1.INTRODUCTION

1.1 PROJECT REVIEW

The electrocardiogram (ECG) is one of the most extensively employed signals used in the diagnosis and prediction of cardiovascular diseases (CVDs). The ECG signals can capture the heart's rhythmic irregularities, commonly known as arrhythmias. A careful study of ECG signals is crucial for precise diagnoses of patients' acute and chronic heart conditions. In this study, we propose a two-dimensional (2-D) convolutional neural network (CNN) model for the classification of ECG signals into eight classes; namely, normal beat, premature ventricular contraction beat, paced beat, right bundle branch block beat, left bundle branch block beat, atrial premature contraction beat, ventricular flutter wave beat, and ventricular escape beat. The one-dimensional ECG time series signals are transformed into 2-D spectrograms through short-time Fourier transform. The 2-D CNN model consisting of four convolutional layers and four pooling layers is designed for extracting robust features from the input spectrograms.

1.2 Purpose

According to the World Health Organization (WHO), cardiovascular diseases (CVDs) are the number one cause of death today. Over 17.7 million people died from CVDs in the year 2017 all over the world which is about 31% of all deaths, and over 75% of these deaths occur in low and middle-income countries. Arrhythmia is a representative type of CVD that refers to any irregular change from the normal heart rhythms. There are several types of arrhythmia including atrial fibrillation, premature contraction, ventricular fibrillation, and tachycardia. Although a single arrhythmia heartbeat may not have a serious impact on life, continuous arrhythmia beats can result in fatal circumstances. In this project, we build an effective electrocardiogram (ECG) arrhythmia classification method using a convolutional neural network (CNN), in which we classify ECG into seven categories, one being normal and the other six being different types of arrhythmia using deep two-dimensional CNN with grayscale ECG images. We are creating a web application where the user selects the image which is to be classified. The image is fed into the model that is trained and the cited class will be displayed on the webpage.

2. LITERATURE SURVEY

2.1 Existing problem

The electrocardiogram (ECG) is one of the most extensively employed signals used in the diagnosis and prediction of cardiovascular diseases (CVDs). The ECG signals can capture the heart's rhythmic irregularities, commonly known as arrhythmias. A careful study of ECG signals is crucial for precise diagnoses of patients' acute and chronic heart conditions. In this study, we propose a two-dimensional (2-D) convolutional neural network (CNN) model for the classification of ECG signals into eight classes; namely, normal beat, premature ventricular contraction beat, paced beat, right bundle branch block beat, left bundle branch block beat, atrial premature contraction beat, ventricular flutter wave beat, and ventricular escape beat. The one-dimensional ECG time series signals are transformed into 2-D spectrograms through short-time Fourier transform. The 2-D CNN model consisting of four convolutional layers and four pooling layers is designed for extracting robust features from the input spectrograms.We achieved a state-of-the-art average classification accuracy of 99.11\%, which is better than those of recently reported results in classifying similar arrythmias.

2.2 References

[1] ***Po-Ya Hsu*** Department of Computer Science & Engineering, University of California San Diego, The USA

Chung-Kuan Cheng Department of Computer Science & Engineering, University of California, San Diego, The USA

https://ieeexplore.ieee.org/document/9176679

[2] ***A. Rajkumar*** Department of Electronics and Communication Engineering, Amrita School of Engineering, Coimbatore, India

M. Ganesan Department of Electronics and Communication Engineering, Amrita School of Engineering, Coimbatore, India

R. Lavanya Department of Electronics and Communication Engineering, Amrita School of Engineering, Coimbatore, India

https://ieeexplore.ieee.org/abstract/document/8728362

[3]***EunKwang Jeon*** Dept. of Computer Science & Engineering, Soonchunhyang University, Asan, South Korea

MinSu Chae Dept. of Computer Science & Engineering, Soonchunhyang University, Asan, South Korea

Sangwook Han Dept. of Computer Science & Engineering, Soonchunhyang University, Asan, South Korea

https://ieeexplore.ieee.org/document/8989066

[4] Amin Ullah University of Engineering and Technology

Taxila Syed Anwar University of Engineering and Technology

Taxila Muhammad Bilal Hankuk University of Foreign Studies

Raja Majid Mehmood Xiamen University Malaysia

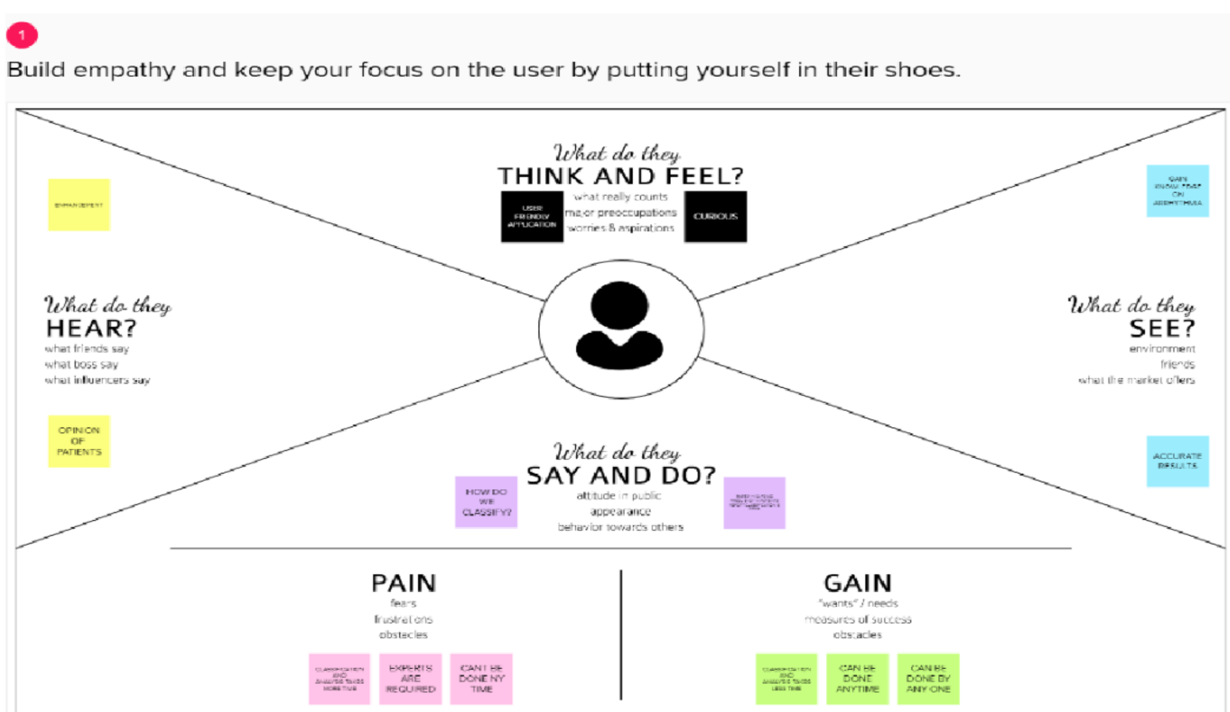
2.3 Problem Statement Definition

Arrhythmia is a representative type of CVD that refers to any irregular change from the normal heart rhythms. There are several types of arrhythmia including atrial fibrillation, premature contraction,ventricular fibrillation,and tachycardia. Although a single arrhythmia heartbeat may not have a serious impact on life, continuous arrhythmia beats can result in fatal circumstances.In this project ,we build an effective electrocardiogram(ECG) arrhythmia classification method using a convolutional neural network (CNN),in which we classify ECG into seven categories,one being normal and the other side being different types of arrhythmia using deep two- dimensional CNN with grayscale ECG images.We are creating a web application where the user selects the image which is to be classified.The image is fed into the model that is trained and the cited class will be displayed on the webpage.

