Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation

A PROJECT REPORT

Submitted by

TEAM ID: PNT2022TMID39864

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Smart Internz

CONTENT

ABSTRACT

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

INTRODUCTION

1.1 Project overview

Using the template from above, here's an example of what a project overview can look like:

Project name*:* Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation

Team Leader: Janani.S

Team Members: R.K.Bhavana, P.K.Bhavani, V.Lavanya

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Business case: To Create a web application for the public that makes easy to predict arrhythmia at early stage and to prevent it.

Problem: It takes time for the doctor to take the ECG report and analyse it, so we have discovered a application.

Goals: Here are some of our main goals with this project:

- To reduce the time for the doctors and patients
- To identify the diseases at early stages.
- To make use of current technology to create a application.

Deliverables: Here are the tasks we hope to complete throughout this project:

- To classify ECG images of the patients.
- To run the application and predict the types of arrhythmia.
- Suggest tips to patients

Risks or obstacles: The risks or obstacles could be:

- **People belief:** People fear out using the online application to take care in health sectors and it can be a major drawback for this application. We can overcome this by creating belief over the customers and audience.
- **Faults and Errors:** As we don't know what the error or fault can occur in the web application, sometimes due to many testcases and high runtime, the output can be a false prediction. We may have to work on it to fix the bugs and errors.

1.2 Purpose:

Why ECG classification is important Classification of arrhythmia signals plays an important role in clinical diagnosis of heart disease. Changes in the normal rhythm of a human heart may result in different cardiac arrhythmias, which may be immediately fatal or cause irreparable damage to the heart sustained over long periods of time. Cardiovascular diseases (CVDs) are the leading cause of death today. The current identification method of the diseases is analyzing the Electrocardiogram (ECG), which is a medical monitoring technology recording cardiac activity. Unfortunately, looking for experts to analyze a large amount of ECG data consumes too many medical resources.

Therefore, the method of identifying ECG characteristics based on machine learning has gradually become prevalent. However, there are some drawbacks to these typical methods, requiring manual feature recognition, complex models, and long training time. The ability to automatically identify arrhythmias from ECG recordings is important for clinical diagnosis and treatment. In this paper we have used machine learning schemes, CNN to classify arrhythmia from ECG medical data sets. The aim of the study is to automatically classify cardiac arrhythmias and to study the performance of machine learning algorithms.

LITERATURE SURVEY

2.1 Existing Problem (ONE-DIMENSIONAL ECG)

The existing model focus on the machine learning techniques using many models and co relation matrix and so , it takes a large time to code and deploy. They are all based on a novel deep learning model for categorizing five classes of cardiac arrhythmia from ECG signals using the MIT-BIH and ST-Petersburg data sets. Evaluate the optimum hyper-parameters of conv1D in terms of Kernel size, number of filters, activation function and number of layers. We combined the Bi-LSTM technique of size 32 based on factorial cross-entropy following the Adam optimizer with an evaluated optimum conv1D.And so 2Dimensional method takes a long time for classification.

Related work

Amin Ullah, 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.

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

Zahra Ebrahimi Deep Learning (DL) has recently become a topic of study in different applications including healthcare, in which timely detection of anomalies on Electrocardiogram (ECG) can play a vital role in patient monitoring. This paper presents a comprehensive review study on the recent DL methods applied to the ECG signal for the classification purposes. This study considers various types of the DL methods such as

Convolutional Neural Network (CNN), Deep Belief Network (DBN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). Mohammad Loni From the 75 studies reported within 2017 and 2018, CNN is dominantly observed as the suitable technique for feature extraction, seen in 52% of the studies. DL methods showed high accuracy in correct classification of Atrial Fibrillation (AF) (100%), Supraventricular Ectopic Beats (SVEB) (99.8%), and Ventricular Ectopic Beats (VEB) (99.7%) using the GRU/LSTM, CNN, and LSTM, respectively. Sonain Jamil, ECG signals provide us with information about the heartbeat. ECGs can detect cardiac arrhythmia. In this article, a novel Deep learning-based approach is proposed to classify ECG signals as normal and into sixteen arrhythmia classes. The ECG signal is preprocessed and converted into a 2D signal using continuous wavelet transform (CWT).

Tran Anh Vu, the accuracy of the classification algorithm we employ is 99.8%, demonstrating the model's validity when compared to other reports' findings. This is the foundation for our algorithm to prove it can be utilized as an efficient model for categorizing arrhythmia using ECG signals. Nguyen Thi Minh Huyen Actually, deep learning algorithms are evolving and highly effective in image analysis and processing. In this research, a dense neural network model is proposed to classify normal and abnormal beats. Shao-Peng Pang, Recently, many models based on the deep neural networks have been applied to the automatic classification of cardiac arrhythmia with great success. However, most models independently extract the internal features of each lead in the 12-lead ECG during the training phase, resulting in a lack of inter-lead features. Here, we propose a general model based on the two-dimensional ECG and ResNet with detached squeeze and-excitation modules (DSE-ResNet) to realize the automatic classification of normal rhythm and 8 cardiac Arrhythmia.

Talal AA Abdullah, the classification comprises five different classes: non-ectopic (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown (Q) beats. The proposed model is trained, validated, and tested using MIT-BIH and St-Petersburg data sets separately. Mohd S Mohd Zahid, the performance of the proposed model based on the MITBIH data set is also compared with the performance of existing models based on the MIT-BIH data set. Anisha Patnaik, In this study, a profound learning system beforehand prepared on an overall picture informational index is moved to do programmed ECG arrhythmia diagnostics by arranging patient ECG's into comparing heart conditions. Arrhythmias are more normal in individuals who are 60 years and more established. Dilip Hingorani, A comparison study was done where validation accuracy is 100% in GoogleNet, 94% in SqueezeNet while it was near 97.33% in AlexNet.

Ramya G. Franklin1 The research was carried to make the assignment computerized by displaying the problem with encoder-decoder methods, by using misfortune appropriation to predict standard or anomalous information. Jeong DU, Electrocardiograms (ECGs) are widely used for diagnosing cardiac arrhythmia based on the deformation of signal shapes due to changes in various heart diseases. However, these abnormal signs may not be observed in some 12 ECG channels, depending on the location, the heart shape, and the type of cardiac arrhythmia. Therefore, it is necessary to closely and comprehensively observe ECG records acquired from 12 channel electrodes to diagnose cardiac arrhythmias accurately. The findings of the related literature analysis show that it will be better if we can transform our signals data into images and then merge signal processing with image processing techniques using deep learning. As a result, we use deep learning models to implement such as, CNN works better and gets higher accuracy using different classifiers.

2.2 REFERENCES

We have included some of the reference papers.

2.2.1 Convolutional neural network for classification of eight types of Arrhythmia using 2D time frequency feature map from standard 12- lead electrocardiogram.

<u>Jeong DU, Lim KM</u>

In the year 2021 Abstract Electrocardiograms (ECGs) are widely used for diagnosing cardiac arrhythmia based on the deformation of signal shapes due to changes in various heart diseases. However, these abnormal signs may not be observed in some 12 ECG channels, depending on the location, the heart shape, and the type of cardiac arrhythmia. Therefore, it is necessary to closely and comprehensively observe ECG records acquired from 12 channel electrodes to diagnose cardiac arrhythmias accurately. In this study, we proposed a clustering algorithm that can classify persistent cardiac arrhythmia as well as episodic cardiac arrhythmias using the standard 12-lead ECG records and the 2D CNN model using the time-frequency feature maps to classify the eight types of arrhythmias and normal sinus rhythm. The standard 12-lead ECG records were provided by China Physiological Signal Challenge 2018 and consisted of 6877 patients. The proposed algorithm showed high performance in classifying persistent cardiac arrhythmias; however, its accuracy was somewhat low in classifying episodic arrhythmias. If our proposed model is trained and verified using more clinical data, we believe it can be used as an auxiliary device for diagnosing cardiac arrhythmia.

2.2.2 Arrhythmia and Disease Classification Based on Deep Learning Techniques

Ramya G. Franklin1, B. Muthukumar

In the year 2021 Abstract Electrocardiography (ECG) is a method for monitoring the human heart's electrical activity. ECG signal is often used by clinical experts in the collected time arrangement for the evaluation of any rhythmic circumstances of a topic. The research was carried to make the assignment computerized by displaying the problem with encoder-decoder methods, by using misfortune appropriation to predict standard or anomalous information. The two Convolutional Neural Networks (CNNs) and the Long Short-Term Memory (LSTM) fully connected layer (FCL) have shown improved levels over deep learning networks (DLNs) across a wide range of applications such as speech recognition, prediction etc., As CNNs are suitable to reduce recurrence types, LSTMs are reasonable for temporary displays and DNNs are appropriate for preparing highlights for a more divisible area. CNN, LSTM, and DNNs are appropriate to view. The complementarity of CNNs, LSTMs, and DNNs was explored in this paper by consolidating them through a single architecture firm. Our findings show that the methodology suggested can expressively explain ECG series and of detection of anomalies through scores that beat other techniques supervised as well as unsupervised technique. The LSTMNetwork and FL also showed that the imbalanced data sets of the ECG beat detection issue have been consistently solved and that they have not been prone to the accuracy of ECG-Signals. The novel approach should be used to assist cardiologists in their accurate and unbiased analysis of ECG signals in telemedicine scenarios.

2.2.3 Arrhythmia Classification Algorithm Based on a Two-Dimensional Image and Modified EfficientNet

Cui-fang Zhao, Wan-Yun Yao, Mei-Juan Yi, Chao Wan, Yong-Le Tian

In the year 2022 Abstract The classification and identification of arrhythmia using electrocardiogram (ECG) signals are of great practical significance in the early prevention and diagnosis of cardiovascular diseases. In this study, we propose an arrhythmia classification algorithm based on two-dimensional (2D) images and modified EfficientNet. First, we developed a method for converting original one-dimensional (1D) ECG signals into 2D image signals. In contrast with the existing classification method that uses only the time-domain features of a 1D ECG signal, the classification of 2D images can consider the spatiotemporal characteristics of the signal. Then, to better assign feature weights, we introduced an attention feature fusion module (AFF) into the EfficientNet network to replace the addition operation in the mobile inverted bottleneck convolution (MBConv) structure of the network. We selected EfficientNet for modification because, compared with most convolutional neural networks (CNNs), EfficientNet does not require manual adjustment of parameters, which improves the accuracy and speed of the network. Finally, we combined the 2D images and the improved EfficientNet network and tested its performance as an arrhythmia classification method. Our experimental results show that the network training of the proposed method requires less equipment and training time, and this method can effectively distinguish eight types of heartbeats in the MIT-BIH arrhythmia database, with a classification accuracy of 99.54%. Thus, the model has a good classification effect.

