Project Report

Team ID	PNT2022TMID26984
	Project - Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation

1. INTRODUCTION

1.1 Project Overview

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 a 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. Our proposed methodology is evaluated on a publicly available MIT-BIH arrhythmia dataset. The performance is significant in other indices as well, including sensitivity and specificity, which indicates the success of the proposed method.

1.2 Purpose

The ECG signal detects abnormal conditions and malfunctions by recording the potential bio-electric variation of the human heart. To overcome the challenge for the visual and physical explanation of the ECG signal, computer-aided diagnostic systems have been developed to identify such signals automatically . ECG signal classification based on different approaches has been presented . dataset. 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 types of arrhythmias. This project helps in finding the type of arrhythmia we have and helps us to keep in track about our health. It also helps to contact the doctor when there is a risk and provide healthy tips and challenges.

2. LITERATURE SURVEY

2.1 Existing problem

The conventional techniques might not achieve efficient results due to the inter-patient variability in ECG signals .Additionally, the efficiency and accuracy of traditional methods could be negatively affected by the increasing size of data .The techniques presented in literature have been applied to smaller datasets; however, for the purpose of generalization, the performance should be tested on larger datasets. There are methods reported that use 2-D

ECG signals however, to the best of our knowledge, there are not clear details on how the 1-D ECG signal is converted to 2-D images for using 2-D CNN models. Most methods have been tested on only a few types of arrhythmia and must be evaluated on all major types of arrhythmia. It should be noted that the performance of methods developed for 1-D ECG signals can be further improved. Towards this end, the major contributions of our proposed work are:

- Spectrograms (2-D images) are employed, which are generated from the 1-D ECG signal using STFT. In addition, data augmentation was used for the 2-D image representation of ECG signals.
- A state-of-the-art performance was achieved in ECG arrhythmia classification by using the proposed CNN-based method with 2-D spectrograms as input.

2.2 References

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- 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. [Google Scholar] [CrossRef]

2.3 Problem Statement Definition

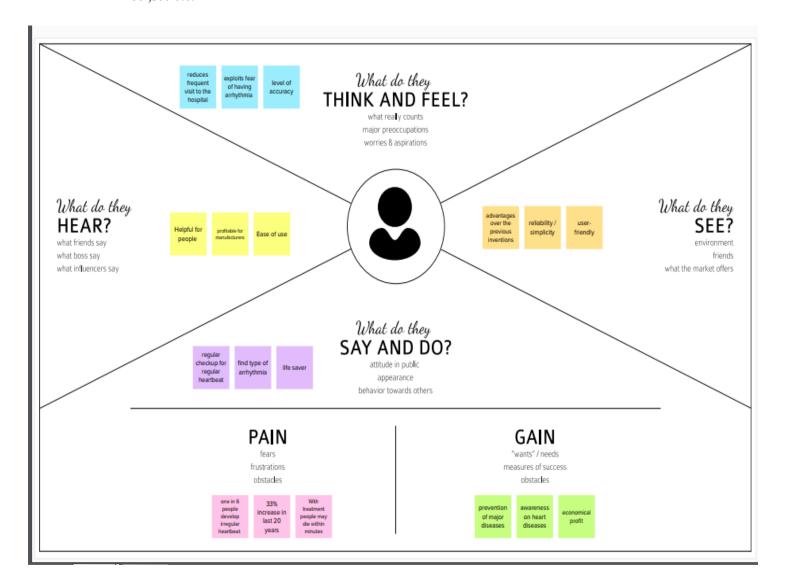
In this study, we proposed a 2-D CNN-based classification model for automatic classification of cardiac arrhythmias using ECG signals. An accurate taxonomy of ECG signals is extremely helpful in the prevention and diagnosis of CVDs. Deep CNN has proven useful in

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 of arrhythmia, 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 reliable operative technique in the diagnosis of CVDs. The proposed scheme can help experts diagnose CVDs by referring to the automated classification of ECG signals. The present research uses only a single-lead ECG signal. The effect of multiple lead ECG data to further improve experimental cases will be studied in future work.

3. IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas:

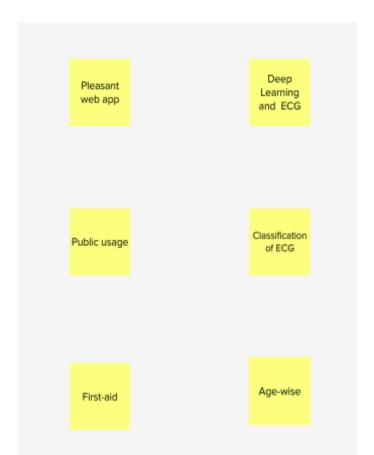
This helps to keep focus on the user by putting yourself in their shoes about how they think and feel, see etc.



3.2 Ideation & Brainstorming:

Helps in unleashing our imagination and helps in shaping concepts.

Person	1		Person	2	
Classification of ECG	CNN & ECG	Easy to use	Separation of OTHER	RNN	Verifiable
Causes	<u></u>	Based on heights	Voice interaction	Making it as an app	confirmation by a doctor
Facts	tracking system		relating to previous issues	accuracy	
Person	3		Person 4	1	
Deep Learning and ECG	Login pages	food practises	ECG uploading types	Pleasant web app	if wish recommend doctor
Instant results	Public usage	Inputs from photos	Age-wise	No	Based on the length of beats
First-aid	Results only for adults		Result in clear means	regular check-ups	

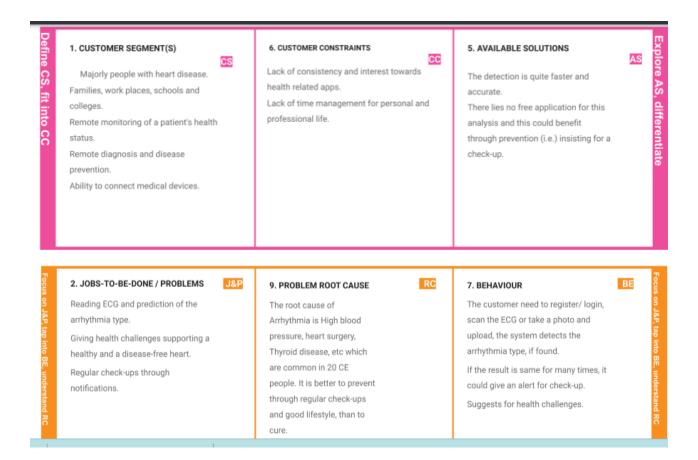


3.3 Proposed Solution:

In recent years deep learning based ECG arrhythmia classification approaches have been proposed due to the novel advances in these studies. Deep learning-based approaches no need to feature extraction steps in contrast to existing pattern recognition studies. The recent findings show that deep neural networks (DNNs) extract representative features directly from input data and classify them with the aid of hidden layers (convolutional and max-pooling layers). DNNs, convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) and combinations of these networks and pattern recognition algorithms were used as deep learning approaches on ECG arrhythmic heartbeat classification.

DNNs models are sent to ECG signals as 1D data form of features. Yıldırım et al. proposed deep bidirectional LSTMs network-based approach with wavelet-based layers that obtained the frequency sub-bands of ECG signals which is achieved 99.39% for five different arrhythmia classification on MIT-BIH

3.4 Problem Solution fit:



4. REQUIREMENT ANALYSIS

4.1 Functional requirement:

3. TRIGGERS TR	10. YOUR SOLUTION SL	8. CHANNELS of BEHAVIOUR CH
Challenges flowing through the app trigger the customer for regular usage. 4. EMOTIONS: BEFORE / AFTER Fear of getting checked for disease, spending to diagnose	The solution fits medical professionals and also to public to detect arrhythmia accurately through ECG and Deep Learning algorithms. The market competition is lower and customer satisfaction could be higher with the enhancements added to the application.	8.1 ONLINE Logging in, uploading of ECR, prediction of arrhythmia type if predicted. 8.2 OFFLINE They would take up heart-related health challenges.
and time doing all these things. Making use of this system can make them relieved and healthier.	This ensures a healthier future generation who could balance their lives.	If predicted with Arrhythmia, go for confirmation with a Cardiologist.