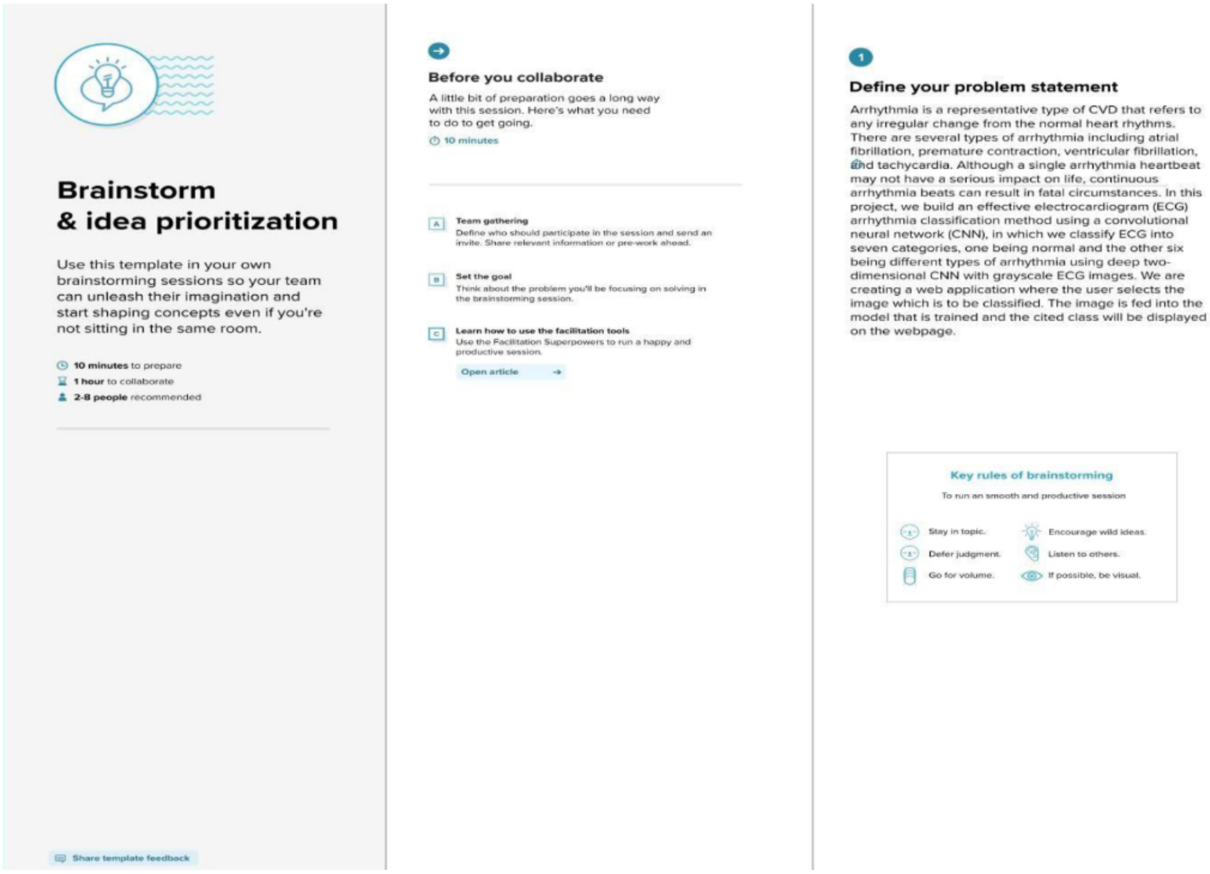
3. IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas

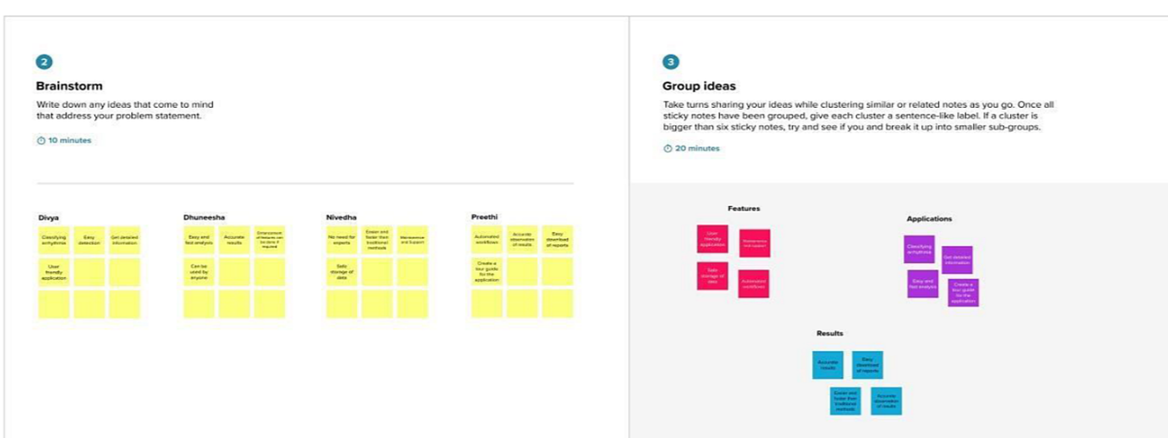
An empathy map is a simple, easy-to-digest visual that captures knowledge about a user's behaviours and attitudes. It is a useful tool to helps teams better understand their users. Creating an effective solution requires understanding the true problem and the person who is experiencing it. The exercise of creating the map helps participants consider things from the user's perspective along with his or her goals and challenges.



3.2 Ideation & Brainstorming



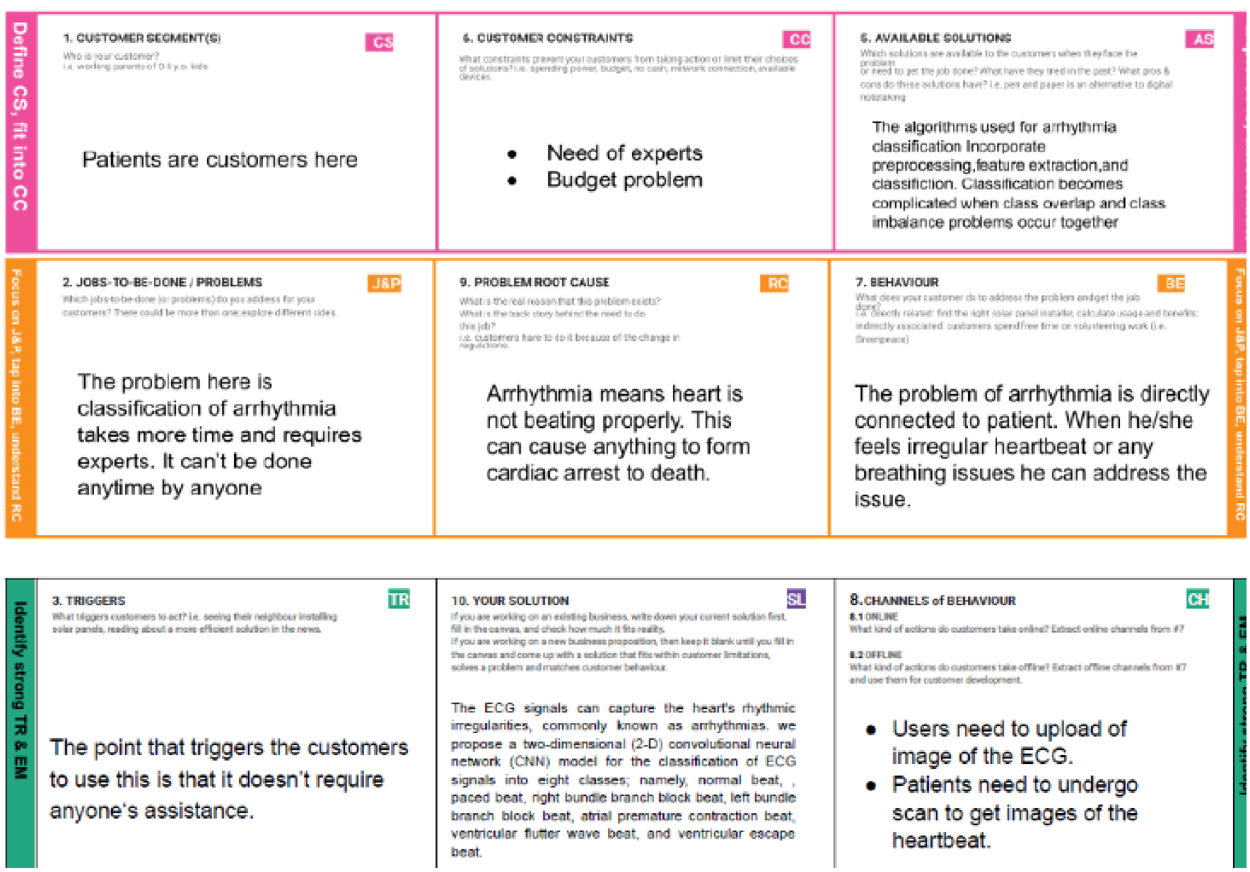
Step-2: Brainstorm, Idea Listing and Grouping