2.2.4 Cardiac Arrhythmia Detection using Deep Learning

Monali Choudhary, Anisha Patnaik, Dipali Phatak, Dhanashri Deokar, Dilip Hingorani

An electrocardiogram (ECG) is a significant indicative device for the appraisal of cardiovascular arrhythmias in clinical daily practice. In this study, a profound learning system beforehand prepared on an overall picture informational index is moved to do programmed ECG arrhythmia diagnostics by arranging patient ECG's into comparing heart conditions. Arrhythmias are more normal in individuals who are 60 years and more established. A convolutional neural organization (in particular AlexNet) is utilized for feature extraction and the removed highlights are taken care of into a basic back spread neural organization to complete the last classification. Fundamental focal point of this investigation is to execute a basic, solid and effectively pertinent learning method for the grouping of the chosen three diverse heart conditions (heart arrhythmia, Congestive Heart Failure, Normal sinus rhythm) so that diagnosis can be done for the same. The results exhibited that the moved profound learning highlight extractor fell with a traditional back proliferation neural organization had the option to get exceptionally elite rates. A comparison study was done where validation accuracy is 100% in GoogleNet, 94% in Squeezenet while it was near 97.33% in AlexNet. Conclusion In this study, ECG Data obtained from the hospital are digitized, pre-processed, converted into scalogram images for classification, feature extraction is done using deep learning and training and validation of data is done. The overall images were classified as heart arrhythmia, Congestive Heart Failure and Normal sinus rhythm. A detailed performance comparison among three networks is done and validation accuracy is checked in all the three cases i.e, 97.33% in AlexNet, 94% in Squeezenet and 100% using Googlenet. With the confusion matrix, we analyzed how many images were incorrectly classified. This investigation was started because of the reality individuals in our nation influenced via cardiovascular illnesses are expanding step by step. Arrhythmias are more normal in individuals who are 60 years and more established. It's to some extent because of mileage of a more established heart.

2.2.5Classification of cardiac arrhythmia using a convolutional neural network and bidirectional long short-term memory

Shahab Ul Hassan, Mohd S Mohd Zahid, Talal AA Abdullah, Khaleel Hussain

In the year 2022 Abstract Cardiac arrhythmia is a leading cause of cardiovascular disease, with a high fatality rate worldwide. The timely diagnosis of cardiac arrhythmias, determined by irregular and fast heart rate, may help lower the risk of strokes. Electrocardiogram signals have been widely used to identify arrhythmias due to their non-invasive approach. However, the manual process is error-prone and time-consuming. A better alternative is to utilize deep learning models for early automatic identification of cardiac arrhythmia, thereby enhancing diagnosis and treatment. In this article, a novel deep learning model, combining convolutional neural network and bi-directional long short-term memory, is proposed for arrhythmia classification. Specifically, the classification comprises five different classes: non-ectopic (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown (Q) beats. The proposed model is trained, validated, and tested using MIT-BIH and St-Petersburg data sets separately. Also, the performance was measured in terms of precision, accuracy, recall, specificity, and f1-score. The results show that the proposed model achieves training, validation, and testing accuracies of 100%, 98%, and 98%, respectively with the MIT-BIH data set. Lower accuracies were shown for the St-Petersburg data set. The performance of the proposed model based on the MIT-BIH data set is also compared with the performance of existing models based on the MIT-BIH data set.

2.3 Problem Statement

Electrocardiography (ECG) is a method for monitoring the human heart's electrical activity. ECG signal is often used by clinical experts in the collected time arrangement for the evaluation of any rhythmic circumstances of a topic. The research was carried to make the assignment computerized by displaying the problem with encoder-decoder methods, by using misfortune appropriation to predict standard or anomalous information. The two Convolutional Neural Networks (CNNs) and the Long Short-Term Memory (LSTM) fully connected layer (FCL) have shown improved levels over deep learning networks (DLNs) across a wide range of applications such as speech recognition, prediction etc., As CNNs are suitable to reduce recurrence types, LSTMs are reasonable for temporary displays and DNNs are appropriate for preparing highlights for a more divisible area. CNN, LSTM, and DNNs are appropriate to view. The complementarity of CNNs, LSTMs, and DNNs was explored in this paper by consolidating them through a single architecture firm. Our findings show that the methodology suggested can expressively explain ECG series and of detection of anomalies through scores that beat other techniques supervised as well as unsupervised technique. The LSTM-Network and FL also showed that the imbalanced data sets of the ECG beat detection issue have been consistently solved and that they have not been prone to the accuracy of ECG-Signals. The novel approach should be used to assist cardiologists in their accurate and unbiased analysis of ECG signals in telemedicine scenarios.

An electrocardiogram (ECG) is a significant indicative device for the appraisal of cardiovascular arrhythmias in clinical daily practice. In this study, a profound learning system beforehand prepared on an overall picture informational index is moved to do programmed ECG arrhythmia diagnostics by arranging patient ECG's into comparing heart conditions. Arrhythmias are more normal in individuals who are 60 years and more established. A convolutional neural organization (in particular AlexNet) is utilized for feature extraction and the removed highlights are taken care of into a basic back spread neural organization to complete the last classification. Fundamental focal point of this investigation is to execute a basic, solid and effectively pertinent learning method for the grouping of the chosen three diverse heart conditions (heart arrhythmia, Congestive Heart Failure, Normal sinus rhythm) so that diagnosis can be done for the same. The results exhibited that the moved profound learning highlight extractor fell with a traditional back proliferation neural organization had the option to get exceptionally elite rates. A comparison study was done where validation accuracy is 100% in GoogleNet, 94% in Squeezenet while it was near 97.33% in AlexNet.

Given the influence of available laboratory equipment, we converted 1D ECG signals into 2D image signals and used spatiotemporal characteristics to perform classification experiments on eight ECG signal types in the MIT-BIH arrhythmia database, achieving relatively high accuracy of 99.54% based on the improved EfficientNet-B0 network. Most medical data sets have sample imbalance problems, which are generally mitigated by increasing a few types of samples or decreasing most types of samples. In this study, we applied the preprocessing method of 1D to 2D ECG signal conversion, which increased the amount of data, and selected the best length. Additionally, we performed data augmentation for two categories, VEB and VFW, and we added four similar groups of different-length images to this data set, which alleviated the data imbalance problem to some extent. Finally, we employed three evaluation indices, namely, sensitivity, specificity, and precision rate ground, to evaluate the model's effect, all of which were found to be high, indicating that the model has a good classification effect.

The automatic classification of electrocardiogram (ECG) signals has played an important role in cardiovascular diseases diagnosis and prediction. Deep neural networks (DNNs), particularly Convolutional Neural Networks (CNNs), have excelled in a variety of intelligent tasks including biomedical and health informatics. Most the existing approaches either partition the ECG time series into a set of segments and apply 1D-CNNs or divide the ECG signal into a set of spectrogram images and apply 2D-CNNs. These studies, however, suffer from the limitation that temporal dependencies between 1D segments or 2D spectrograms are not considered during network construction. Furthermore, meta-data including gender and age has not been well studied in these researches. To address those limitations, we propose a multi-module Recurrent Convolutional Neural Networks (RCNNs) consisting of both CNNs to learn spatial representation and Recurrent Neural Networks (RNNs) to model the temporal relationship. Our multi-module RCNNs architecture is designed as an end-to-end deep framework with four modules: (i) timeseries module by 1D RCNNs which extracts spatio-temporal information of ECG time series; (ii) spectrogram module by 2D RCNNs which learns visual-temporal representation of ECG Spectrogram; (iii) metadata module which vectorizes age and gender information; (iv) fusion module which semantically fuses the information from three above modules by a transformer encoder. Ten-fold cross validation was used to evaluate the approach on the MIT-BIH arrhythmia database (MIT-BIH) under different network configurations. The experimental results have proved that our proposed multi-module RCNNs with transformer encoder achieves the state-of-the-art with 99.14% F1 score and 98.29% accuracy

IDEATION AND PROPOSED SOLUTION

2-D ECG

3.1 Empathy Map Canvas

An empathy map canvas is a more in-depth version of the original empathy map, which helps identify and describe the user's needs and pain points. And this is valuable information for improving the user experience.

Teams rely on user insights to map out what is important to their target audience, what influences them, and how they present themselves. This information is then used to create personas that help teams visualize users and empathize with them as individuals, rather than just as a vague marketing demographic or account number.

An empathy map canvas helps brands provide a better experience for users by helping teams understand the perspectives and mindsets of their customers. Using a template to create an empathy map canvas reduces the preparation time and standardizes the process so you create empathy map canvases of similar quality.

Fig: Empathy map

3.2 Ideation and Brain Stroming

Ideation is often closely related to the practice of brainstorming, a specific technique that is utilized to generate new ideas. A principal difference between ideation and brainstorming is that ideation is commonly more thought of as being an individual pursuit, while brainstorming is almost always a group activity. Brainstorming is usualy conducted by getting a group of people together to come up with either general new ideas or ideas for solving a specific problem or dealing with a specific situation.

Participants in a brainstorming session are encouraged to freely toss out whatever ideas may occur to them. The thinking is that by generating a large number of ideas, the brainstorming group is likely to come up with a suitable solution for whatever issue they are addressing.

The lines between ideation and brainstorming have become a bit more blurred with the development of several brainstorming software programs, such as Bright idea and Idea wake. These software programs are designed to encourage employees of companies to generate new ideas for improving the companies' operations and, ultimately, bottom-line profitability.

The programs often combine the processes of ideation and brainstorming in that individual employees can use them, but companies may simulate brainstorming sessions by having several employees all utilize the software to generate new ideas intended to address a specific purpose.

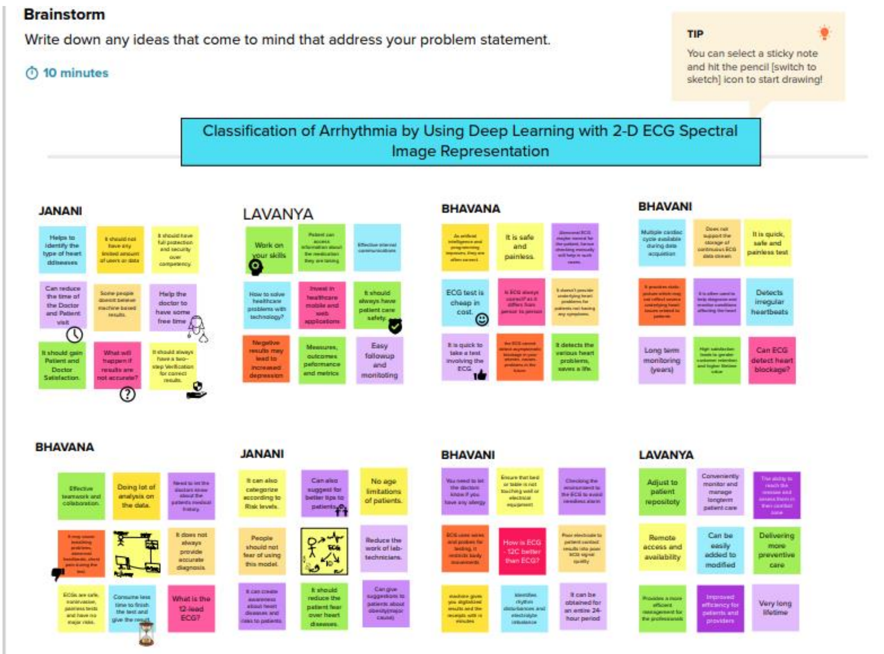


Fig: Brain Stroming

3.3 Proposed System

Project team shall fill the following information in proposed solution template.