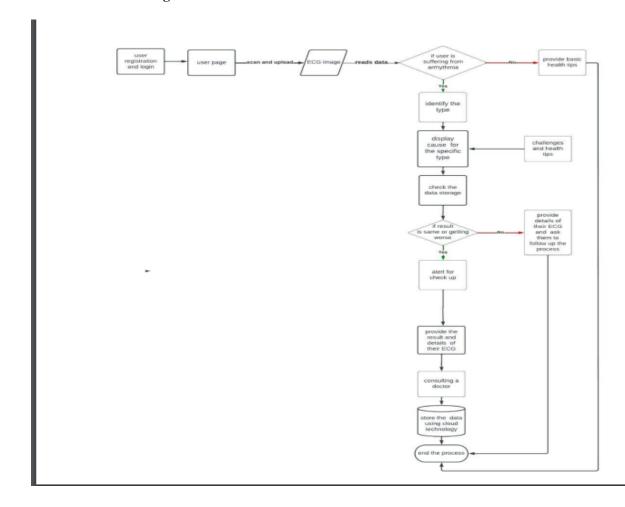
FR	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
No.		
FR-1	User Registration	Registration through Form
FR-2	User Confirmation	Confirmation via OTP
FR-3	user login	login with registration id
FR-4	upload ecg	read data and predict arithmetic type
FR-5	Challenges and notifications	Giving health challenges and healthy tips Remembering to take medicines Remembering to take regular checkup and doctor consultations.

4.2 Non-Functional requirements:

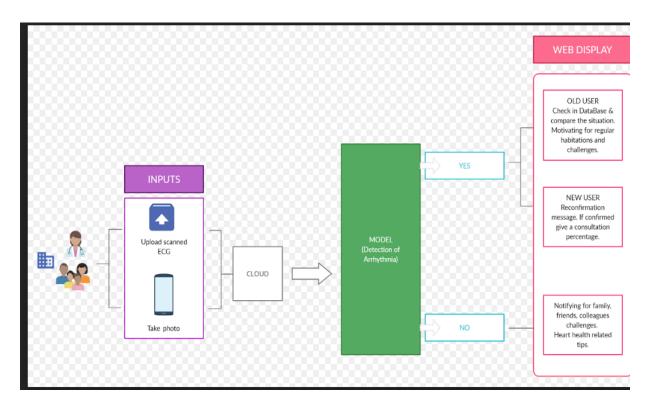
FR No.	Non-Functional Requirement	Description
NFR-1	Usability	Improves ease of use. Improves interest toward their own health.
NFR-2	Security	Uses cloud technology. The data of the user are well secured and there would be no interference into the system.
NFR-3	Reliability	It is a conventional referral system.
NFR-4	Performance	detection is faster and accurate. No fee application and could benefit users through prevention .
NFR-5	Availability	easily available in any areas at any time .
NFR-6	Scalability	scalable through tie ups with government hospitals , agri technologies or corporates.