3.3 Proposed Solution

Classification of arrhythmia using deep learning with 2d ECG spectral image representation.To create an application that is used to classify the arrhythmia and provide more detailed information about it. Here we use deep learning techniques and with the help of 2D ECG spectral image to classify the arrhythmia.Provides accurate results and detailed information required by the users or patients.Users or customers can easily use the app because of its user friendly interface and simplicity. Can be used by anyone at any time.As this application can be very useful for the earlier and fast classification of arrhythmia it we be used by many patients suffering by it.Experts guidance is not required when we have a app that can be used by anyone. Data of the patient will be securely stored and maintained for future purposes

3.4 Problem Solution fit



4.REQUIREMENT ANALYSIS

4.1 Functional requirement

FR-1 Registration through Form Registration through mail.

FR-2 Confirmation via Email Confirmation via OTP

FR-3 Get User Input Upload image as jpeg Upload image as png

FR-4 Save Image Images are saved in the uploads folder

FR-5 Chat with Doctor Consult with Doctor

FR-6 Report Generation Get complete Report

4.2 Non-Functional requirements

NFR-1 Usability Classification of Arrhythmia with the help of AI.

NFR-2 Security User’s data cannot be accessed by unauthorised people.

NFR-3 Reliability The system performs without failure.

NFR-4 Performance High accuracy.

NFR-5 Availability Anyone who is authorised.

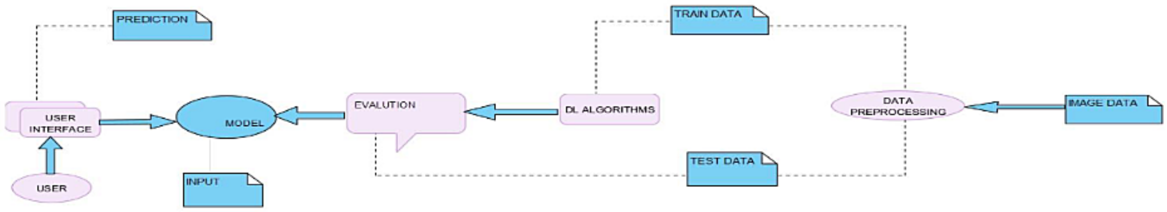
NFR-6 Scalability Does not affect the performance even though used by many users.

5.PROJECT DESIGN

5.1 Data Flow Diagrams

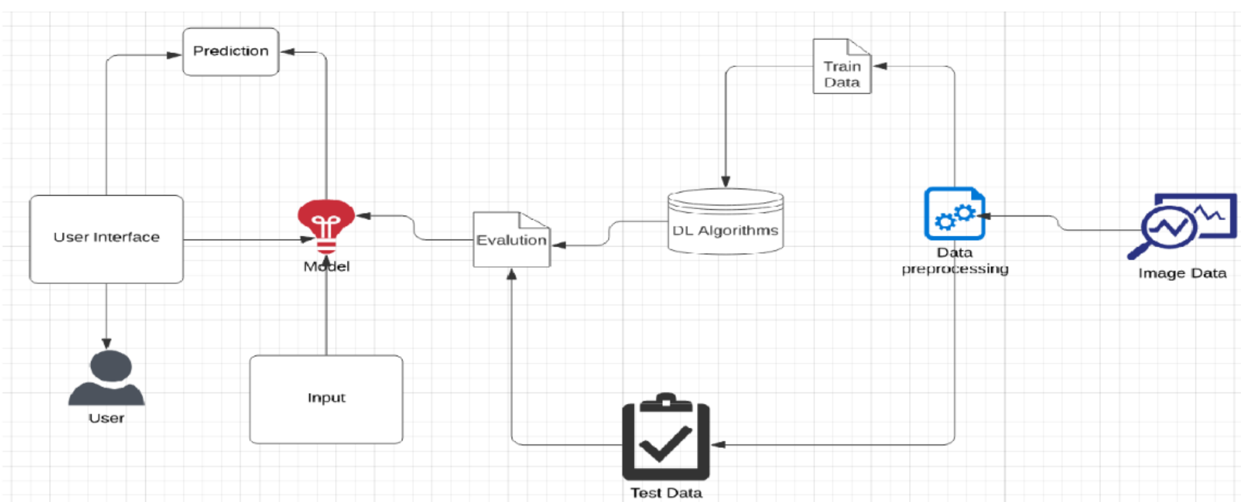
A data flow diagram (DFD) maps out the flow of information for any process or system. It uses defined symbols like rectangles, circles and arrows, plus short text labels, to show data inputs, outputs, storage points and the routes between each destination.

.