S. No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	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 2D spectrograms through short time Fourier transform. The 2D 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. 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. The performance is significant in other indices as well, including sensitivity and specificity, which indicates the success of the proposed method.
2.	Idea / Solution description	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. Our proposed methodology is evaluated on a publicly available MIT-BIH arrhythmia 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. The performance is significant in other indices as well, including sensitivity and specificity, which indicates the success of the proposed method

3.	Novelty / Uniqueness	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. The performance is significant in other indices as well, including sensitivity and specificity, which indicates the success of the proposed method
4.	Social Impact / Custo mer Satisfaction	1. Upgradeable Software 2. Works well with Unstructured Data 3. Better Self-Learning Capabilities 4. Supports Parallel and Distributed Algorithms. 5. Cost Effectiveness 6. Low cost maintenanc
5.	Business Model (Reve nue Model)	Drivers of medical device growth -India •Higher disposable incomes •Increase in public spend on healthcare •Increase in penetration of health insurance •Models of healthcare emerging •Many avenues for funding
6.	Scalability of the Soluti on	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. Using 2-D images, can classify eight kinds of arrhythmia, namely, NOR, VFW, PVC, VEB, RBB, LBB, PAB, and APC, and it achieved97.91% average sensitivity, 99.61% specificity, 99.11% average accuracy, and98.59% 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

3.4 Problem Solution fit

The Problem-Solution Fit simply means that you have found a problem with your customer and that the solution you have realized for it solves the customer’s problem.

What is important go/no-go parts of your business, product, or service? Map these out and, as much as possible, once you have found a quantifiable problem with the customer, it is fairly easy to measure the effectiveness of your solution. Make sure you have sufficient evidence that your product or service solves the customer’s problem.

Fig: problem solution fit

Requirement Analysis

4.1 Functional Requirements

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	• Registration through Form • Registration through Gmail • Registration through User ID and Password • Registration through sign in process • Registration through Linked IN • Registration through Phone number • Registration through OTP
FR-2	User Confirmation	• Confirmation via Email • Confirmation via OTP • Confirmation via Message • Confirmation via Call • Confirmation via Face Detection • Confirmation via Image Identification • Confirmation via Captcha • Confirmation via Fingerprint • Confirmation via Iris Scanning
FR-3	Data Management	This can be done by • By using the Cloud Storage and Drive • By using the External Hard Drive • By clearing out the documents of last 3 years and 5 years. • By clearing out the cache • By cleaning out the death persons data
FR-4	Authorization levels	This can be done by • Giving access to only specific people with username and password. • By having persons identification and marks. • By using authentication code. • By giving access to information only
FR-5	Historical data	• It should contain a historical data of the patient information and their ECG results. • It should also contain a patient heart beat levels and blood pressure level. • To display the official result. • It should also track the patient heart beat level and their blood pressure levels. • It should also contain a complex type and cases of patients treated
FR-6	Certification Requirements	The machine can be certified by various standards and technicians such as: • Certified Phlebotomy Technician (CPT)

		• Certified Clinical Medical Assistant (CCMA) • Certified Medical Assistant (CMA) • Certified Nursing Assistant (CNA) • Registered behavior technician (RBT) • Certified Professional Coder (CPC) • Certified Pharmacy Technician (CPhT)

4.2 Non-Functional Requirements

Following are the non-functional requirements of the proposed solution.

FR No.	Non-Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
NFR-1	Usability	• To automatically classify heart disease, estimated peaks, durations between different peaks, and other ECG signal features were used to train a machine-learning model.
NFR-2	Security	The security measures can be include in the machine learning models such as: • Launch ML instances in a VPC • Use least privilege to control access to ML article • Use data encryption • Use Secrets Manager to protect credentials • Monitor model input and output • Enable logging for model access Use version control on model artifacts
NFR-3	Reliability	• Reliability specifies how likely the system or its element would run without a failure for a given period of time under predefined conditions. • Traditionally, this probability is expressed in percentages. • For instance, if the system has 85 percent reliability for a month, this means that during this month, under normal usage conditions, there's an 85 percent chance that the system won't experience critical failure.
NFR-4	Performance	• An electrocardiogram records the electrical signals in the heart. • It's a common and painless test used to quickly detect heart problems and monitor the heart's health. The performance increases with the size of data and number of users.
NFR-5	Availability	• The device performs with all remote monitoring devices, such as wristbands, are becoming increasingly common, facilitating collection of large ECG databases.

		• As a consequence, a lot of work has been devoted to automatic interpretation of this kind of data. • The deep learning models have proven to be useful in increasing the effectiveness of diagnoses of cardiovascular diseases using ECG signals. As the information and machines can be used from anywhere and everywhere.
NFR-6	Scalability	• The application is always user flexible and can store large amount of data. • The data's can be stored in computerized form instead of storing in handwritten files and data in the hospital, labs.

Project Design

5.1 Dataflow diagram (ECG)

A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system. A neat and clear DFD can depict the right amount of the system requirement graphically. It shows how data enters and leaves the system, what changes the information, and where data is stored.