5. PROJECT DESIGN

5.1 Data flow diagram:



5.2 Solution & Technical Architecture:



5.3 User Stories:

User Stories

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer (Mobile user)	Registration	USN-1	As a user, I can register for the application by entering details in form and verifying OTP using mobile number.	I can access my account / dashboard	High	Sprint-1
		USN-2	As a user, I will receive confirmation message once I have registered for the application	I can receive confirmation message	High	Sprint-1
	Login	USN-3	As a user, I can log into the application by entering my mobile number	I can access my account / dashboard	High	Sprint-1
	Dashboard	USN-4	As a user,I can view the previous results.	I can access my dashboard	medium	sprint-1
Customer (Web user)	registration	USN-5	As a user, I can register for the user account by entering details in form and verifying OTP using mobile number.	I can access my account / dashboard	high	sprint-1
		USN-6	As a user, I will receive confirmation message once I have registered for the user account	I can receive confirmation message	high	sprint-1
	Login	USN-7	As a user, I can log into the page by entering my mobile number.	I can access my account / dashboard	high	sprint-1
	Dashboard	USN-8	As a user,I can view the previous results	I can access my dashboard.	medium	sprint-1
Customer Care Executive	chat	USN-9	I can contact and resolve queries initiated by the user.	can view user data	medium	sprint-2
Administrator	Accessing database	USN-10	As an administrator,I can maintain the user database	can view and modify database	high	sprint-1
		USN -11	As an administrator,I can add new user.	can accept new user in the application.	low	sprint-1
	Health tips	USN-12	As an administrator,I can create and modify health tips to the user	I can give health advice	medium	sprint-2

6. PROJECT PLANNING & SCHEDULING

6.1 Sprint Planning & Estimation

Project Planning Phase Project Planning Template (Product Backlog, Sprint Planning, Stories, Story points)

Date	18 October 2022
Team ID	PNT2022TMID26984
	Project - Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation
Maximum Marks	8 Marks

Product Backlog, Sprint Schedule, and Estimation (4 Marks)

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Registration	USN-1	I'm a patient registering application through the form with the help of assistance.	2	High	Rashmi
Sprint-1		USN-2	As a user, I will receive confirmation through OTP once I have registered for the application.	1	High	Vishnu Varthini
Sprint-1	Model Training	USN-3	As a user, I expect the result to be accurate	1	High	Sandhya
Sprint-2	Login	USN-	As a user, I can log into the application by entering my email & password.	2	High	Rashmi, Vishnu Varthini
Sprint-2	Dashboard	INFO	Information regarding arrhythmia.	1	Low	Vishnu Varthini
		PREDICT	Read data and predict arrhythmia type.	2	High	Sandhya, Vishnu Varthini
		RESULT	As a user, I expect the result to be clear to understand and the situation I'm in.		High	
Sprint-3	Notifications	USN-4	As a user I get health challenges and health tips, reminders to take medicines, to take regular checkups, and doctor consultations.	1	Medium	Saranya
Sprint-4	Notification random	USN-5	The notifications are random in challenges and health tips.	1	Low	Saranya

6.2 Sprint Delivery Schedule

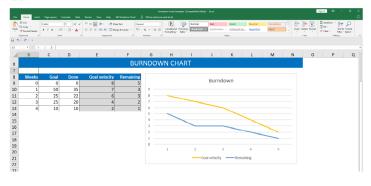
Project Tracker, Velocity & Burndown Chart: (4 Marks)

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	20	4 Days	01 Nov 2022	04 Nov 2022	15	11 Nov 2022
Sprint-2	20	4 Days	05 Oct 2022	09 Nov 2022	17	12 Nov 2022
Sprint-3	20	4 Days	10 Nov 2022	13 Nov 2022	16	13 Nov 2022
Sprint-4	20	4 Days	14 Nov 2022	19 Nov 2022	19	14 Nov 2022

Velocity:

AV = 20/16 = 1.25

Burndown Chart:



6.3 Reports from JIRA

	ост	NOV	DEC	JAN '23
IBM-1 Registration				
• IBM-2 Verification				
IBM-3 Model Training				
▶ IBM-4 Login				
IBM-5 Dash Board-INFO				
■ IBM-6 Dash Board-PREDICT				
▶ IBM-7 Dash Board-RESULT				
IBM-8 Notification				
■ IBM-9 Notification Random				

