !
NFR-5	**Availability**	Anytime anywhere available web application almost can found in all popular search engines like Google, etc.. Were user are requested to have good internet connection.
NFR-6	**Scalability**	More than one type of classification can be done as multiple images can be uploaded.. Reduced traffic in case of multiple user interaction.

5. PROJECT DESIGN

5.1 Data Flow Diagrams :



5.2 Solution & Technical Architecture :

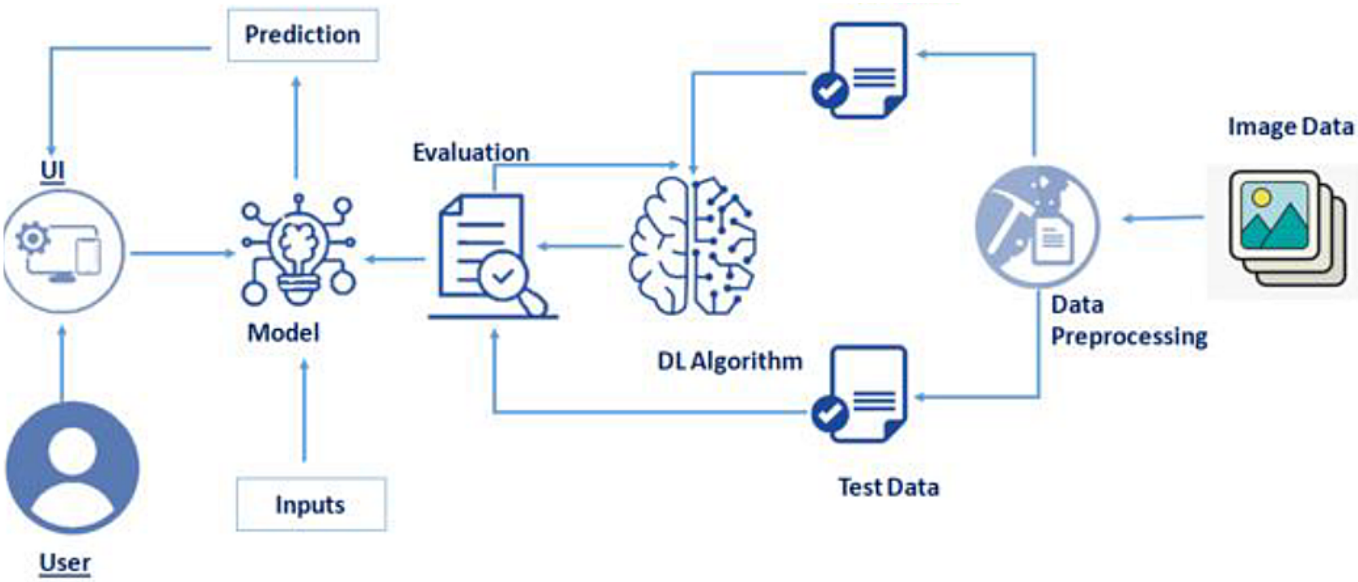


Table-1 : Components & Technologies:

S.No	Component	Description	Technology
1.	User Interface	Web UI	HTML, CSS, JS, Python.
2.	Application Logic-1	Data Preprocessing	Keras, Tensorflow, Numpy - (Importing Essentisl Libraries)
3.	Application Logic-2	CNNModel Creating	Keras, Tensorflow, Numpy - (Importing Essentisl Libraries)
4.	Application Logic-2	WebApplication (UI)	Flask
5.	Database	Images (Jpeg, PNG, Jpg, etc..)	Uploads Folder !
6.	File Storage	File storage requirements (only if necessary)	IBM BlockStorage / Google Drive (Depends On Preference)
7.	External API	Keras	Image Processing API.
8.	Deep Learning Model	Electrocardiogram (ECG)arrhythmia classification	2D ImageECG Spectral Image Representation Model.
9.	Infrastructure (Server/ Cloud)	Application Deployment on Webserver	Flask—a Python WSGIHTTP server.

Table-2: Application Characteristics:

S.No	Characteristics	Description	Technology
1.	Open-Source Frameworks	Flask	Werkzeug, Jinja2, Sinatra Ruby framework
2.	Security Implementations	CSRF protection, secure flag for cookies	Flask-WTF, SESSION_COOKIE_SECURE
3.	Scalable Architecture	Micro Services	Micro web application framework by Flask.
4.	Availability	-built-in development server and fastdebugger -integrated support for unit testing -RESTful request dispatchingJinja2 templating Unicode based	Werkzeug, Jinja2, Sinatra Rubyframework
5.	Performance	ORM-agnostic, web framework, WSGI 1.0 compliant, HTTP request handlingfunctionality High Flexibility	SQLAlchemy, extensions, Werkzeug, Jinja2, Sinatra Rubyframework.