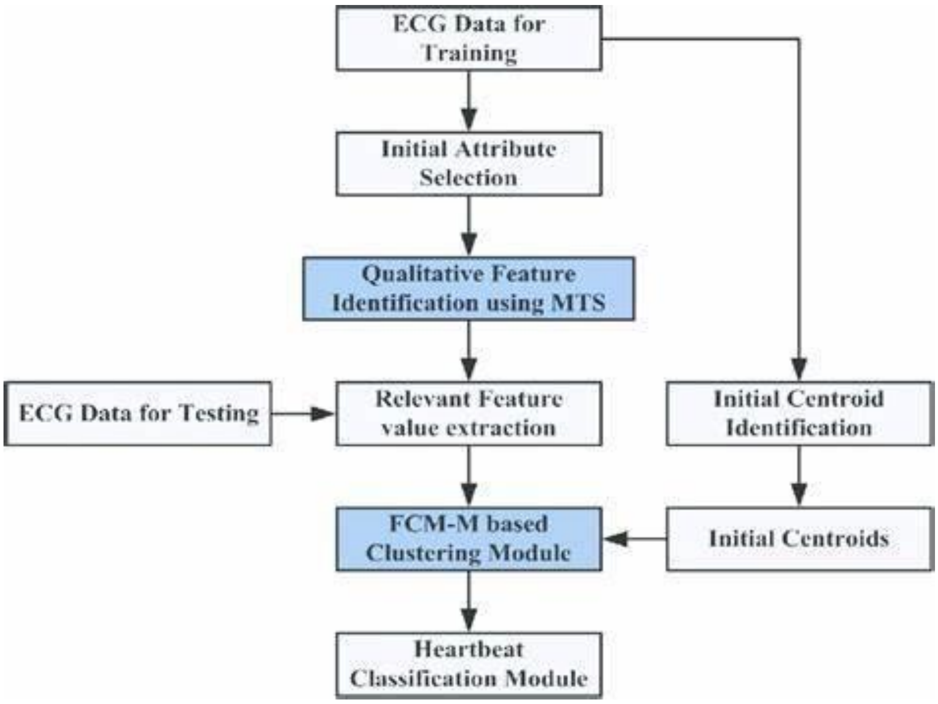


Fig: ECG-Data flow diagram

5.2 Solution and Technical Architecture (ECG)

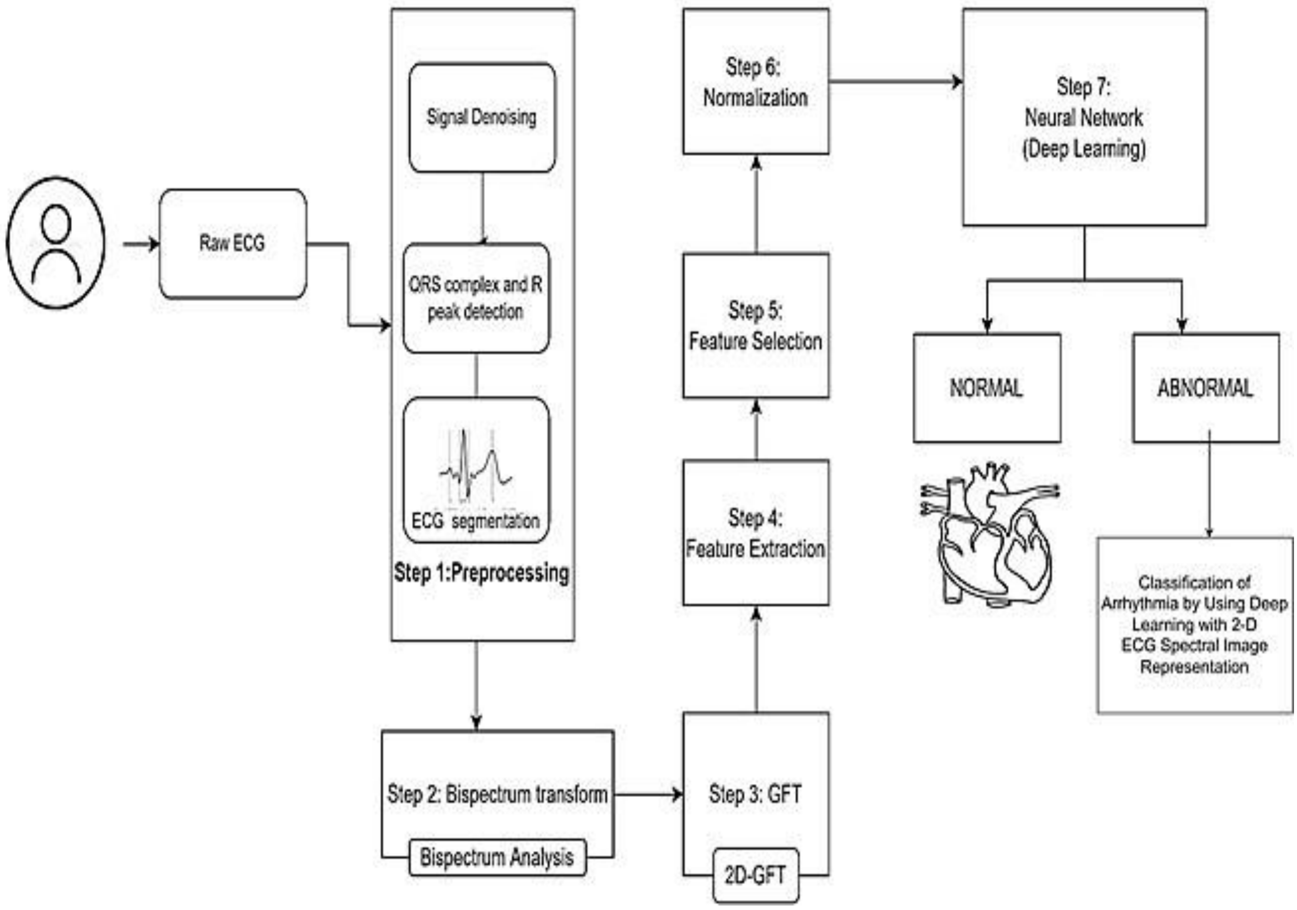


Fig: solution and technical architecture ECG

5.3 User Stories

User types	Functional requirements	User story Number	User Story/ Task	Acceptance criteria	priority	Release
Patient/doctor (web user)	Web interface	USN-1	As a user, I can access the web interface	I can login to my account	High	Sprint-1
Patient/doctor (web user)	Dashboard	USN-2	As a user, I can access the dashboard /Homepage	I can view the homepage	High	Sprint-1
Patient/doctor (web user)	Types of Arrhythmia	USN-3	As a user, I can view various articles about different kinds of arrhythmia	I can view the articles	Low	Sprint-1
Patient/doctor (web user)	Page navigation	USN-4	As a user, I can access several tabs and pages on the interface	I can view different pages and navigate	Medium	Sprint-2
Patient/doctor (web user)	Info and about page	USN-5	As a user, I can see the info and about page for the web interface	I can view the info and about page	Medium	Sprint-2
Patient/doctor (web user)	Page to send input	USN-6	As a user, I can see an option to upload input image of ECG	I can view the input page	High	Sprint-3
Patient/doctor (web user)	Prediction result page	USN-7	As a user, I can see the predicted result for the	I can view the prediction	High	Sprint-3

			given ECG image			
Patient/doctor (web user)	Type of arrhythmia	USN-8	As a user, I can see the type of arrhythmia	I can view the type of arrhythmia page	High	Sprint-3
Patient/doctor (web user)	Side effects page	USN-9	As a user, I can see the various side effects of the predicted arrhythmia	I can view the side effects page	Low	Sprint-4
Patient/doctor (web user)	Prediction history page	USN-10	As a user, I can see the various predictions done in the past	I can view the prediction history page	Medium	Sprint-4
Patient/doctor (web user)	Type of CVD page	USN-11	As a user, I can see the predicted type of CVD based on predicted arrhythmia	I can view the type of CVD page	High	Sprint-4
Patient/doctor (web user)	Performance metrics	USN-12	As an administrator, I can see the number of people who are using the developed interface	I can view the performance metrics	Medium	Sprint-4

Project Planning and Scheduling

6.1 Sprint Planning and Estimation

In the sprint delivery plan, there are four delivery plans. it is to measure and track the success of the delivery of the projects. To determine what the Sprint Goal should be, we should consider the three questions:

1.Why do we carry out the Sprint? Why is it worthwhile to run a sprint? What should be achieved?

2.How do we reach its goal? Which artifice, validation technique, and test group are used?

3.How do we know the goal has been met? For instance, at least three of the five users conduct the usability test successfully in less than a minute.

So, sprints are:

Every single module is assigned to team-mates, so that the work can be collaborated and completed easily.

SPRINT 1:

- The team should conduct a survey of the project developed.
- The team should have a proof of the results been executed.
- The team should start by completing the milestones.

SPRINT 2:

- The team should monitor the efficiency of the process.
- The team should show a demo to the team mentors.
- The team should analyze the project specification.

SPRINT 3:

- The team-mates should always work in coordination.
- The team-mates should understand the project work flow and structure.
- The team-mates should have a complete knowledge of the project

SPRINT 4:

- The team should always be updating the project as per the recent trends and requirements.
- The team should finally deploy and train the project.
- The team should always have a check on the result of the projects.

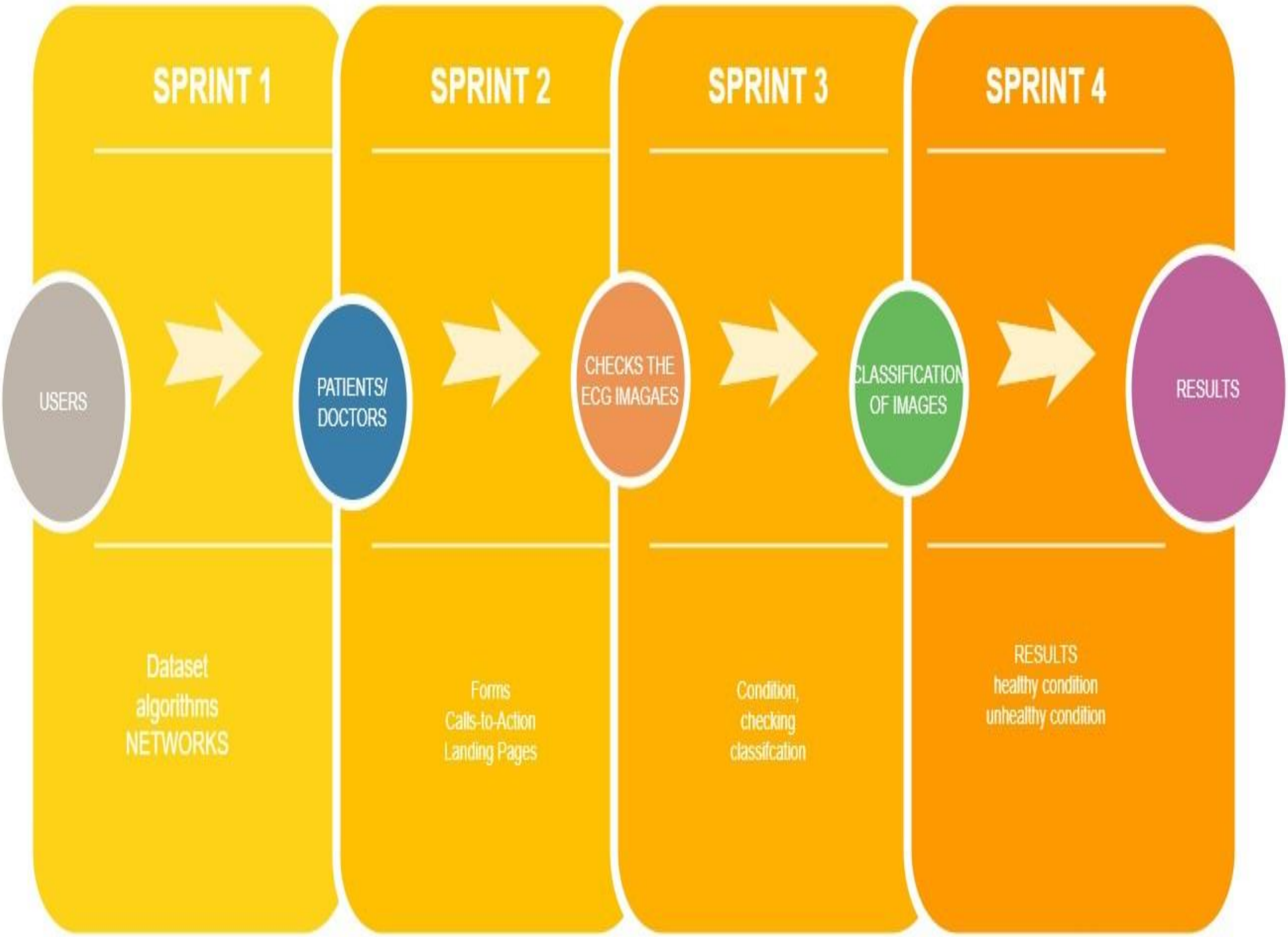
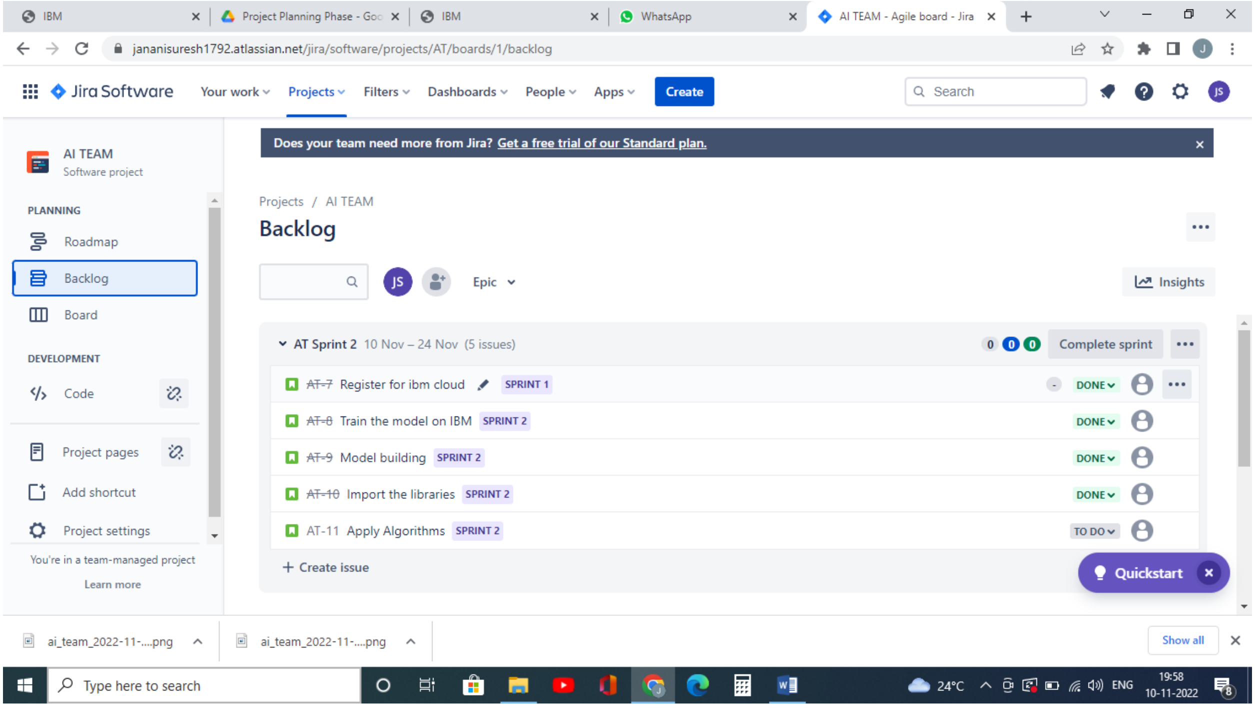