7. TESTING

7.1 Test Cases

2. Defect Analysis

This report shows the number of resolved or closed bugs at each severity level, and how they were resolved

,					
Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	8	4	2	3	18
Duplicate	2	1	3	0	6
External	0	3	2	2	7
Fixed	3	15	2	18	38
Not Reproduced	0	1	0	0	1
Skipped	1	0	1	0	2
Won't Fix	0	5	0	2	7
Totals	14	29	10	25	79

3. Test Case Analysis

This report shows the number of test cases that have passed, failed, and untested

This report shows the number of test ouse	3 that have passe	u, idilou, dilu u	inconcu	
Section	Total Cases	Not Tested	Fail	Pass
Print Engine	7	0	0	7
Client Application	4	0	0	3
Security	1	0	0	1

Outsource Shipping	1	0	0	1
Exception Reporting	1	0	0	1
Final Report Output	4	0	0	4
Version Control	2	0	0	1

7.2 User Acceptance Testing

Project Development Phase Model Performance Test

Date	15 November 2022	
Team ID	PNT2022TMID26984	
Project Name	Project - Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image	
	Representation	
Maximum Marks	10 Marks	

Model Performance Testing:

Project team shall fill the following information in model performance testing template.

S.No.	Parameter	Values	Screenshot
1.	Model Summary	The model is built with CNN and trained in IBM Cloud. The web application works with HTML, CSS, and JS integrated into the flask. It detects the classification of Arrhythmia and normal ECG with the CNN model.	Sea Continued and Association of
2.	Accuracy	Training Accuracy - 0.9861 Validation Accuracy - 0.9134	

8. RESULTS

8.1 Performance Metrics:

The results obtained by the networks that use features extracted from deep full convolutional layers (6th and 7th) of the AlexNet proved that the deeper layers of a deep convolutional neural network trained on a very large annotated data set can be generic enough to be transferred and implemented for ECG arrhythmia classification task[11]. A very high correct validation accuracy (97.33%) is obtained of the proposed system demonstrated that the transferred deep learning feature extractor cascaded with a simple back propagation neural network is an efficient automatic cardiac arrhythmia detection method. Additionally, transferring a pre-trained deep CNN eliminates the need for high expertise and computational power required for training a deep convolutional neural network from scratch. The results of AlexNet show that a large, deep convolutional neural network is capable of achieving record-breaking results on a highly challenging dataset using purely supervised learning. AlexNet implementation is very easy after the release of so many deep learning libraries.

9. ADVANTAGES & DISADVANTAGES

Advantages:

For smaller amounts of training data, DL methods face the overfitting problem since the model highly pays attention to training data and does not generalize well for the test data. Thus, shallow techniques provide better performance on small amounts of data samples.

Disadvantages:

The main limitations of the method include the increased computational cost with the addition of more networks. The method is most likely to fail due to the failure of models incorporated with the merger. That being said, at least one model will produce noteworthy results.

10. CONCLUSION

The study presented results of a review on different methods for classifying arrhythmia on ECG signals. The objective of the review method was to investigate the most powerful Deep Learning methods detecting various types of arrhythmia. Technical details of the common methods were discussed. The GRU/LSTM, CNN, and LSTM, showed outstanding results for correct classification of Atrial Fibrillation, Supraventricular Ectopic Beats, and Ventricular Ectopic Beats, respectively. It is also concluded that the use of a proper type of Deep Learning method can considerably improve the classification performance for the corresponding application.

11. FUTURE SCOPE

Recent trend of research in this scope shows that dynamic classification methods that are capable of learning both short and long term contents of the signal in an efficient way, would be employed for such applications. CNN has shown excellent performance in classifying different types of arrhythmia. This powerful method would be one of the most efficient learning tools for this application.