5.3 User Stories :

User Type	Functional Requirement(Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer (Web user)	Storage	USN-1	As a user, I can access my images storedfromGoogle Drive if necessary.	I can access my account/drive.	Medium	Sprint-4
	Registration	USN-2	As a user, I can register for the application through Gmail.	I can receive confirmation email & clickconfirm	Low	Sprint-3
		USN-3	As a user, I can register for the applicationthrough website.	I can register & accessthedashboard with website login in IBM cloud	Medium	Sprint-2
		USN-4	As a user, I am ableto upload the necessary images.		High	Sprint-1
	Dashboard	USN-5	As a user, I can shareuser report and viewed my result	I can access the website	Medium	Sprint-2
Admin		USN-6	As an Admin, I gave userall the data available to run thetest.	I can manage web/account/dashboard	High	Sprint-1
		USN-7	As an Admin, I can manage the ArrhythmiaClassification details. If normal or abnormal the UI model will share the result for the dashboard.	I can manage the websitemonitoring	High	Sprint-1

6. PROJECT PLANNING & SCHEDULING

6.1 Sprint Planning & Estimation :

Sprint	Functional Requirement (Epic)	User Story Number	User Story/ Task	Story Points	Priority	Team Members
Sprint-4	Storage	USN-1	As a user, I can accessmy images storedfrom Google Drive if necessary.	1	Medium	Keerthana
Sprint-3	Registration	USN-2	As a user,I can register for the application through Gmail.	1	Low	Kanagaraj
Sprint-2		USN-3	As a user,I can register for theapplication through website.	1	Medium	Nithish
Sprint-1		USN-4	As a user, I am ableto upload thenecessary images.	2	High	Nithish
Sprint-2	Dashboard	USN-5	As a user,I can share user reportand viewed my result.	1	Medium	Deepan
Sprint-1		USN-6	As an Admin, I gave user all the dataavailable to run the test.	2	High	Nithish
Sprint-1		USN-7	As an Admin, I can manage the Arrhythmia Classification details. If normal or abnormal theUI model will share the result for the dashboard.	2	High	Deepan

Sprint	Total Story Points	Duration	Sprint StartDate	SprintEnd Date (Planned)	Story Points Completed (as on Planned End Date)	SprintRele ase Date (Actual)
Sprint-1	20	6 Days	24 Oct 2022	29 Oct 2022	20	29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022		
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022		
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022		

Velocity:

Imagine we have a 10-day sprint duration, and the velocity of the team is 20 (points per sprint). Let's calculate the team's average velocity (AV) periteration unit (story points per day)

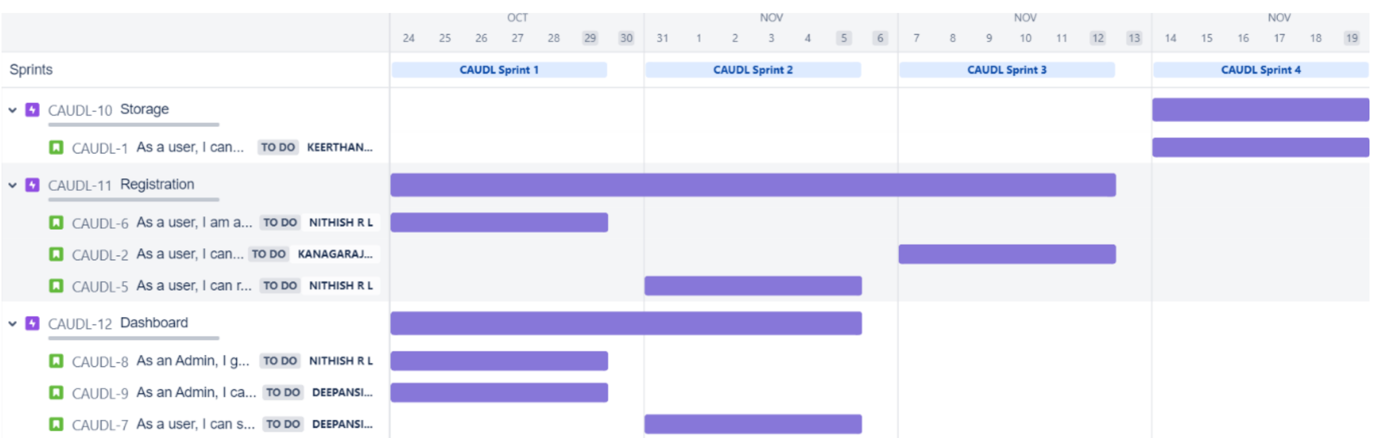
$$AV = \frac{sprint\ duration}{velocity} = \frac{20}{10} = 2$$