Fig: Sprint Planning

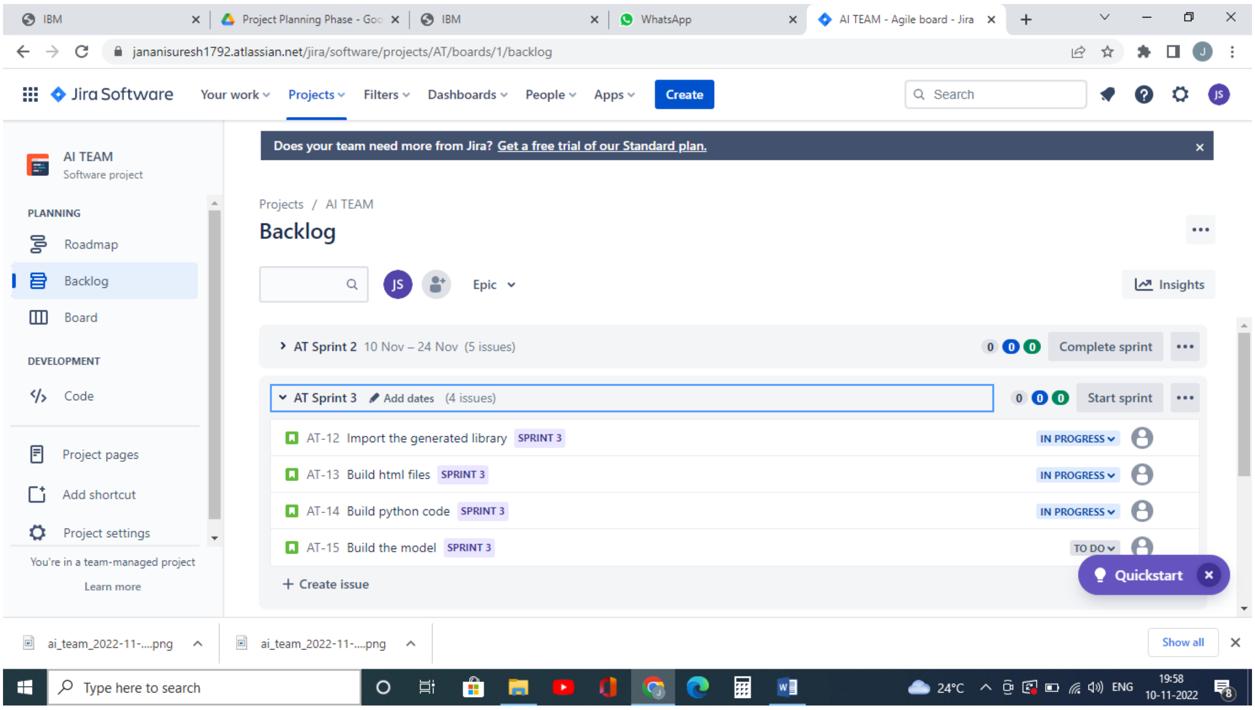
6.2 Sprint Delivery Schedule

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Registration	USN-1	As a user, I can register for the application by entering my email, password, and confirming my password.	2	High	JANANI
Sprint-1		USN-2	As a user, I will receive confirmation email once I have registered for the application	1	High	BHAVANA
Sprint-2		USN-3	As a user, I can register for the application through Facebook	2	Low	LAVANYA
Sprint-1		USN-4	As a user, I can register for the application through Gmail	2	Medium	BHAVANI
Sprint-1	Login	USN-2	As a user, I can log into the application by entering email & password	1	High	BHAVANA,BHAVANI,JANANI,LAVANYA
Sprint 2	Dashboard	USN-3	The user can upload the pics and click on predict	20	Medium	BHAVANA,BHAVANI,JANANI,LAVANYA
Sprint 3		USN-4	Then the results is been loaded	20	High	BHAVANA,BHAVANI,JANANI,LAVANYA
Sprint 4		USN-5	Finally publish the results.	20	Medium	BHAVANA,BHAVANI,JANANI,LAVANYA