Future work will focus on the extension of these results to the five heartbeat classes recommended by the AAMI. Another important aspect not covered in our study is the fixed heartbeat window length that can be inappropriate in the case of fast and slowly varying heart rhythms when changing physical activity. Thus, there is a need to study adaptive beat size segmentation. The understanding of the exact relation between underlying physiology and features is a potential question to address. However, there are no conclusive guidelines about which features should be used to diagnose arrhythmias from the ECG using computer aided systems.

12. APPENDIX

about.html

```
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta http-equiv="X-UA-Compatible" content="IE=edge">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>Classification Of Arrhythmia using ECG</title>
  link href="https://cdn.jsdelivr.net/npm/bootstrap@5.2.1/dist/css/bootstrap.min.css" rel="stylesheet"
   integrity="sha384-iYQeCzEYFbKjA/T2uDLTpkwGzCiq6soy8tYaI1GyVh/UjpbCx/TYkiZhlZB6+fzT"
   crossorigin="anonymous">
</head>
<body style="font-family: ui-monospace; background-color: #dbdee1;">
  <nav class="navbar navbar-expand-lg" style="background-color: #104E8B;">
    <div class="container-fluid">
      <a class="navbar-brand" href="about.html"></a>
         <div class="navbar-nav">
           <a class="nav-link active" aria-current="page" href="{{url_for('about')}}">HOME</a>
           <a class="nav-link" href="{{url_for('info')}}"> INFO</a>
           <a class="nav-link" href="{{url_for('predict')}}">PREDICT</a>
         </div>
      </div>
  </nav>
  <div class="content">
    <h1>ECG Arrhythmia Classification Using CNN</h1>
```

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.

```
</div>
 <style>
  h1{
    display: flex;
 justify-content: space-around;
 background-size:cover;
 align-items: center;
 background-color: #f5f5f5;
  }
  p {
    display: flex;
 flex-direction: column;
 align-items: center;
 width: 100%;
 height: 100%;
                                                                              background-image:
 url('https://th.bing.com/th/id/OIP.9Kd8bXZvdQYmMmQh-wcBkQHaFj?pid=ImgDet&rs=1');
  background-size: cover;
  background-position: center;
  background-repeat: no-repeat;
    }
</style>
```

<script src="https://cdn.jsdelivr.net/npm/bootstrap@5.2.1/dist/js/bootstrap.bundle.min.js"
integrity="sha384-u1OknCvxWvY5kfmNBILK2hRnQC3Pr17a+RTT6rIHI7NnikvbZIHgTPOOmMi4
66C8" crossorigin="anonymous"></script>

```
</body>
</html>
info.html
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta http-equiv="X-UA-Compatible" content="IE=edge">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>Classification Of Arrhythmia using ECG</title>
  k href="https://cdn.jsdelivr.net/npm/bootstrap@5.2.1/dist/css/bootstrap.min.css" rel="stylesheet"
   integrity="sha384-iYQeCzEYFbKjA/T2uDLTpkwGzCiq6soy8tYaI1GyVh/UjpbCx/TYkiZhlZB6+fzT"
   crossorigin="anonymous">
</head>
<body style="font-family: ui-monospace; background-color: #dbdee1;">
  <nav class="navbar navbar-expand-lg" style="background-color: #104E8B;">
    <div class="container-fluid">
       <a class="navbar-brand" href="{{url_for('info')}}"></a>
         <div class="navbar-nav">
            <a class="nav-link active" aria-current="page" href="{{url for('about')}}">HOME</a>
            <a class="nav-link" href="{{url for('info')}}">INFO</a>
            <a class="nav-link" href="{{url_for('predict')}}">PREDICT</a>
         </div>
    </div>
  </nav>
  <div class="content">
    <h1>Electrocardiography (ECG)</h1>
    <div class="image">
       <img src="{{url_for('static',filename='images/ecg.jpg')}}" alt="" width="500px" height="500px">
    </div>
```

Electrocardiography is a non-invasive technique to determine the condition of human heart and detect any abnormal cardiac behavior. An electrocardiogram (ECG) is a simple test that can be used to check your heart's rhythm and electrical activity. Sensors attached to the skin are used

to detect the electrical signals produced by your heart each time it beats. These signals are recorded

by a machine and are looked at by a doctor to see if they're unusual. An ECG may be requested by a heart specialist (cardiologist) or any doctor who thinks you might have a problem with your heart, including your GP. The test can be carried

out by a specially trained healthcare professional at a hospital, a clinic or at your GP surgery. The P wave records the electrical activity of the atria. The QRS wave records the electrical activity of the ventricles, and the T wave records the heart's return to the resting state.