6.2 Sprint Delivery Schedule :

Title	Description	Date
Literature Survey andInformation Gathering	Gathering Information by referring the technical papers, research publications etc	10 September 2022
Prepare Empathy Map	To capture user pain and gainsPrepare List of Problem Statement	17 September 2022
Ideation	Prioritise a top 3 ideas based on feasibility and Importance	18 September 2022
Proposed Solution	Solution include novelty, feasibility, business model, social impact and scalability of solution	1 October 2022

Problem Solution Fit	Solution fit document	1 October 2022
Solution Architecture	Solution Architecture	1 October 2022
Customer Journey	To Understand User Interactions and experienceswith application	8 October 2022
Functional Requirement	Prepare functional Requirement	9 October 2022
Data flow Diagrams	Data flowdiagram	11 October 2022
Technology Architecture	Technology Architecture diagram	15 October 2022
Milestone & sprintdelivery plan	Activity what we done&further plans	21 October 2022
Project Development- Delivery of sprint 1,2,3&4	Develop and submit the developed codeby testing it	24 October 2022 – 19 November 2022

6.3 Reports from JIRA :



7. CODING & SOLUTIONING

7.1 Feature :

Model Building

Model Building :

Adding Layers :

In [9]:

```
#Import req. Lib.
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Convolution2D, MaxPooling2D, Flatten, Dense
```

In [10]:

```
# Build a CNN Block:
model = Sequential() #intializing sequential model
model.add(Convolution2D(32,(3,3),activation='relu', input_shape=(64,64,3))) #convolution layer
model.add(MaxPooling2D(pool_size=(2, 2))) #Maxpooling layer
model.add(Flatten()) #Flatten layer
model.add(Dense(400,activation='relu')) #Hidden Layer 1
model.add(Dense(200,activation='relu')) #Hidden Layer 2
model.add(Dense(6,activation='softmax')) #Output Layer
```

Compiling :

In [11]:

```
# Compiling The Model...
model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
```

Fit / Train The Model :

In [12]:

```
#Train Model:
model.fit_generator(ftrain,
                    steps_per_epoch=len(ftrain),
                    epochs=10,
                    validation_data=ftest,
                    validation_steps=len(ftest))
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future versio
n. Please use `Model.fit`, which supports generators.
```

```
Epoch 1/10
154/154 [==============================] - 35s 176ms/step - loss: 1.5479 - accuracy: 0.5302 - val_loss: 1.3259 - val_accuracy: 0.4988
Epoch 2/10
154/154 [==============================] - 27s 174ms/step - loss: 0.6284 - accuracy: 0.7950 - val_loss: 0.7936 - val_accuracy: 0.7398
```


```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future versio
n. Please use `Model.fit`, which supports generators.
```

```
Epoch 1/10
154/154 [==============================] - 35s 176ms/step - loss: 1.5479 - accuracy: 0.5302 - val_loss: 1.3259 - val_accuracy: 0.4988
Epoch 2/10
154/154 [==============================] - 27s 174ms/step - loss: 0.6284 - accuracy: 0.7950 - val_loss: 0.7936 - val_accuracy: 0.7398
```


```
Epoch 3/10
154/154 [==============================] - 30s 193ms/step - loss: 0.3648 - accuracy: 0.8883 - val_loss: 0.5895 - val_accuracy: 0.8147
Epoch 4/10
154/154 [==============================] - 27s 174ms/step - loss: 0.2853 - accuracy: 0.9141 - val_loss: 0.4523 - val_accuracy: 0.8394
Epoch 5/10
154/154 [==============================] - 27s 174ms/step - loss: 0.2442 - accuracy: 0.9243 - val_loss: 0.4683 - val_accuracy: 0.8321
Epoch 6/10
154/154 [==============================] - 26s 171ms/step - loss: 0.2142 - accuracy: 0.9339 - val_loss: 0.5106 - val_accuracy: 0.8278
Epoch 7/10
154/154 [==============================] - 27s 172ms/step - loss: 0.1898 - accuracy: 0.9400 - val_loss: 0.4912 - val_accuracy: 0.8309
Epoch 8/10
154/154 [==============================] - 27s 173ms/step - loss: 0.1736 - accuracy: 0.9469 - val_loss: 0.4330 - val_accuracy: 0.8513
Epoch 9/10
154/154 [==============================] - 27s 173ms/step - loss: 0.1513 - accuracy: 0.9538 - val_loss: 0.5544 - val_accuracy: 0.8344
Epoch 10/10
154/154 [==============================] - 27s 173ms/step - loss: 0.1351 - accuracy: 0.9572 - val_loss: 0.6018 - val_accuracy: 0.8500
```