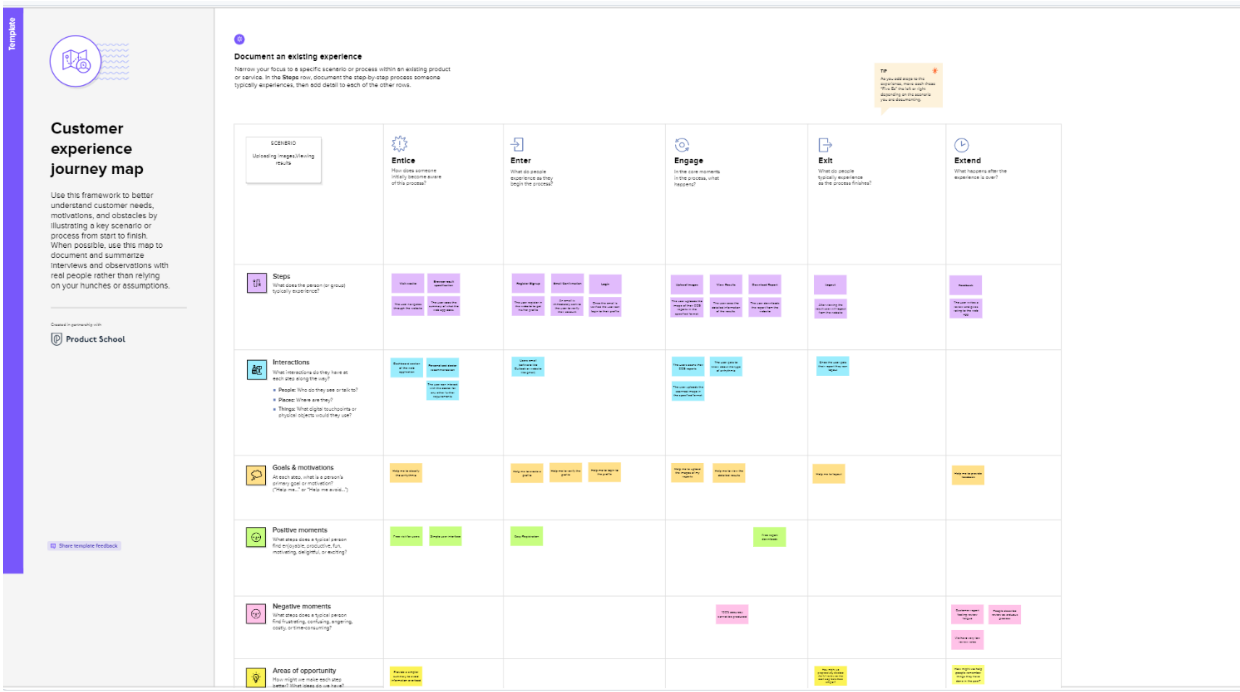


5.2 Solution & Technical Architecture

Technical architecture—which is also often referred to as application architecture, IT architecture, business architecture, etc.—refers to creating a structured software solution that will meet the business needs and expectations while providing a strong technical plan for the growth of the software application through its lifetime. IT architecture is equally important to the business team and the information technology team.Technical architecture includes the major components of the system, their relationships, and the contracts that define the interactions between the components. The goal of technical architects is to achieve all the business needs with an application that is optimised for both performance and security.



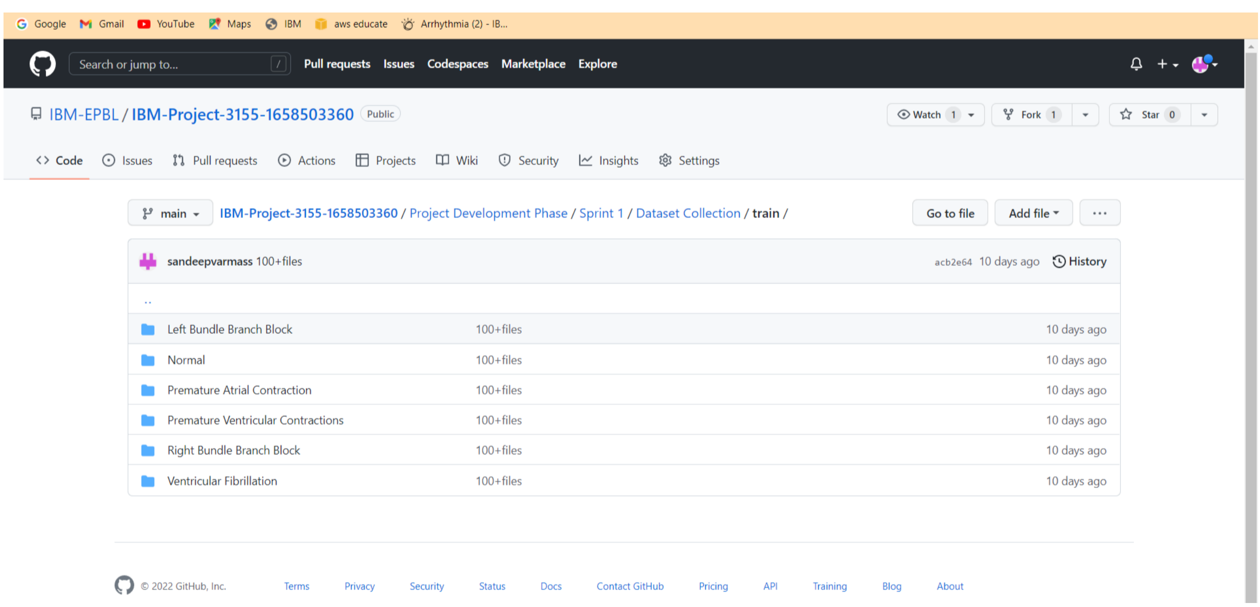
5.3 User Stories



6.PROJECT PLANNING & SCHEDULING

6.1 Sprint Planning & Estimation SPRINT 1

- Download the dataset



● Image Preprocessing

Import the ImageGenerator

Import the ImageDataGenerator library

```
[ ] from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

Configure ImageGenerator

Configure ImageDataGenerator Class

```
[ ] train_datagen=ImageDataGenerator(rescale=1./255,zoom_range=0.2,vertical_flip=True,horizontal_flip=True)
```

```
[ ] test_data=ImageDataGenerator(rescale=1./255)
```

Apply ImageGenerator functionality and trainset

Apply ImageDataGenerator functionality to trainset and testset

```
[ ] x_train=train_datagen.flow_from_directory(r"/content/drive/MyDrive/Project Development Phase/data/train",target_size=(64,64),class_mode="categorical",batch_size=

    Found 15341 images belonging to 6 classes.
```

```
[ ] x_test=test_data.flow_from_directory(r"/content/drive/MyDrive/Project Development Phase/data/test",target_size=(64,64),class_mode="categorical",batch_size=128)

    Found 6825 images belonging to 6 classes.
```

```
[ ] x_train.class_indices

    {'Left Bundle Branch Block': 0,
     'Normal': 1,
     'Premature Atrial Contraction': 2,
     'Premature Ventricular Contractions': 3,
     'Right Bundle Branch Block': 4,
     'Ventricular Fibrillation': 5}
```

● Model Building

Import Libraries

MODEL BUILDING

Import the libraries

```
[ ] from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Dense,Convolution2D,MaxPooling2D,Flatten
```

Initialize the model

Initialize the model

```
[ ] model=Sequential()
```

Adding CNN layers

```
[ ] model.add(Convolution2D(32,(3,3),activation="relu",strides=(1,1),input_shape=(64,64,3)))
```

```
[ ] model.add(MaxPooling2D(pool_size=(2,2)))
```

```
[ ] model.add(Flatten())
```

```
[ ] model.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 62, 62, 32)        896

 max_pooling2d (MaxPooling2D  (None, 31, 31, 32)       0
 )

 flatten (Flatten)           (None, 30752)             0

=================================================================
Total params: 896
Trainable params: 896
```


Adding Dense Layers

Adding Dense layer

Hidden layer

```
[ ] model.add(Dense(500,activation="relu"))
```

```
[ ] model.add(Dense(500,activation="relu"))
```

Output layer

```
[ ] model.add(Dense(6,activation="softmax"))
```

Train the model

```
[ ] Epoch 1/5
120/120 [==============================] - 140s 1s/step - loss: 0.1920 - accuracy: 0.9401 - val_loss: 0.4968 - val_accuracy: 0.8731
Epoch 2/5
120/120 [==============================] - 147s 1s/step - loss: 0.1607 - accuracy: 0.9512 - val_loss: 0.5703 - val_accuracy: 0.8727
Epoch 3/5
120/120 [==============================] - 142s 1s/step - loss: 0.1358 - accuracy: 0.9572 - val_loss: 0.4914 - val_accuracy: 0.8831
Epoch 4/5
120/120 [==============================] - 140s 1s/step - loss: 0.1181 - accuracy: 0.9640 - val_loss: 0.5450 - val_accuracy: 0.8794
Epoch 5/5
120/120 [==============================] - 133s 1s/step - loss: 0.1109 - accuracy: 0.9666 - val_loss: 0.4703 - val_accuracy: 0.8801
<keras.callbacks.History at 0x7f527adbd750>
```