Doctors study the shape and size of the waves, the time between waves and the rate and regularity of beating.

```
<h1>When is an ECG is used?</h1>
```

An ECG is often used alongside other tests to help diagnose and monitor conditions affecting the heart. It can be used to investigate symptoms of a possible heart problem, such as chest pain, palpitations (suddenly noticeable heartbeats), dizziness and

shortness of breath. An ECG can help detect:

```
Arrhythmias - Where the heart beats too slowly, too quickly, or irregularly.
```

Coronary Heart Disease - Where the heart's blood supply is blocked or interrupted by a build-up of fatty substances.

```
Heart Attacks - Where the supply of blood to the heart is suddenly blocked.
Ii>
Cardiomyopathy - Where the heart walls become thickened or enlarged.
Ii>
Symptoms of Arrhythmia</h1>
```

An arrhythmia may not cause any obvious symptoms. You may notice symptoms such as a slow or irregular heartbeat or notice pauses between heartbeats.

You may also feel like your heart is skipping a beat, fluttering, pounding, or beating too hard or too fast.

```
Other symptoms may include:
  ul class="bullet">
  <|i>
     Chest pain or discomfort, difficulty breathing.
  Difficulty breathing, or gasping during sleep.
  <|i>
     Dizziness and fainting.
  Tiredness or weakness.
  A fluttering feeling in your neck or chest
  Low blood pressure
  A series of ECGs can also be taken over time to monitor a person already diagnosed with a
heart condition or taking medication known to potentially affect the heart.
<h1>Normal ECG</h1>
<div class="image">
          <img src="{{url for('static',filename='images/normalecg.jpg')}}" alt="" width="500px"</pre>
height="500px">
</div>
A normal ECG is illustrated above. Note that the heart is beating in a regular sinus rhythm
between 60 - 100 beats per minute (specifically 82 bpm). All the important intervals on this
recording are within normal ranges.
<h1>Abnormal ECG</h1>
```

<img src="{{url_for('static',filename='images/abnormalecg.jpg')}}" alt="" height="500px"

<div class="image">

width="500px">

```
Electrocardiographic abnormalities include first-degree heart block, right and left bundle
   branch block, premature atrial and ventricular contractions.
    <h1>Self care tips to control Arrthymia</h1>
    Some of the everyday life style remedies are given below. Although it can help to stop
   palpitations, medical attention may be necessary for frequent or severe symptoms.
    ul class="bullet">
      >
         Perform relaxation techniques like meditation, yoga and light exercise.
      <1i>
        Quit smoking and other tobacco products.
      <|i>
        Keep blood pressure and cholesterol levels under control.
      <|i>
        Maintain healthy weight. Eat heart-healthy foods.
      </div>
                  src="https://cdn.jsdelivr.net/npm/bootstrap@5.2.1/dist/js/bootstrap.bundle.min.js"
   integrity="sha384-u1OknCvxWvY5kfmNBILK2hRnQC3Pr17a+RTT6rlHI7NnikvbZlHgTPOOmMi4"
   66C8" crossorigin="anonymous"></script>
</body>
</html>
predict.html
<html lang="en">
```