Out[12]:

Saving The Model :

In [13]:

```
#Save Model
model.save('CAUDL.h5')
```

Testing The Model :

In [14]:

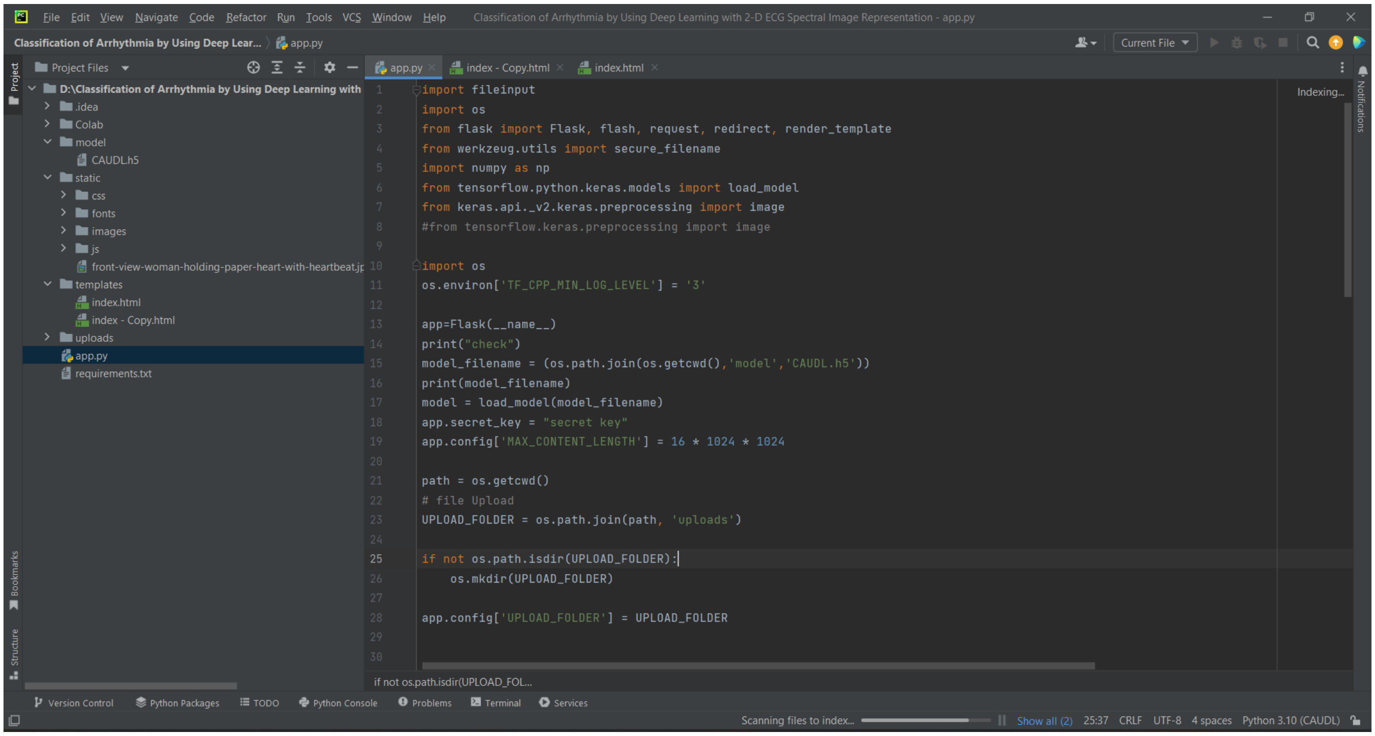
```
#Import req. Lib.
from tensorflow.keras.preprocessing import image
import numpy as np
```