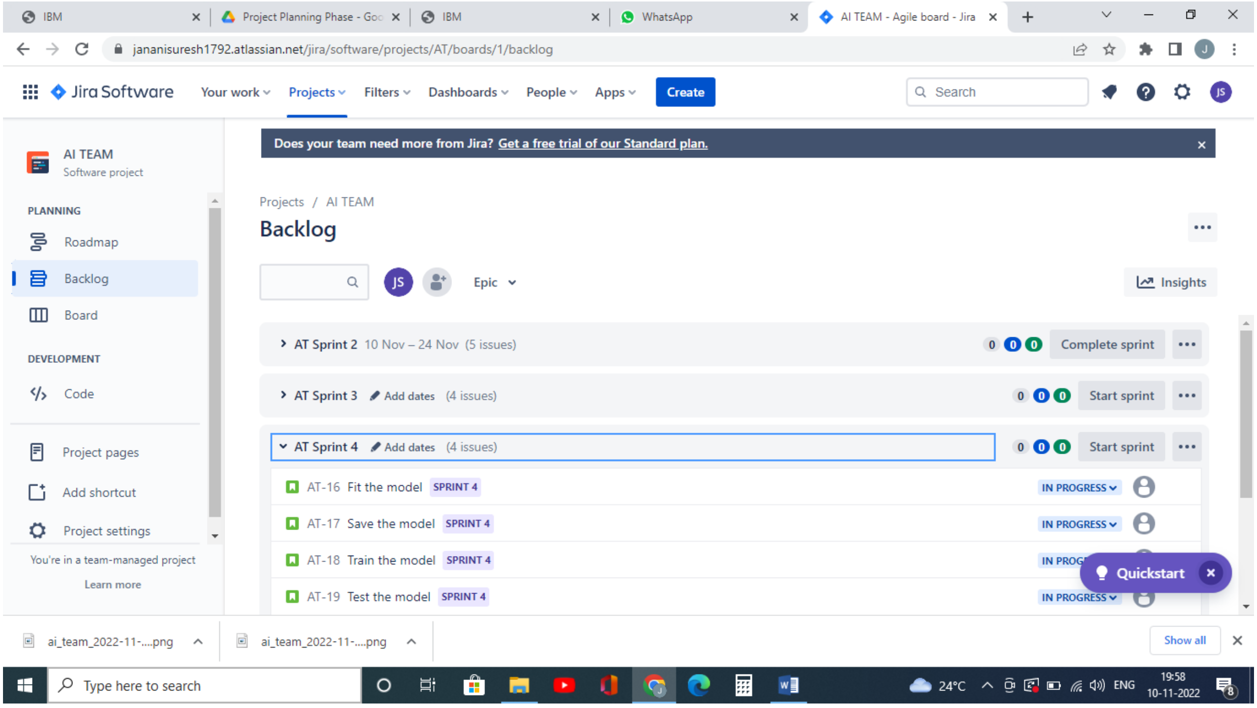
6.3 Reports from JIRA



Backlog 1

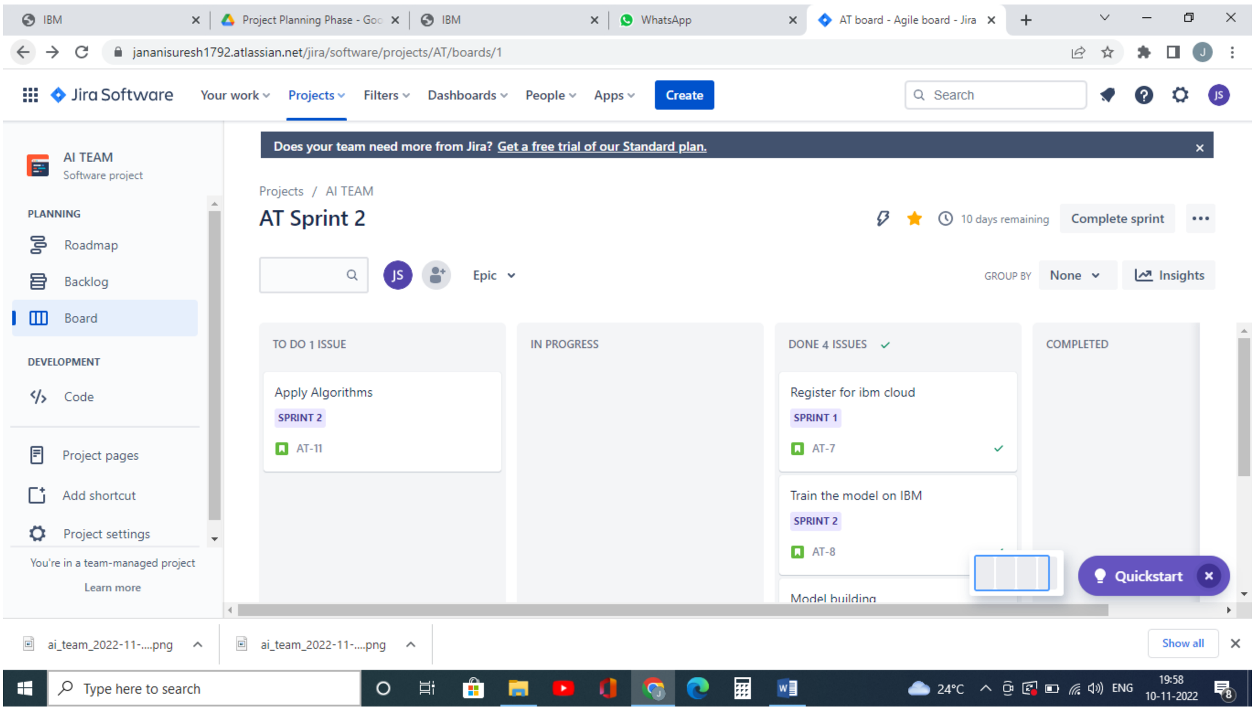


Backlog 2



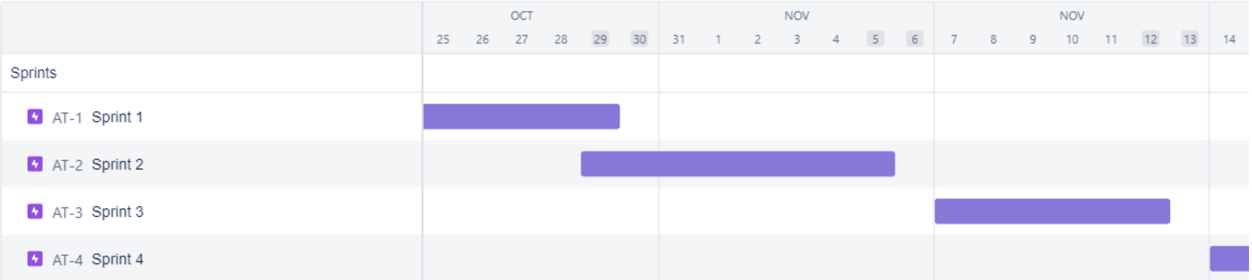
Backlog 3

Board

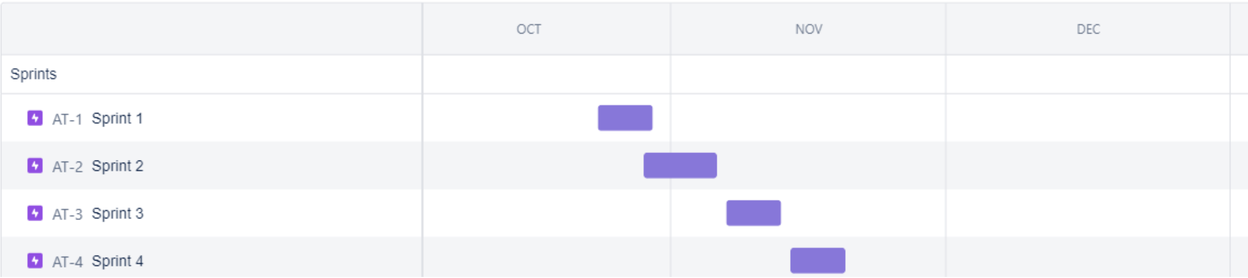


Board Map

Roadmap

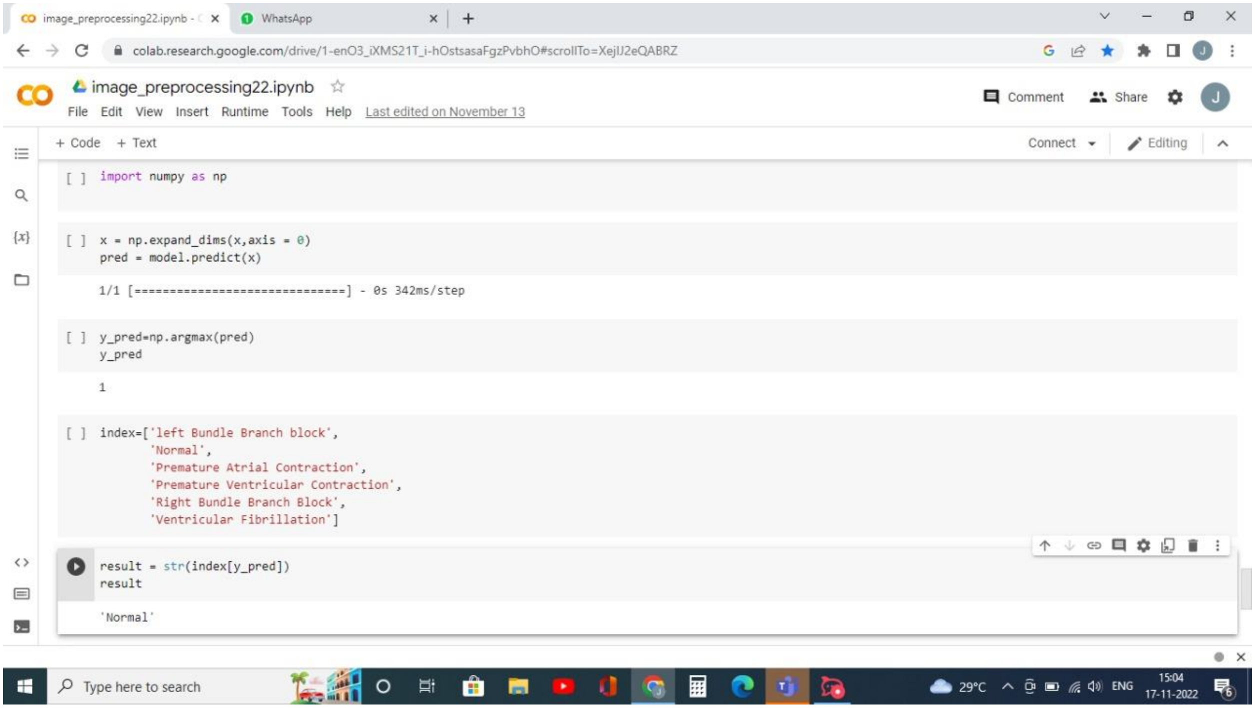


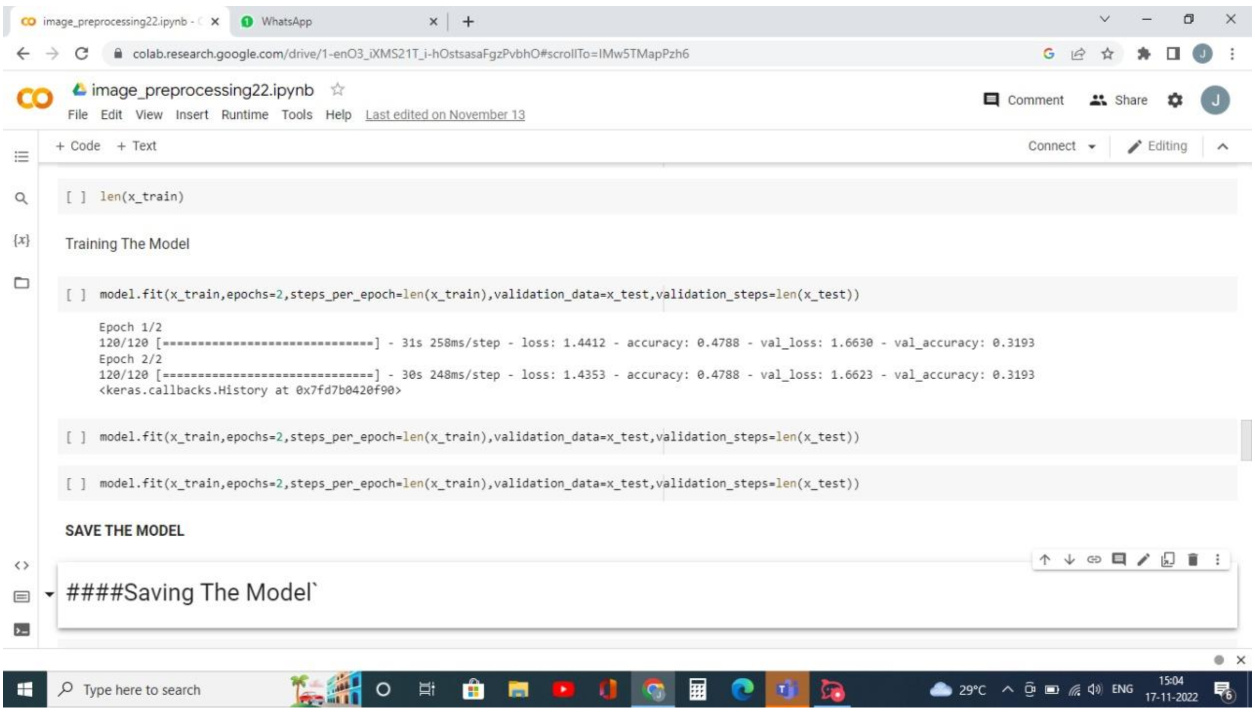
Roadmap 1



Roadmap 2

CODING & SOLUTIONING





Adding CNN Layers

```
model.add(Conv2D(32,(3,3),activation='relu',strides=(1,1),input_shape=(64,64,3)))
model.add(MaxPool2D(pool_size=(2,2)))
```

```
model.add(Conv2D(32,(3,3),activation='relu'))
model.add(MaxPool2D(pool_size=(2,2)))
```

```
model.add(Flatten())
model.summary()
```

Adding Dense Layers

Hidden Layer

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

```
model.add(Dense(units = 128,kernel_initializer = "random_uniform",activation = "relu"))
```