```
[ ] model.fit(x_train,epochs=5,steps_per_epoch=len(x_train),validation_data=x_test,validation_steps=len(x_test))

Epoch 1/5
120/120 [==============================] - 127s 1s/step - loss: 0.1022 - accuracy: 0.9692 - val_loss: 0.5888 - val_accuracy: 0.8659
Epoch 2/5
120/120 [==============================] - 139s 1s/step - loss: 0.0934 - accuracy: 0.9710 - val_loss: 0.5789 - val_accuracy: 0.8689
Epoch 3/5
120/120 [==============================] - 128s 1s/step - loss: 0.0862 - accuracy: 0.9729 - val_loss: 0.4989 - val_accuracy: 0.8848
Epoch 4/5
120/120 [==============================] - 128s 1s/step - loss: 0.0778 - accuracy: 0.9765 - val_loss: 0.6542 - val_accuracy: 0.8759
Epoch 5/5
120/120 [==============================] - 137s 1s/step - loss: 0.0793 - accuracy: 0.9745 - val_loss: 0.5369 - val_accuracy: 0.8844
<keras.callbacks.History at 0x7f527adc0a50>
```


Save the model

Save the model

```
[ ] model.save('arrhythmia.h5')
```

Testing Model

Testing the model

```python
import numpy as np
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
```

```python
model=load_model('arrhythmia.h5')
```

```python
img=image.load_img("/content/drive/MyDrive/Project Development Phase/data/test/Right Bundle Branch Block/fig_101.png",target_size=(64,64))
```

```python
img
```

```python
x=image.img_to_array(img)
```

```python
x
```



```
       [255., 255., 255.]]]], dtype=float32)
```

```python
pred=model.predict(x)
```

```
1/1 [==============================] - 0s 43ms/step
```

```python
pred
```

```
array([[0., 0., 0., 0., 1., 0.]], dtype=float32)
```

```python
index=['Left Bundle Branch Block',
 'Normal',
 'Premature Atrial Contraction',
 'Premature Ventricular Contractions',
 'Right Bundle Branch Block',
 'Ventricular Fibrillation']
```

```python
index[np.argmax(pred)]
```

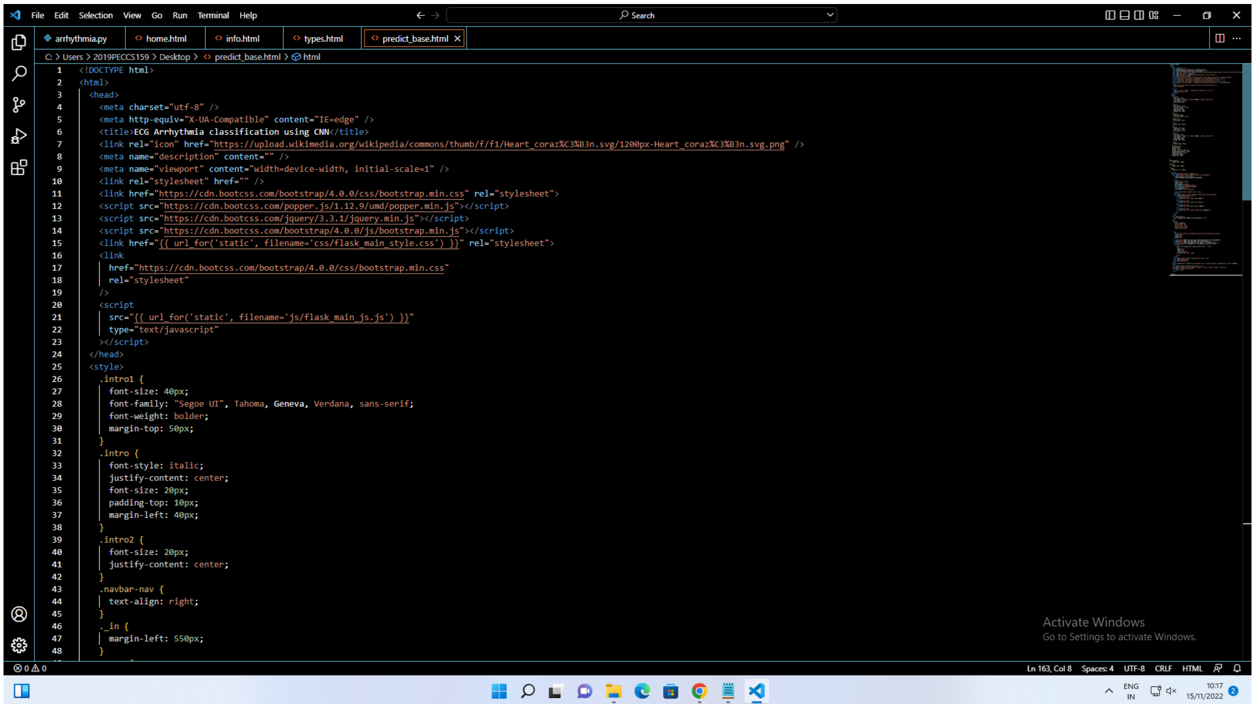
```
'Right Bundle Branch Block'
```


SPRINT 2

home.html

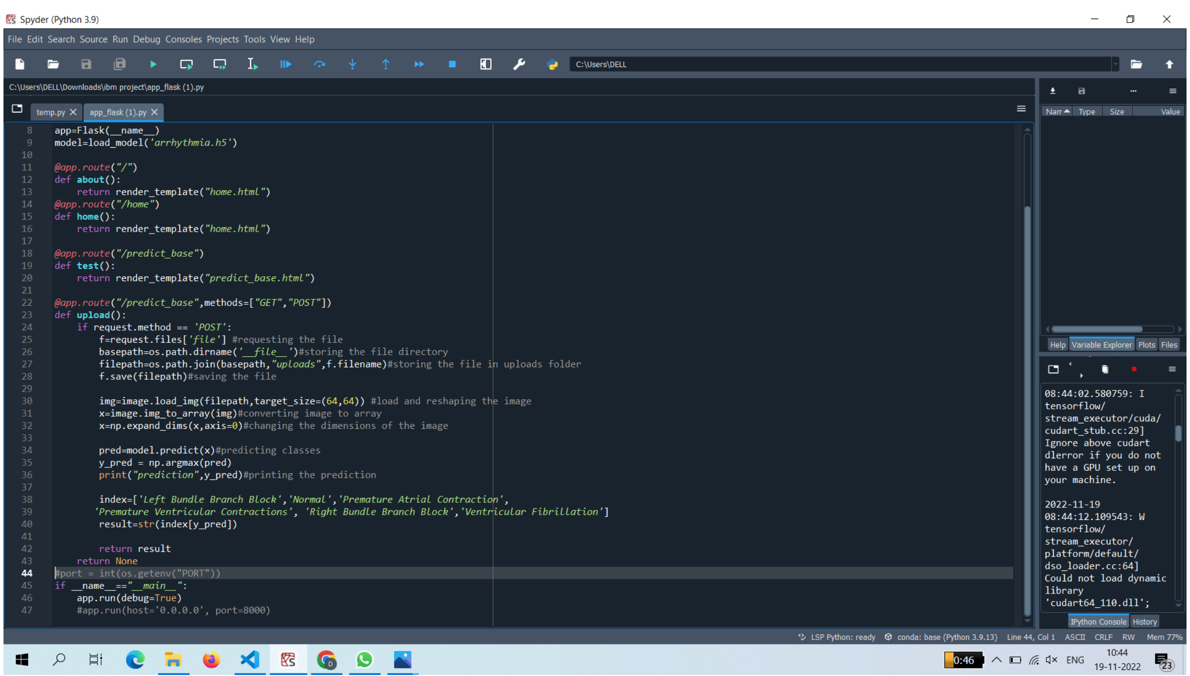
```html
<!DOCTYPE html>
<html>
  <head>
    <meta charset="utf-8" />
    <meta http-equiv="X-UA-Compatible" content="IE=edge" />
    <title>ECG Arrhythmia classification using CNN</title>
    <link rel="icon" href="https://upload.wikimedia.org/wikipedia/commons/thumb/f/f1/Heart_coraz%C3%B3n.svg/1200px-Heart_coraz%C3%B3n.svg.png" />
    <meta name="description" content="" />
    <meta name="viewport" content="width=device-width, initial-scale=1" />
    <link rel="stylesheet" href="" />
    <link
      href="https://cdn.bootcss.com/bootstrap/4.0.0/css/bootstrap.min.css"
      rel="stylesheet"
    />
  </head>
  <style>
    .intro1 {
      font-size: 40px;
      font-family: "Segoe UI", Tahoma, Geneva, Verdana, sans-serif;
      font-weight: bolder;
    }
    .intro {
      font-style: italic;
      justify-content: center;
      font-size: 20px;
      padding-top: 50px;
      margin-left: 200px;
      margin-right: 200px;
    }
    .intro2 {
      font-size: 20px;
      justify-content: center;
    }