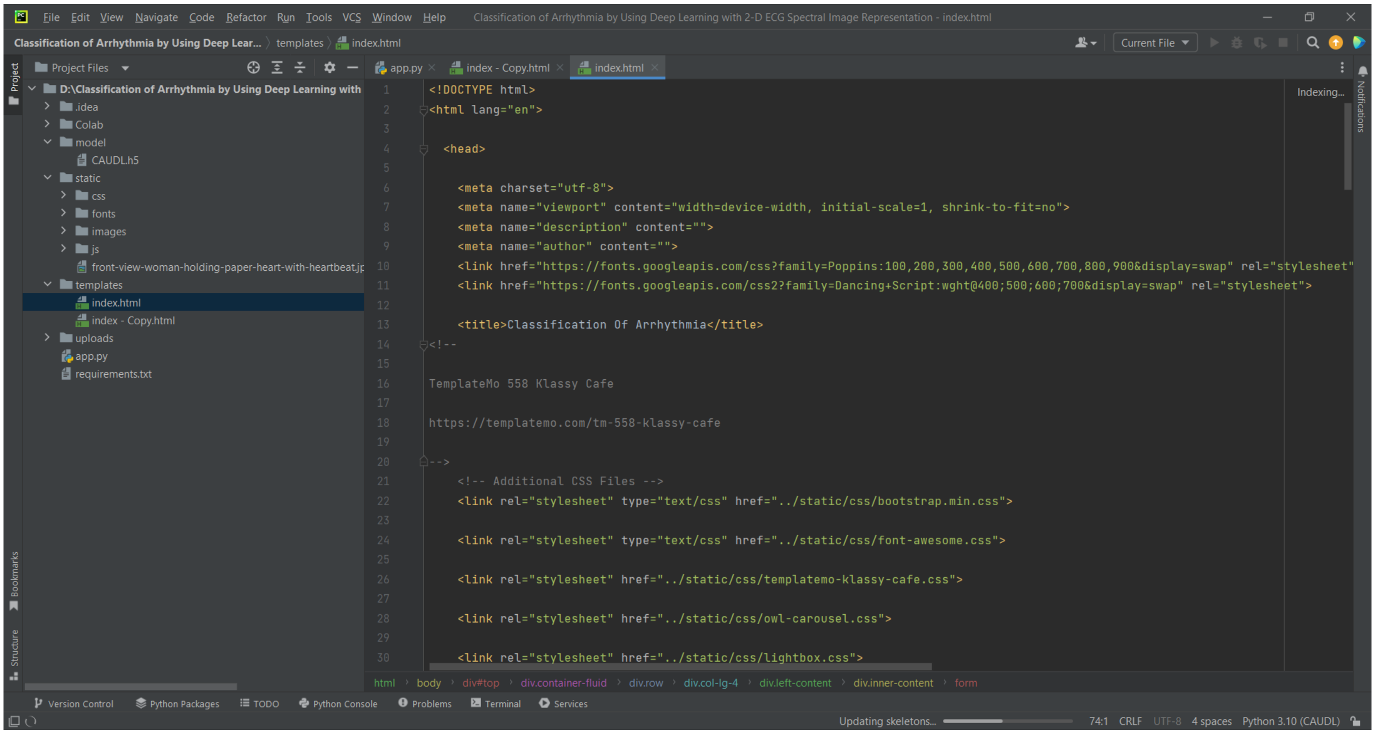
In [15]:

```
#Testing No 1 :-
img = image.load_img('/content/data/test/Left Bundle Branch Block/fig_5910.png',target_size=(64,64)) #Reading image
f = image.img_to_array(img) #Converttinng image to array
```