MODEL BUILDING

Importing The Libraries

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

from tensorflow.keras.layers import Conv2D
```

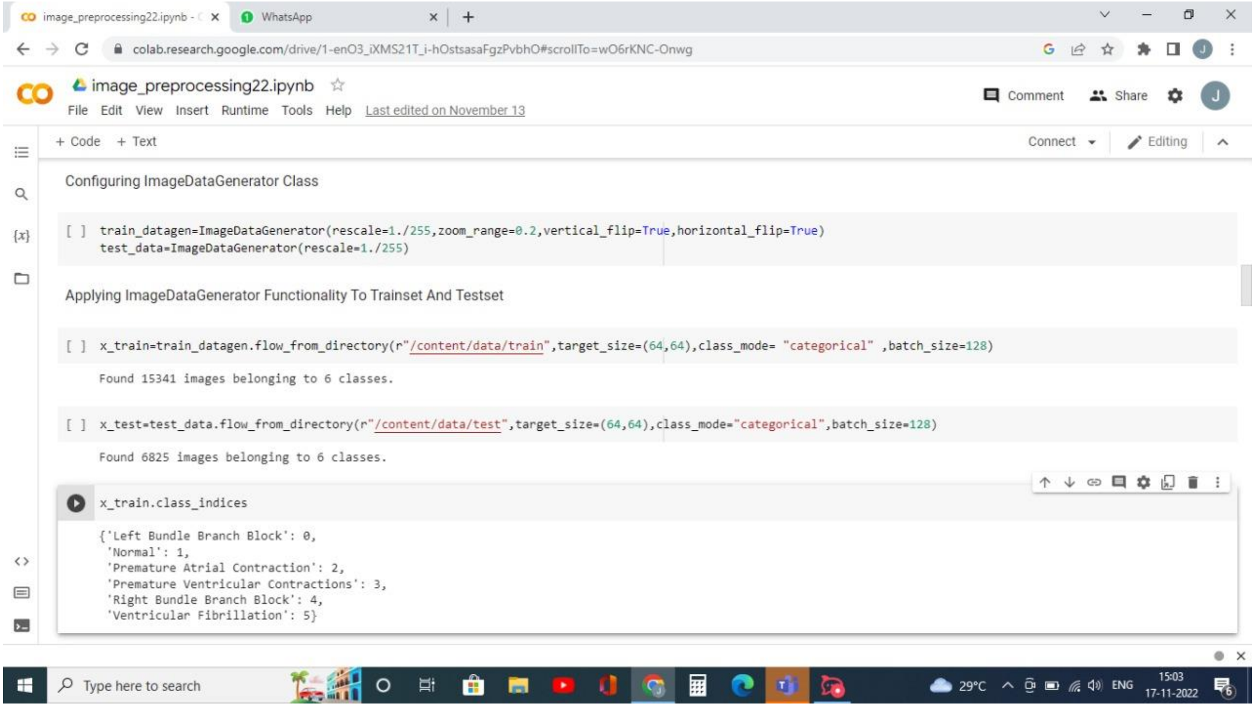
```
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import MaxPool2D
```

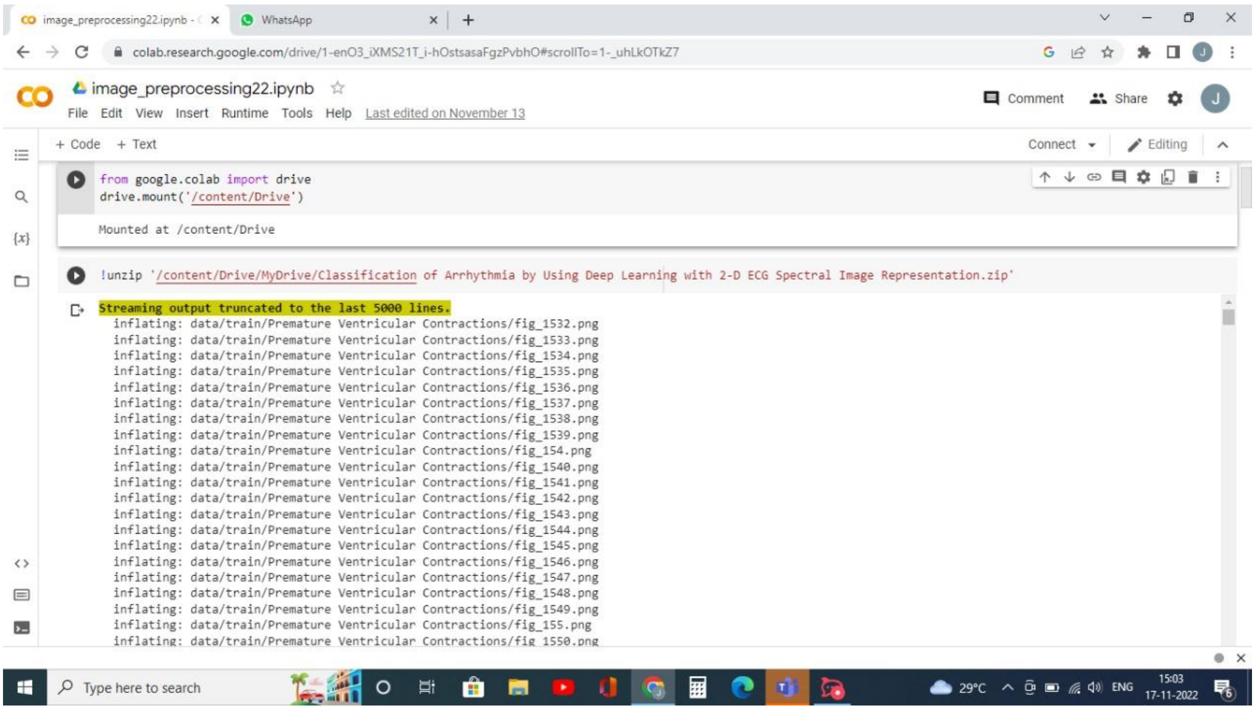
Initialising The Model

```
model=Sequential()
```

Adding CNN Layers

```
model.add(Conv2D(32,(3,3),activation='relu',strides=(1,1),input_shape=(64,64,3)))
model.add(MaxPool2D(pool_size=(2,2)))
```


image_preprocessing22.ipynb
WhatsApp
colab.research.google.com/drive/1-enO3_iXMS21T_i-hOstsasaFgzPvbhO#scrollTo=wO6rKNC-Onwg
image_preprocessing22.ipynb
File Edit View Insert Runtime Tools Help Last edited on November 13
Comment Share
+ Code + Text
Connect Editing
Configuring ImageDataGenerator Class
train_datagen=ImageDataGenerator(rescale=1./255,zoom_range=0.2,vertical_flip=True,horizontal_flip=True)
test_data=ImageDataGenerator(rescale=1./255)
Applying ImageDataGenerator Functionality To Trainset And Testset
x_train=train_datagen.flow_from_directory(r"/content/data/train",target_size=(64,64),class_mode= "categorical" ,batch_size=128)
Found 15341 images belonging to 6 classes.
x_test=test_data.flow_from_directory(r"/content/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}
Type here to search
29°C ENG 15:03 17-11-2022


image_preprocessing22.ipynb
WhatsApp
colab.research.google.com/drive/1-enO3_iXMS21T_i-hOstsasaFgzPvbhO#scrollTo=1-_uhLkOTkZ7
image_preprocessing22.ipynb
File Edit View Insert Runtime Tools Help Last edited on November 13
Comment Share
+ Code + Text
Connect Editing
from google.colab import drive
drive.mount('/content/Drive')
Mounted at /content/Drive
!unzip '/content/Drive/MyDrive/Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation.zip'
Streaming output truncated to the last 5000 lines.
inflating: data/train/Premature Ventricular Contractions/fig_1532.png
inflating: data/train/Premature Ventricular Contractions/fig_1533.png
inflating: data/train/Premature Ventricular Contractions/fig_1534.png
inflating: data/train/Premature Ventricular Contractions/fig_1535.png
inflating: data/train/Premature Ventricular Contractions/fig_1536.png
inflating: data/train/Premature Ventricular Contractions/fig_1537.png
inflating: data/train/Premature Ventricular Contractions/fig_1538.png
inflating: data/train/Premature Ventricular Contractions/fig_1539.png
inflating: data/train/Premature Ventricular Contractions/fig_154.png
inflating: data/train/Premature Ventricular Contractions/fig_1540.png
inflating: data/train/Premature Ventricular Contractions/fig_1541.png
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inflating: data/train/Premature Ventricular Contractions/fig_1549.png
inflating: data/train/Premature Ventricular Contractions/fig_155.png
inflating: data/train/Premature Ventricular Contractions/fig_1550.png
Type here to search
29°C ENG 15:03 17-11-2022

7.1 FEATURE 1

- To examine the arrhythmia classification techniques as practically implemented.
- Identify the latest research trends and publication interests based on arrhythmia classification.
- To overview the existing research studies based on arrhythmia classification benefits and research direction.
- Identifying and selecting the best-suited articles that match the primary objectives of this research study are to identify the latest trends of deep neural networks for arrhythmia classification techniques.
- Can be easily added to modified.
- Delivering more preventive care.
- Improved efficiency for patients and providers.
- Provides a more efficient management for the professionals.
- Conveniently monitor and manage long term patient care.

7.2 Feature 2

- we use Convolutional Neural Network (CNN) a DL algorithm which is efficient in classifying signals
- Electrocardiography as a diagnostic tool for detecting heart disease is increasingly supported by algorithms based on machine learning.
- Identifies rhythm disturbances and electrolyte imbalance.
- ECG uses wires and probes for testing, it restricts body movements.
- Machine gives you digitalized results and the receipts with in minutes.
- ECGs are safe, noninvasive, painless tests and have no major risks.
- It can also categorize according to Risk levels.
- Can reduce the time of the Doctor and Patient visit.
- It is quick, safe and painless test, it provides static picture which may not reflect severe underlying heart issues related to patient.

TESTING

8.1 Use cases

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	12	5	3	2	22
Duplicate	1	0	2	0	3
External	2	3	0	1	6
Fixed	11	2	4	20	37
Not Reproduced	0	0	1	0	1
Skipped	0	0	1	1	2
Won't Fix	0	5	2	1	8
Totals	26	15	14	25	79

8.2 USER ACCEPTANCE TESTING

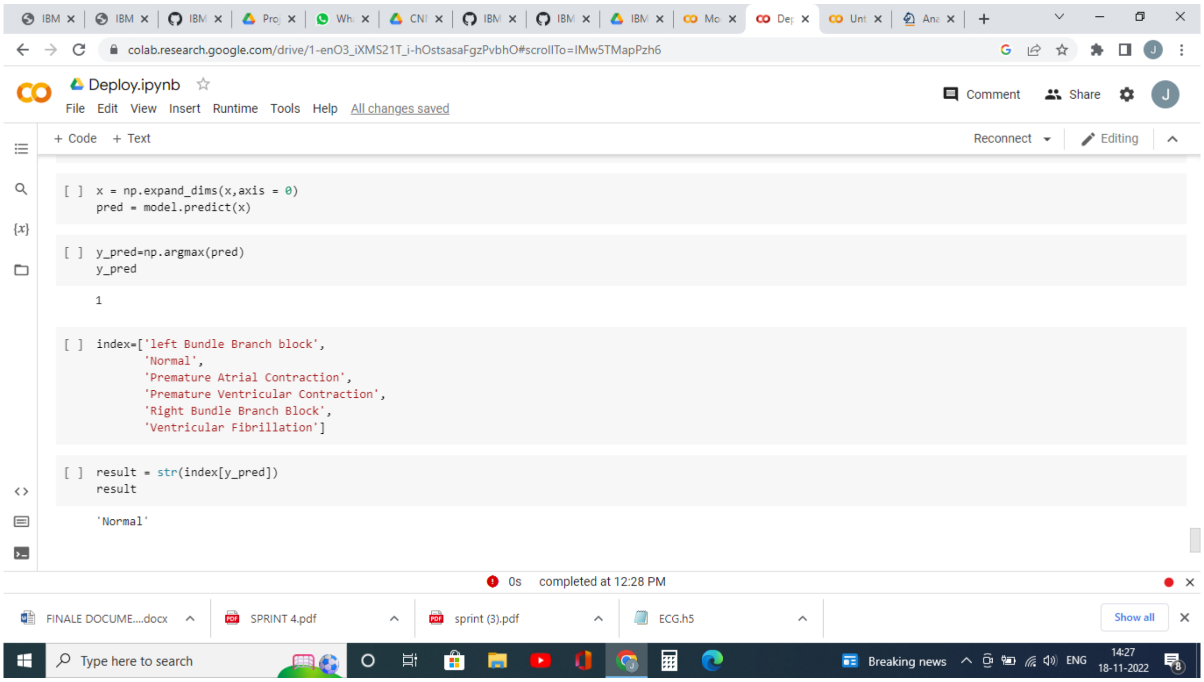
Test Case Analysis

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

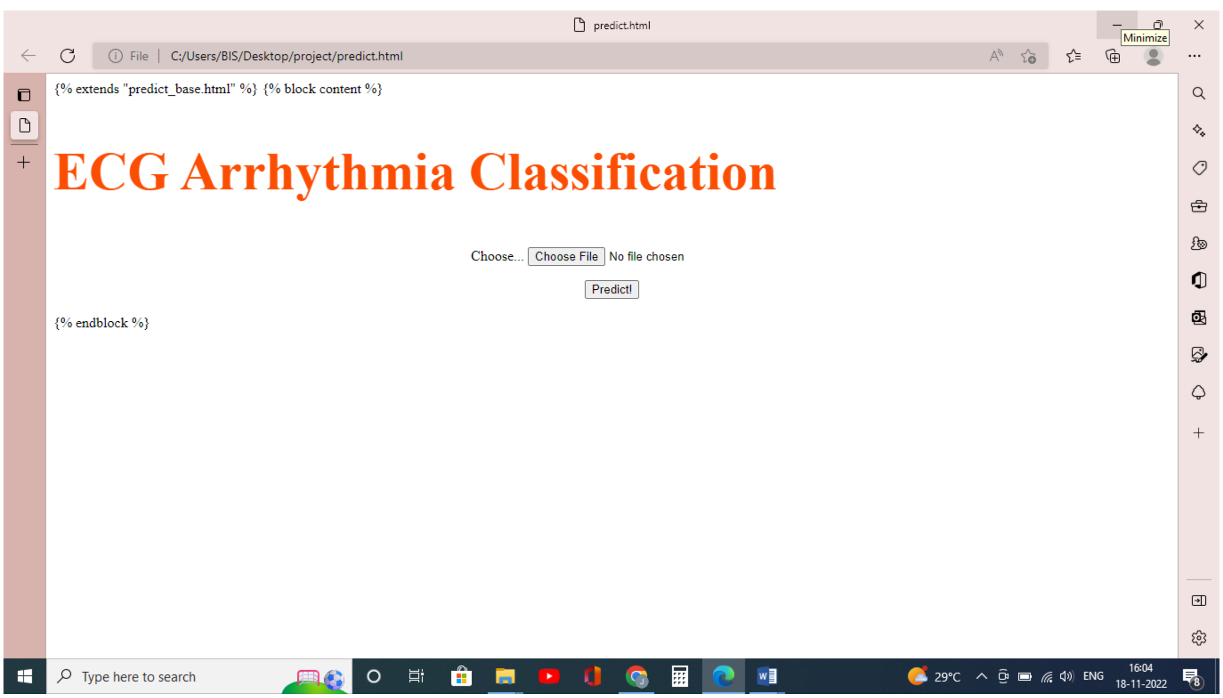
Section	Total Cases	Not Tested	Fail	Pass
Print Engine	5	0	0	5
Client Application	50	0	0	50
Security	3	0	0	3
Outsource Shipping	3	0	0	3
Exception Reporting	7	0	0	7
Final Report Output	5	0	0	5
Version Control	2	0	0	2

RESULTS

Performance Metrics



Predicted as normal



Web application

ADVANTAGES & DISADVANTAGES

ADVANTAGES:

- Arrhythmia is broadly categorized into bradyarrhythmias and tachyarrhythmia based on the heart rate. They are further divided according to the origin, means of transmission, and syndromes associated with it.
- Classification of electrocardiogram (ECG) signals plays an important role in clinical diagnosis of heart disease.
- An arrhythmia means the heart is not beating in the proper rhythm. This can cause anything from minor symptoms all the way to cardiac arrest and death. Since different rhythm disturbances need different treatments, diagnosing the precise type of arrhythmia is important.
- It can detect at a early stage and prevent the patients.

DISADVANTAGES:

- In general, complications of heart arrhythmias may include stroke, sudden death and heart failure. Heart arrhythmias are associated with an increased risk of blood clots. If a clot breaks loose, it can travel from the heart to the brain, causing a stroke.
- If not treated, arrhythmias can damage the heart, brain, or other organs. This can lead to life-threatening stroke, heart failure, or cardiac arrest. During cardiac arrest, the heart suddenly and unexpectedly stops beating, causing death if it is not treated within minutes.
- Arrhythmias are more common in people who are aged 60 years and older. It's in part due to wear and tear of an older heart. Other health or heart problems may also play a role. People who are older are more likely to have many health problems.

CONCLUSION

In medical practices, heart monitoring system plays vital role to diagnosis the heart arrhythmias problems. In this paper, we developed a model for identify the different heart arrhythmias abnormalities. For the computational analysis ECG records are utilized the MIT-BIH arrhythmia dataset which contain 16 different subclasses.

They are reducing the noise and obtaining the QRS beats using the adaptive threshold technique. The extracted features are fed into a simple back propagation neural network to classify the input ECG beats. The accuracy level of final result is obtained as 98% with proposed system general sparsed neural network.

It is demonstrated that the general sparsed neural network can efficiently classify and predict the different arrhythmia conditions. The general sparsed neural network (GSNN) has been very helpful with great precision and speed in implementing Arrhythmia disease. The developed model will be very helpful in medical practitioner to read the ECG signal to gives the more details about the heart problems.

FUTURE SCOPE

The future works will include performance enhancement by examining and comparing the classification accuracy of ECG beat classification algorithm with other classifier using deep learning. This project will have a greater scope in identifying and detecting the disease early life stage. In this modern world, everything is becoming digital, so this model will have a great scope.

- with time and research opportunities, unsupervised learning methods may deliver models that will closely mimic human behavior. The apparent conflict between consumer data protection laws and research needs of high volumes of consumer data will continue.
- This Disease Prediction system can be used for urgent guidance on their illness according to the details and symptoms they will feed to the web-based application. Here, some intelligent data processing techniques are used to get the most accurate disease that would be related to the patient's details.
- By analyzing how data is filtered through an ANN's layers and how the layers interact with one another, a DL algorithm can 'learn' to make correlations and connections in the data. These capabilities make DL algorithms innovative tools with the potential to change healthcare.

APPENDIX

Source Code

Import the Libraries:

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

Adding CNN Layers:

```
model = Sequential()
model.add(Convolution2D(32,(3,3),input_shape = (64,64,3),activation =
"relu"))
model.add(MaxPooling2D(pool_size = (2,2)))
model.add(Convolution2D(32,(3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Flatten()) # ANN Input...
```

Adding Dense Layers:

```
model.add(Dense(units = 128,kernel_initializer = "random_uniform",activation
= "relu"))
model.add(Dense(units = 128,kernel_initializer = "random_uniform",activation
= "relu"))
model.add(Dense(units = 128,kernel_initializer = "random_uniform",activation
= "relu"))
model.add(Dense(units = 128,kernel_initializer = "random_uniform",activation
= "relu"))
model.add(Dense(units = 128,kernel_initializer = "random_uniform",activation
= "relu"))
```

Adding Output Layer:

```
model.add(Dense(units = 6,kernel_initializer = "random_uniform",activation =
"softmax"))
model.summary()
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 62, 62, 32)        896

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

```
 conv2d_1 (Conv2D)           (None, 29, 29, 32)        9248

 max_pooling2d_1 (MaxPooling  (None, 14, 14, 32)       0
 2D)

 flatten (Flatten)           (None, 6272)              0

 dense (Dense)               (None, 128)               802944

 dense_1 (Dense)             (None, 128)               16512

 dense_2 (Dense)             (None, 128)               16512

 dense_3 (Dense)             (None, 128)               16512

 dense_4 (Dense)             (None, 128)               16512

 dense_5 (Dense)             (None, 6)                 774

=================================================================
Total params: 879,910
Trainable params: 879,910
Non-trainable params: 0
_________________________________________________________________
model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accu
racy'])
```

Train the model:

```
model.fit_generator(generator=x_train,steps_per_epoch = len(x_train),
epochs=9, validation_data=x_test,validation_steps = len(x_test))
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: UserWarning:
`Model.fit_generator` is deprecated and will be removed in a future version.
Please use `Model.fit`, which supports generators.
  """Entry point for launching an IPython kernel.
Epoch 1/9
480/480 [==============================] - 41s 66ms/step - loss: 1.3631 - acc
uracy: 0.5007 - val_loss: 1.6149 - val_accuracy: 0.4544
Epoch 2/9
480/480 [==============================] - 31s 65ms/step - loss: 0.7976 - acc
uracy: 0.6908 - val_loss: 0.9267 - val_accuracy: 0.6988
Epoch 3/9
480/480 [==============================] - 34s 71ms/step - loss: 0.3399 - acc
uracy: 0.8819 - val_loss: 0.6958 - val_accuracy: 0.7965
Epoch 4/9
480/480 [==============================] - 30s 63ms/step - loss: 0.2286 - acc
uracy: 0.9223 - val_loss: 0.5724 - val_accuracy: 0.8095
Epoch 5/9
480/480 [==============================] - 30s 63ms/step - loss: 0.1798 - acc
uracy: 0.9439 - val_loss: 0.4829 - val_accuracy: 0.8488
Epoch 6/9
```

```
480/480 [==============================] - 30s 63ms/step - loss: 0.1416 - acc
uracy: 0.9555 - val_loss: 0.5124 - val_accuracy: 0.8549
Epoch 7/9
480/480 [==============================] - 30s 62ms/step - loss: 0.1068 - acc
uracy: 0.9662 - val_loss: 0.5708 - val_accuracy: 0.8585
Epoch 8/9
480/480 [==============================] - 30s 63ms/step - loss: 0.0917 - acc
uracy: 0.9710 - val_loss: 0.4615 - val_accuracy: 0.8714
Epoch 9/9
480/480 [==============================] - 30s 62ms/step - loss: 0.0796 - acc
uracy: 0.9750 - val_loss: 0.7387 - val_accuracy: 0.8535
```

Save the model:

```
#Saving Model.
model.save('ECG.h5')
```

Testing the model:

```
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
model=load_model('ECG.h5')
img=image.load_img("/content/fig_44.png",target_size=(64,64))
x=image.img_to_array(img)
img


import numpy as np
x=np.expand_dims(x,axis=0)
pred = model.predict(x)
y_pred=np.argmax(pred)
y_pred
1/1 [==============================] - 0s 151ms/step
4
index=['left Bundle Branch block',
       'Normal',
       'Premature Atrial Contraction',
       'Premature Ventricular Contraction',
       'Right Bundle Branch Block',
       'Ventricular Fibrillation']
result = str(index[y_pred])
result
'Right Bundle Branch Block'
```

GitHub & Project Demo Link

https://github.com/IBM-EPBL/SI-GuidedProject-5933-1665834113