</div>

```
<head>
<meta charset="UTF-8">
<meta name="viewport" content="width=device-width, initial-scale=1.0">
<meta http-equiv="X-UA-Compatible" content="ie=edge">
<title> Classification Of Arrhythmia using ECG</title>
<link href="https://cdn.bootcss.com/bootstrap/4.0.0/css/bootstrap.min.css" rel="stylesheet">
<script src="https://cdn.bootcss.com/popper.js/1.12.9/umd/popper.min.js"></script>
<script src="https://cdn.bootcss.com/jquery/3.3.1/jquery.min.js"></script>
<script src="https://cdn.bootcss.com/bootstrap/4.0.0/js/bootstrap.min.js"></script>
<style>
}
#result{
 color: #8B0000;
}
body{
  background-image: url("https://wallpaperaccess.com/full/173246.jpg");
 background-size: cover
}
</style>
</head>
<body style="font-family: ui-monospace; background-color: #dbdee1;">
  <nav class="navbar navbar-expand-lg" style="background-color: #104E8B;">
    <div class="container-fluid">
       <a class="navbar-brand" href="about.html"></a>
         <div class="navbar-nav">
            <a class="nav-link active" aria-current="page" href="{{url_for('about')}}">HOME</a>
            <a class="nav-link" href="{{url_for('info')}}"> INFO</a>
            <a class="nav-link" href="{{url_for('predict')}}">PREDICT</a>
         </div>
       </div>
  </nav>
<div class="container">
```

```
<div id="content" style="...">
<div class="container">
  <div class="row">
  <div class="col-sm-6 bd">
  <h3> ARRHYTHMIA CLASSIFICATION </h3>
 <br><br>>
 <div class="col-sm-6">
  <div>
   <h4> Click on the "Choose File" button to upload your ECG file: </h4>
  <form action="https://localhost:5000/" id="upload-file" method="post">
   <label for="imageUpload" class="upload-label">
   </label>
   <input type="file" name="image" id="ImageUpload" accept=".png, .jpg, .jpeg">
  </form>
  </div>
  <div class="image-section" style="...">
    <div class="img-preview">
    <div id="ImagePreview">
    </div>
   </div>
 </div>
 <div>
  <button type="button" class="btn3 btn-info btn-lg" id="btn-predict">PREDICT! </button>
  </div>
  </div>
  <div class="loader" style="...."></div>
  <h3>
    <span id="result"> </span>
 </h3>
</div>
 </div>
</div>
```

```
</div>
</div>
</body>
<footer>
<script src="{{url_for('static', filename='js/main.js')}}" type="text/javascript"></script>
</footer>
</html>
app.py
import os
import numpy as np
from flask import Flask, render_template, request
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
app = Flask(__name__)
model = load_model('ECG.h5')
@app.route('/')
def about():
  return render_template('about.html')
@app.route('/about')
def home():
  return render_template('about.html')
@app.route('/info')
def info():
  return render_template('info.html')
```

```
@app.route('/predict')
def predict():
  return render template('predict.html')
@app.route("/predict", methods=['GET', 'POST'])
def upload():
  if request.method == 'POST':
    f = request.files['image']
    basepath = os.path.dirname( file )
    filepath = os.path.join(basepath, 'uploads', f.filename)
    f.save(filepath)
    img = image.load_img(filepath, target_size=(64, 64))
    x = image.img_to_array(img)
    x = np.expand dims(x, axis=0)
    pred = np.argmax(model.predict(x), axis=1)
    index = ['Left Bundle Branch Block', 'Normal', 'Premature Atrial Contraction',
          'Premature Ventricular Contractions', 'Right Bundle Branch Block', 'Ventricular Fibrillation']
    text = "Arrhythmia Type:"+str(index[pred[0]])
     return text
if __name__ == "__main__":
  app.run(debug=False)
```

GITHUB LINK

https://github.com/IBM-EPBL/IBM-Project-914-1658330363

PROJECT DEMO LINK

https://drive.google.com/file/d/1KGG8EI9F6kW6CZ6KJnki2 c oKrFEYDp/view?usp=sharing