    .navbar-nav {
      text-align: right;
    }
    ._in {
      margin-left: 550px;
    }
  </style>
  <body style="background-color: #f4c2c2">
    <nav class="navbar navbar-expand-lg navbar-dark bg-danger">
      <a class="navbar-brand" href="#"
        >ECG Arrhythmia classification using CNN</a
      >
      <button
        class="navbar-toggler"
```

predict.html



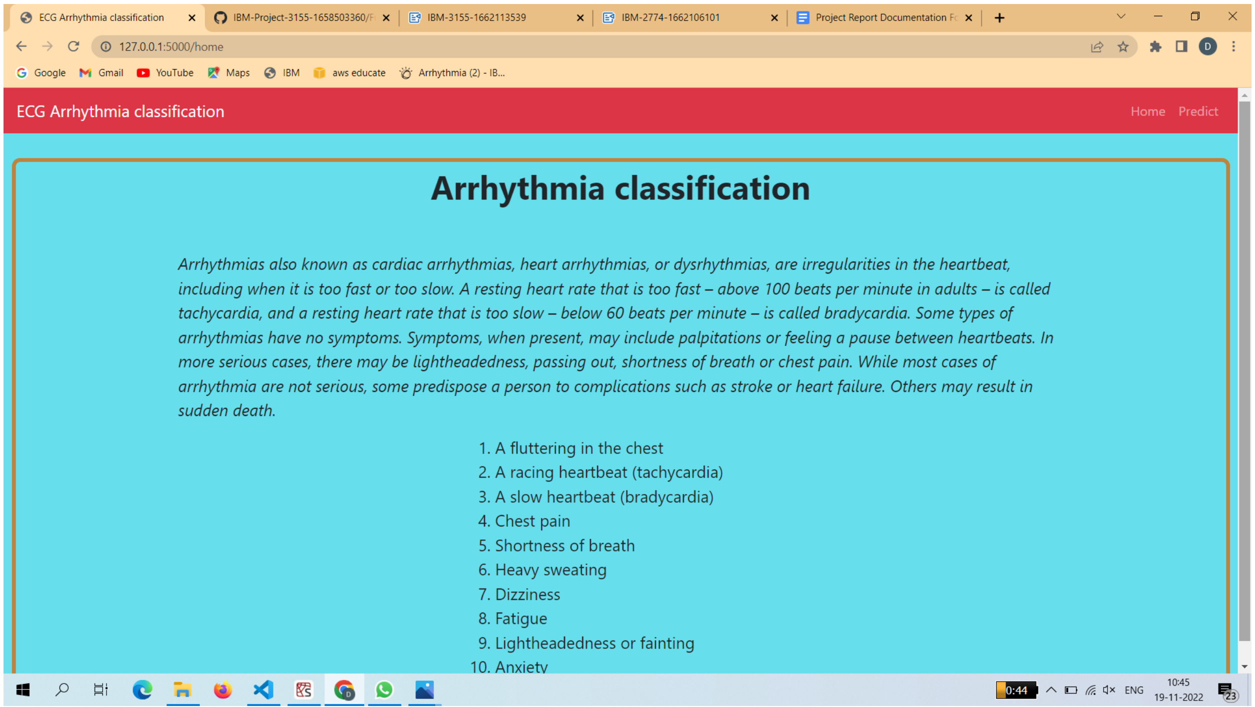
SPRINT 3

app.flask.py

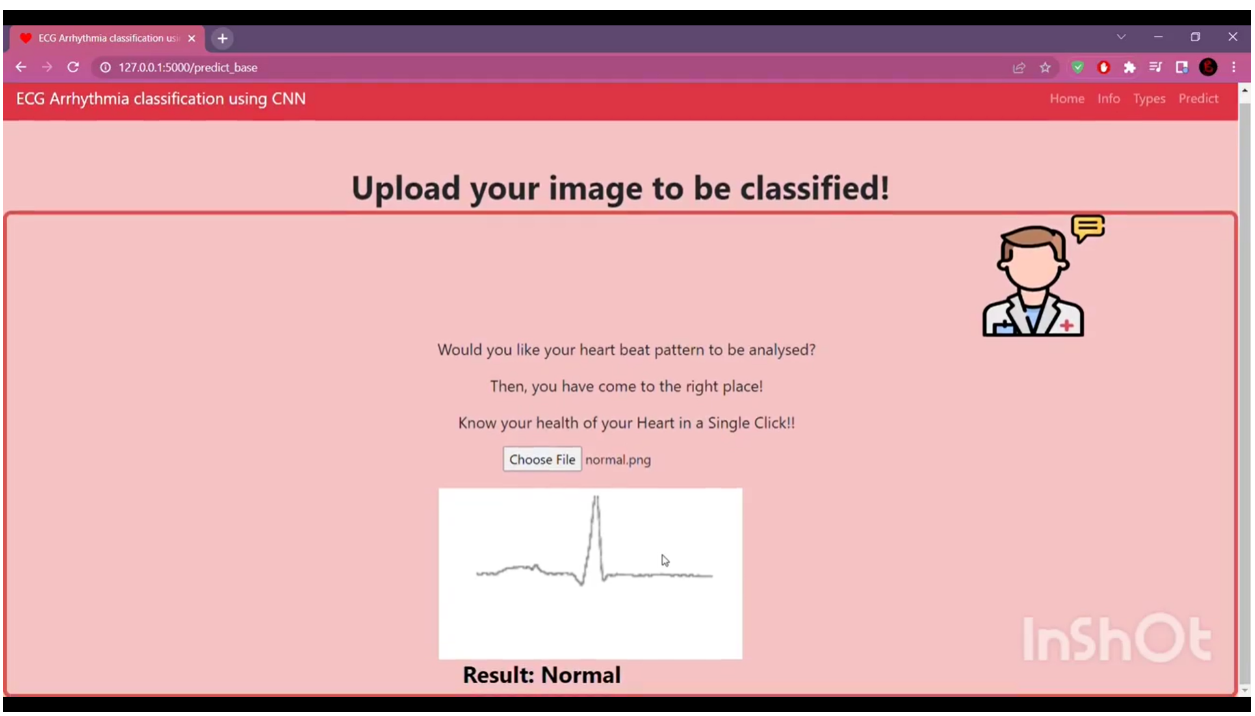


SPRINT4

home page



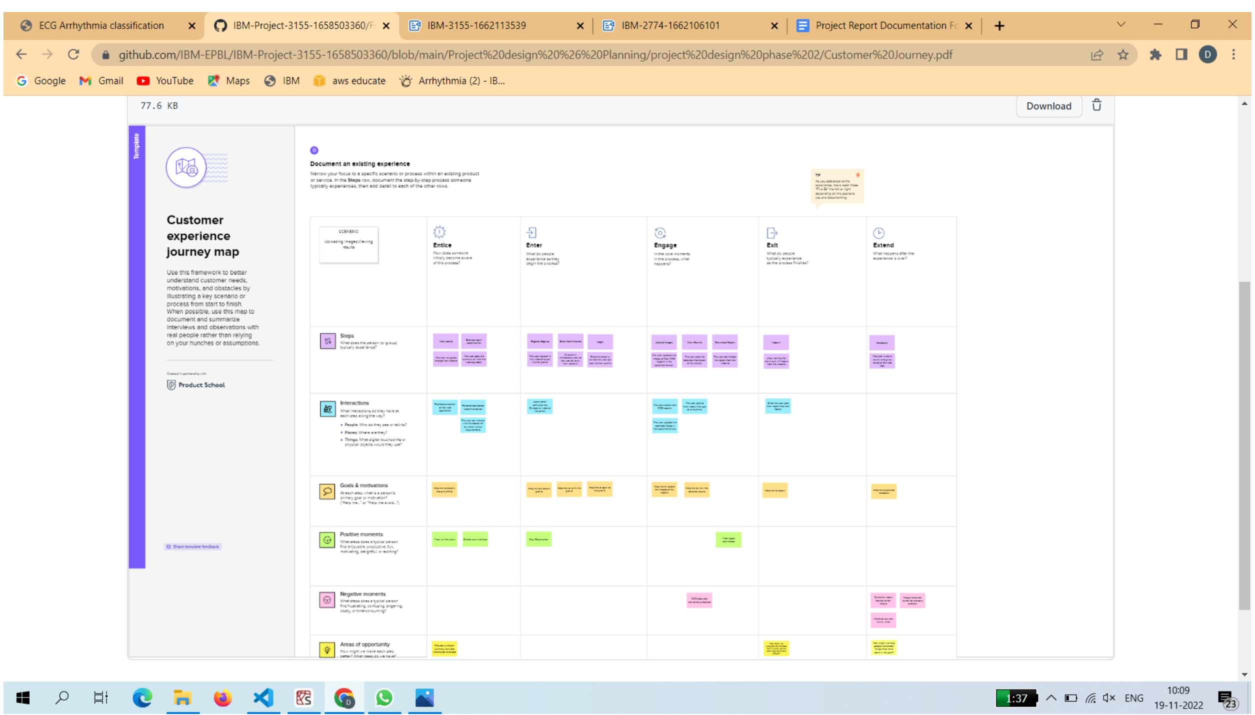
predict page



6.2 Sprint Delivery Schedule

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint Start Date	Story Points Completed	Sprint Release Date
Sprint-1	20	2 days	10-nov-2022	10-nov-2022	20	10-nov-2022
Sprint-2	20	2 days	12-nov-2022	12-nov-2022	40	12-nov-2022
Sprint-3	20	2 days	14-nov-2022	14-nov-2022	60	14-nov-2022
Sprint-4	20	2 days	18-nov-2022	18-nov-2022	80	18-nov-2022

6.3 Reports from JIRA



7. CODING & SOLUTIONING

7.1 Feature 1

Classifies the type of arrhythmia with one click