7.2 Feature :

Local Deployment





7.3 Feature : (Cloud deployment)

```
Epoch 1/10
154/154 [==============================] - 35s 176ms/step - loss: 1.5479 - accuracy: 0.5302 - val_loss: 1.3259 - val_accuracy: 0.4988
Epoch 2/10
154/154 [==============================] - 27s 174ms/step - loss: 0.6284 - accuracy: 0.7950 - val_loss: 0.7936 - val_accuracy: 0.7398
Epoch 3/10
154/154 [==============================] - 30s 193ms/step - loss: 0.3648 - accuracy: 0.8883 - val_loss: 0.5895 - val_accuracy: 0.8147
Epoch 4/10
154/154 [==============================] - 27s 174ms/step - loss: 0.2853 - accuracy: 0.9141 - val_loss: 0.4523 - val_accuracy: 0.8394
Epoch 5/10
154/154 [==============================] - 27s 174ms/step - loss: 0.2442 - accuracy: 0.9243 - val_loss: 0.4683 - val_accuracy: 0.8321
Epoch 6/10
154/154 [==============================] - 26s 171ms/step - loss: 0.2142 - accuracy: 0.9339 - val_loss: 0.5106 - val_accuracy: 0.8278
Epoch 7/10
154/154 [==============================] - 27s 172ms/step - loss: 0.1898 - accuracy: 0.9400 - val_loss: 0.4912 - val_accuracy: 0.8309
Epoch 8/10
154/154 [==============================] - 27s 173ms/step - loss: 0.1736 - accuracy: 0.9469 - val_loss: 0.4330 - val_accuracy: 0.8513
Epoch 9/10
154/154 [==============================] - 27s 173ms/step - loss: 0.1513 - accuracy: 0.9538 - val_loss: 0.5544 - val_accuracy: 0.8344
Epoch 10/10
154/154 [==============================] - 27s 173ms/step - loss: 0.1351 - accuracy: 0.9572 - val_loss: 0.6018 - val_accuracy: 0.8500
```

Out[12]:

Saving The Model :

In [13]:

```
#Save Model
model.save('CAUDL.h5')
```

Testing The Model :

In [14]:

```
#Import req. Lib.
from tensorflow.keras.preprocessing import image
import numpy as np
```

In [15]:

```
#Testing No 1 :-
img = image.load_img('/content/data/test/Left Bundle Branch Block/fig_5910.png',target_size=(64,64)) #Reading image
f = image.img_to_array(img) #Converting image to array
software_space_uid
```

Out[41]: 'acd9c798-6974-5d2f-a657-ce06e986df4d'

In [46]:

```
model_details = client.repository.store_model(model="/content/CAUDL.tgz", meta_props={
    client.repository.ModelMetaNames.NAME:"CAUDL Model",
    client.repository.ModelMetaNames.TYPE:"tensorflow_2.7",
    client.repository.ModelMetaNames.SOFTWARE_SPEC_UID:software_space_uid
})
```

In [47]:

```
model_details
```

Out[47]:

```
{'entity': {'hybrid_pipeline_software_specs': [],
  'software_spec': {'id': 'acd9c798-6974-5d2f-a657-ce06e986df4d',
   'name': 'tensorflow_rt22.1-py3.9'},
  'type': 'tensorflow_2.7'},
 'metadata': {'created_at': '2022-11-10T07:57:58.856Z',
  'id': '09cf5e5e-0210-4ba0-a675-9e899b2a62c2',
  'modified_at': '2022-11-10T07:58:15.333Z',
  'name': 'CAUDL Model',
  'owner': 'IBMid-662003X5JS',
  'resource_key': 'f907a1c2-19cc-43c4-ba52-a676e90d1034',
  'space_id': '8cb20b68-2b1b-4080-b28b-d2e165f03ac8'},
 'system': {'warnings': []}}
```

If Want To Get Model After Sometime / Days :

In [48]:

```
model_id = client.repository.get_model_id(model_details)
model_id
```

Out[48]: '09cf5e5e-0210-4ba0-a675-9e899b2a62c2'

Downloading Model Again :

In [49]:

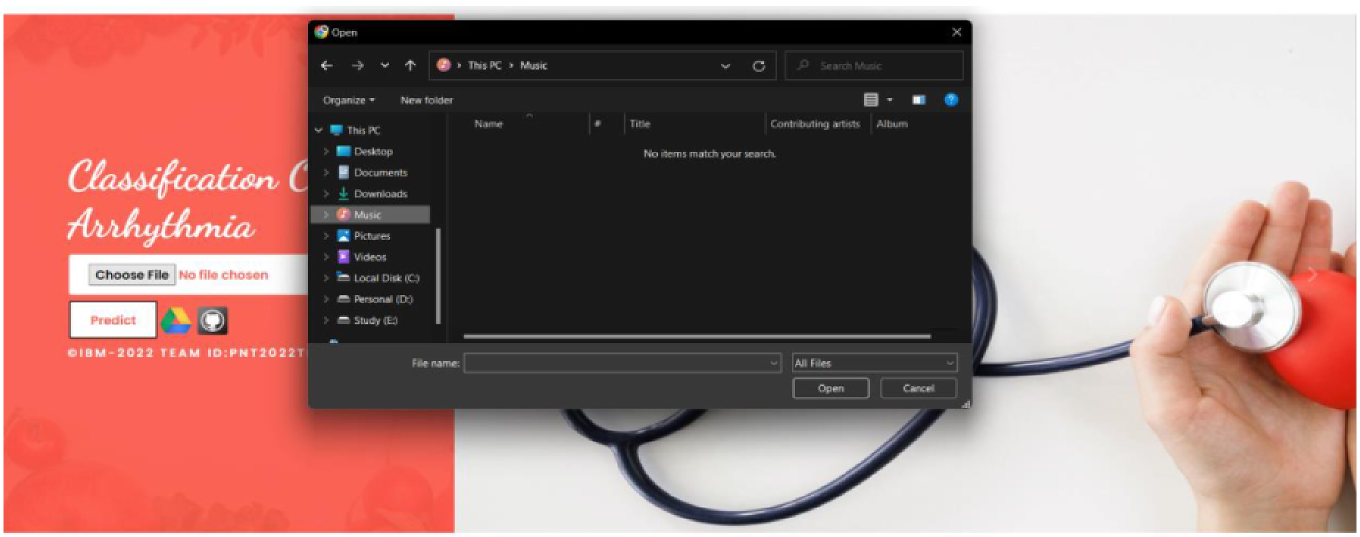
```
client.repository.download(model_id,"CAUDL_IBM_Model.tgz")
```

Successfully saved model content to file: 'CAUDL_IBM_Model.tgz'

Out[49]: '/content/CAUDL_IBM_Model.tgz'

WebPage (UI application open successfully)

Click (choose file to upload)



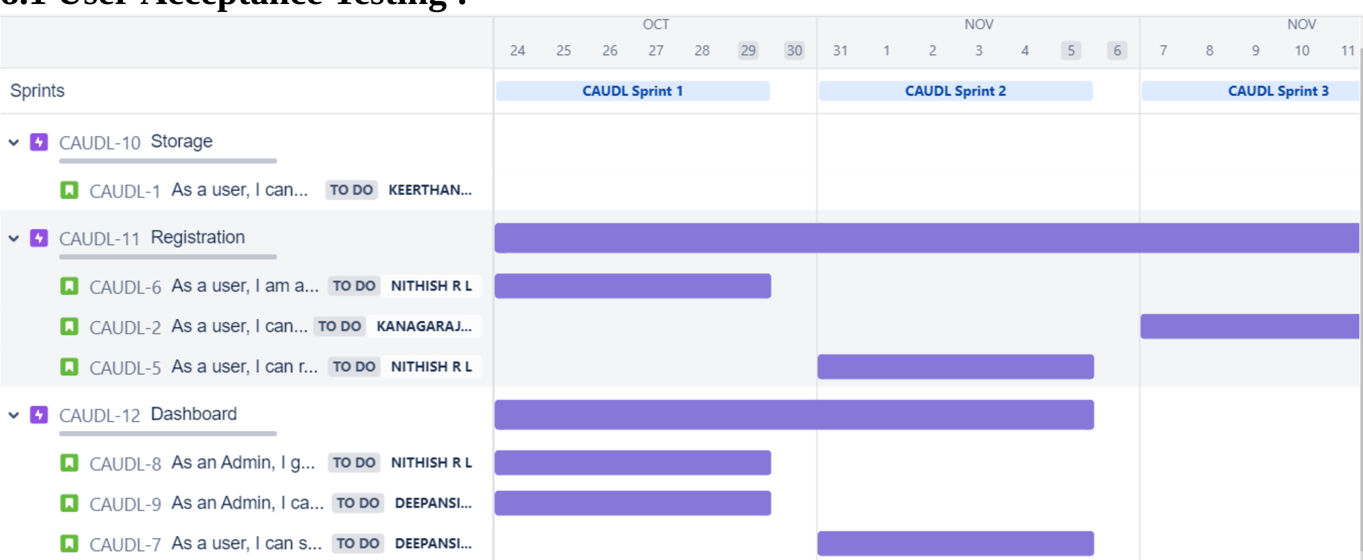
8.TESTING

8.1 Test Cases :

Date	17-Nov-22
Team ID	PNT2022TMID42525
Project Name	Classification of Arrhythmia by Us
Maximum Marks	4 marks

Test Scenario	Pre-Requisite	Steps To Execute	Test Data	Expected Result	Actual Result	Status	Commnets
Verify user is able to access the landing page..	-	1.Enter URL and click go 2.Click choose File Option 3.Choose a image from local directory. 4.Click predict to view result !	https://drive.google.com/file/d/1kkp-sPu5FzARcNgdZ_WoXSsxWqN5dBR9/view?usp=sharing	Predicted result popup should display.	Working as expected	Pass	-
Verify the UI elements in Login/Signup popup	-	1.Sliding Banner 2.Buttons	https://drive.google.com/file/d/1kkp-sPu5FzARcNgdZ_WoXSsxWqN5dBR9/view?usp=sharing	Application should show below UI elements: a.choose file box b.Predict button box	Working as expected	Pass	-

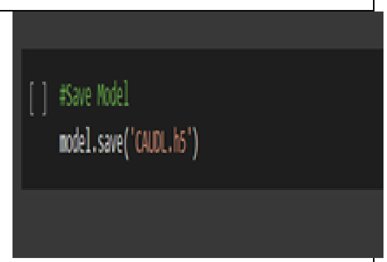
8.1 User Acceptance Testing :



9. RESULTS

9.1 Performance Metrics :

Model Performance Testing :

S.No.	Parameter	Values	Screenshot
1.	Model Summary	**CNN Model – Classification of Arrhythmia**	
2.	Accuracy	Training Accuracy - 0.9572 Validation Accuracy - 0.8500	

10 ADVANTAGES & DISADVANTAGES

ADVANTAGES :

- Available 24/7 across the globe
- Direct connection with the patient
- No queueing in responses
- Updated to the latest details
- Easy to setup and communicate

DISADVANTAGES :

- Limited Response Scaling
- Frequent Maintenance
- Misreading of Queries
- Connectivity Issues

11. CONCLUSION

CONCLUSION :

In this study, we proposed a 2-D CNN-basedclassification model for automatic classification of cardiac arrhythmias using ECG signals.An accurate taxonomyof ECG signals is extremely helpful in the prevention and diagnosis of CVDs. Deep CNN has proven useful in enhancing the accuracy of diagnosis algorithms in the fusion of medicine and modern machine learning technologies. The proposed CNN-based classification algorithm, using 2-D images, can classify eight kinds ofarrhythmia, namely, NOR, VFW, PVC, VEB, RBB, LBB, PAB, and APC, and it achieved 97.91% average sensitivity, 99.61% specificity, 99.11% average accuracy, and 98.59% positive predictive value (precision). These results indicate that the prediction and classification of arrhythmia with 2-D ECG representation as spectrograms and the CNN model is a reliableoperative technique in the diagnosis of CVDs. The proposed schemecan help expertsdiagnose CVDs by referring to the automated classification ofECG signals. The present research uses only a single-lead ECG signal. The effect of multiple lead ECGdata to further improve experimental cases will be studied in future work.

12. FUTURE SCOPE

FUTURE SCOPE:

Automatic heartbeat classification is essential for real-time applications in detection of cardiac arrhythmias. Programmed heartbeat order is basic for continuous applications in the location of cardiovascular arrhythmias. The acquiredconsequences of this proposal recommendthat there is a potential development of future in programmed ECG orderframeworks. The frameworks must incorporate four conclusive advances: pre-handling, QRS complex discovery,highlights extraction and order of pulses. The further exertionof this work should move towards proposing new component extraction and arrangement strategies.

The future is using this detection of cardiac arrhythmia tools in wearable devices so that they could continuously monitor the health of the person and send alerts when there is an abnormality. We additionally recommend the utilization of new patternsto catch the ECG signal,for example, off-the-individual methodologies, for the elaboration of new databases. In any case, we accept that the making of such databases would be an extraordinary test in light of the fact that, other than the money related costs included, they would need to be consolidated into gauges, for example,AAMI measures to contactthe ideal crowd.

13. APPENDIX

Source Code :

https://drive.google.com/file/d/1glYdhMqgpRNtpBPRLMXIK3ZCos2UrzBZ/view?usp=share_link

GitHub:

https://github.com/IBM-EPBL/IBM-Project-4307-1658728397.git

Project Demo Link :
https://drive.google.com/file/d/13f76TvtvKTHS3qJrqaOVOzsPmCsv_wvU/view?usp=share_link