```
import os
import numpy as np
from flask import Flask,request,render_template

from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image

app=Flask(__name__)
model=load_model('arrhythmia.h5')

@app.route("/")
def about():
    return render_template("home.html")
@app.route("/home")
def home():
    return render_template("home.html")

@app.route("/predict_base")
def test():
    return render_template("predict_base.html")

@app.route("/predict_base",methods=["GET","POST"])
def upload():
    if request.method == 'POST':
        f=request.files['file'] #requesting the file
        basepath=os.path.dirname('__file__')#storing the file directory
        filepath=os.path.join(basepath,"uploads",f.filename)#storing the file in uploads folder
        f.save(filepath)#saving the file

        img=image.load_img(filepath,target_size=(64,64)) #load and reshaping the image
        x=image.img_to_array(img)#converting image to array
        x=np.expand_dims(x,axis=0)#changing the dimensions of the image
```

```
        pred=model.predict(x)#predicting classes
        y_pred = np.argmax(pred)
        print("prediction",y_pred)#printing the prediction

        index=['Left Bundle Branch Block','Normal','Premature Atrial Contraction',
       'Premature Ventricular Contractions', 'Right Bundle Branch Block','Ventricular Fibrillation']
        result=str(index[y_pred])

        return result
    return None
#port = int(os.getenv("PORT"))
if __name__=="__main__":
    app.run(debug=True)
    #app.run(host='0.0.0.0', port=8000)
```

7.2 Feature 2

User friendly interface

```
<!DOCTYPE html>
<html>
  <head>
    <meta charset="utf-8" />
    <meta http-equiv="X-UA-Compatible" content="IE=edge" />
    <title>ECG Arrhythmia classification</title>

    <meta name="description" content="" />
    <meta name="viewport" content="width=device-width, initial-scale=1" />
    <link rel="stylesheet" href="" />
    <link
      href="https://cdn.bootcss.com/bootstrap/4.0.0/css/bootstrap.min.css"
      rel="stylesheet"
    />
  </head>
```

```
<style>
  .intro1 {
    font-size: 40px;
    font-family: "Segoe UI", Tahoma, Geneva, Verdana, sans-serif;
    font-weight: bolder;
  }
  .intro {
    font-style: italic;
    justify-content: center;
    font-size: 20px;
    padding-top: 50px;
    margin-left: 200px;
    margin-right: 200px;
  }
  .intro2 {
    font-size: 20px;
    justify-content: center;
  }

  .navbar-nav {
    text-align: right;
  }
  ._in {
    margin-left: 550px;
  }
</style>
<body style="background-color: #67deeb">
  <nav class="navbar navbar-expand-lg navbar-dark bg-danger">
    <a class="navbar-brand" href="#"
```

```
  >ECG Arrhythmia classification</a
 >
 <button
  class="navbar-toggler"
  type="button"
  data-toggle="collapse"
  data-target="#navbarNavAltMarkup"
  aria-controls="navbarNavAltMarkup"
  aria-expanded="false"
  aria-label="Toggle navigation"
 >
  <span class="navbar-toggler-icon"></span>
 </button>
 <div class="navbar-collapse collapse w-100 order-3 dual-collapse2">
  <ul class="navbar-nav ml-auto">
   <li class="nav-item">
    <a class="nav-link" href="/home">Home</a>
   </li>
   <li class="nav-item">
    <a class="nav-link" href="/predict_base">Predict</a>
   </li>
  </ul>
 </div>
</nav>
<div
 style="
  border: #c0833e;
  border-width: 5px;
  border-style: solid;
```

border-radius: 10px;

rate that is too slow – below 60 beats per minute – is called bradycardia.

Some types of arrhythmias have no symptoms.

Symptoms, when present, may include palpitations or feeling a pause between heartbeats.

In more serious cases, there may be lightheadedness, passing out, shortness of breath or chest pain.

While most cases of arrhythmia are not serious, some predispose a person to complications such as stroke or heart failure.

Others may result in sudden height: max-content;

margin-top: 30px;

margin-left: 10px;

margin-right: 10px;

"

>

<div class="intro1">

<center>Arrhythmia classification</center>

</div>

<div>

<p class="intro">

Arrhythmias also known as cardiac arrhythmias, heart arrhythmias, or dysrhythmias, are irregularities in the heartbeat,

including when it is too fast or too slow.

A resting heart rate that is too fast – above 100 beats per minute in adults – is called tachycardia,

and a resting heart death.

</p>

</div>

```
    <div class="intro2">


      <ol class="_in">
        <li>A fluttering in the chest</li>
        <li>A racing heartbeat (tachycardia)</li>
        <li>A slow heartbeat (bradycardia)</li>
        <li>Chest pain</li>
        <li>Shortness of breath</li>
        <li>Heavy sweating</li>
        <li>Dizziness</li>
        <li>Fatigue</li>
        <li>Lightheadedness or fainting</li>
        <li>Anxiety</li>
      </ol>
 </div>
   </div>
  </body>
</html>
```

8.Testing

8.1 User Acceptance Testing

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	10	4	2	3	19
Duplicate	1	0	3	0	4
External	2	3	0	1	6
Fixed	10	2	4	10	26
Not Reproduced	0	0	1	0	1
Skipped	0	0	1	1	2
Won't Fix	0	4	1	1	6
Totals	22	15	10	30	77

9. Performance Metrics

10.ADVANTAGES & DISADVANTAGES

ADVANTAGES

● Provides accurate results and detailed information required by the users or patients.

● Users or customers can easily use the app because of its user-friendly interface and simplicity.

● Can be used by anyone at any time.

● As this application can be very useful for the earlier and fast classification of arrhythmia it we be used by many patients suffering from it.

● Experts guidance is not required when we have a app that can be used by anyone.

● Data of the patient will be securely stored and maintained for future purposes.

11.Conclusion

Arrhythmia is a severe CVD that can be predicted via ECG segment processing. Arrhythmia must be accurately diagnosed and prevented early to reduce cardiac disease. Our proposed system model met the study's primary goal of assisting doctors in swiftly determining the kind of ECG or verifying their diagnostics in a medical context while maintaining a high level of precision and cost. In this work, a CNN-Bi-LSTM model is proposed to categorise five categories of ECG fragments to construct an effective and resilient autonomous computer-aided diagnosis system. The developed network achieved maximum accuracies of 100%, 98.0%, and 98.0% of training, validation, and testing using MIT-BIH data set. In comparison, the St-Petersburg data set achieved 98.0%, 95.0%, and 95.0% accuracies of training, validation, and testing in identifying arrhythmia. This research showed many advantages, including its ability to help clinicians reliably make ECG recording-related clinical decisions. Moreover, it was intended to be as simple as possible while delivering the most significant performance. The described method is straightforward for health professionals and does not involve signal modification or feature extraction. Additionally, this research focused only on one kind of CVD, namely, arrhythmia, whereas the manifestations of cardiac disease are often complex and varied. As a result, more types of ECG data will need to be added to broaden the scope of the planned network.

12.FUTURE SCOPE

- To upload dataset and store patient details
- Online doctor consultation

13.APPENDIX

Source Code

1) Model Building Code

```
from google.colab import drive

drive.mount('/content/drive')

cd /content/drive/MyDrive/Project Development Phase
```

#Import the ImageDataGenerator library

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

#Configure ImageDataGenerator Class

train_datagen=ImageDataGenerator(rescale=1./255,zoom_range=0.2,vertical_flip=True,horizontal_flip=True)

test_data=ImageDataGenerator(rescale=1./255)

#Apply ImageDataGenerator functionality to trainset and testset

x_train=train_datagen.flow_from_directory(r"/content/drive/MyDrive/ProjectDevelopment Phase/data/train",target_size=(64,64),class_mode="categorical",batch_size=128)

x_test=test_data.flow_from_directory(r"/content/drive/MyDrive/ProjectDevelopment Phase/data/test",target_size=(64,64),class_mode="categorical",batch_size=128)

x_train.class_indices

#MODEL BUILDING

#Import the libraries

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Dense,Convolution2D,MaxPooling2D,Flatten

#Initialize the model

model=Sequential()

#Adding CNN layers

model.add(Convolution2D(32,(3,3),activation="relu",strides=(1,1),input_shape=(64,64,3)))

model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Flatten())

model.summary()

#Adding Dense layer

#Hidden layer

model.add(Dense(500,activation="relu"))

model.add(Dense(500,activation="relu"))

#Output layer

model.add(Dense(6,activation="softmax"))

#Configure the learning process

model.compile(loss="categorical_crossentropy",optimizer="adam",metrics=['accuracy'])

len(x_train)

#Train the model

model.fit(x_train,epochs=5,steps_per_epoch=len(x_train),validation_data=x_test,validation_step
s=len(x_test))

model.fit(x_train,epochs=5,steps_per_epoch=len(x_train),validation_data=x_test,validation_step
s=len(x_test))

model.fit(x_train,epochs=5,steps_per_epoch=len(x_train),validation_data=x_test,validation_step
s=len(x_test))

model.fit(x_train,epochs=5,steps_per_epoch=len(x_train),validation_data=x_test,validation_step
s=len(x_test))

#Save the model

model.save('arrhythmia.h5')

#Testing the model

import numpy as np

from tensorflow.keras.models import load_model

from tensorflow.keras.preprocessing import image

img=image.load_img("/content/drive/MyDrive/Project Development Phase/data/test/Premature
Ventricular Contractions/VEBfig_11.png",target_size=(64,64))

```
x=image.img_to_array(img)

x=np.expand_dims(x,axis=0)

pred=model.predict(x)


index=['Left Bundle Branch Block', 'Normal',  'Premature Atrial Contraction', 'Premature Ventricular Contractions', 'Right Bundle Branch Block',  'Ventricular Fibrillation']


index[np.argmax(pred)]
```

App.py source code

```
import os
import numpy as np
from flask import Flask,request,render_template

from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image

app=Flask(__name__)
model=load_model('arrhythmia.h5')

@app.route("/")
def about():
    return render_template("home.html")
@app.route("/home")
def home():
    return render_template("home.html")
```

```
@app.route("/predict_base")
def test():
    return render_template("predict_base.html")

@app.route("/predict_base",methods=["GET","POST"])
def upload():
    if request.method == 'POST':
        f=request.files['file'] #requesting the file
        basepath=os.path.dirname('__file__')#storing the file directory
        filepath=os.path.join(basepath,"uploads",f.filename)#storing the file in uploads folder
        f.save(filepath)#saving the file

        img=image.load_img(filepath,target_size=(64,64)) #load and reshaping the image
        x=image.img_to_array(img)#converting image to array
        x=np.expand_dims(x,axis=0)#changing the dimensions of the image

        pred=model.predict(x)#predicting classes
        y_pred = np.argmax(pred)
        print("prediction",y_pred)#printing the prediction

        index=['Left Bundle Branch Block','Normal','Premature Atrial Contraction',
       'Premature Ventricular Contractions', 'Right Bundle Branch Block','Ventricular Fibrillation']
        result=str(index[y_pred])

        return result
    return None
#port = int(os.getenv("PORT"))
if __name__=="__main__":
    app.run(debug=True)
```

```
    #app.run(host='0.0.0.0', port=8000)
```

GitHub

https://github.com/IBM-EPBL/IBM-Project-3155-1658503360

Project Demo Link

https://github.com/IBM-EPBL/IBM-Project-3155-1658503360/upload/main/project%20Demo