

DYPIU

**Internship report**

**ECG HEART RATE CATEGORIZATION**

**Submitted to D Y Patil International University, Akurdi, Pune in partial fulfilment of full-time degree.**

Master of Computer Applications

**Submitted By:**

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Under the Guidance of

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This report is submitted for the partial fulfillment of DYPIU Internship, which is part of the First Year Master of Computer Applications curriculum, under my supervision and guidance.

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**DECLARATION**

I, hereby declare that the following Internship which is being presented in the Project entitled as **ECG HEART RATE CATEGORIZATION** is an authentic documentation of my own original work to the best of my knowledge. The following Internship and its report in part or whole, has not been presented or submitted by me for any purpose in any other institute or organization. Any contribution made to my work, with whom I have worked at D Y Patil International University, Akurdi, Pune is explicitly acknowledged in the report.

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i

**CERTIFICATE**



**CERTIFICATE OF COMPLETION**

This is to certify that **Kamna Singh** has done his/her internship at D Y Patil International University, Akurdi, from [16/04/2023] To [29/04/2023].

She has worked on a project titled **ECG HEART RATE CATEGORIZATION**. This project was aimed at **categorizing ECG images into normal and abnormal heart rate signals**. As part of the project, she has done **model building using deep learning.**

During her internship she has demonstrated her skills with self-motivation to learn new skills. Her performance exceeded our expectations and she was able to complete the project on time.

We wish her all the best for her upcoming career.

|  |  |  |
| --- | --- | --- |
| **(Dr. Vaishnaw Kale)** | **(Dr. Maheshwari Biradar)** | **(Dr. Bahubali Shiragapur)** |
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With due respect, we express our deep sense of gratitude to our respected guide and coordinator (Name of mentor), for his/her valuable help and guidance. We are thankful for the encouragement that he/she has given us in completing this **DYPIU Internship successfully**.

It is imperative for us to mention the fact that the report of internship could not have been accomplished without the periodic suggestions and advice of our project supervisor Dr. Vaishnaw Kale.

We are also grateful to our respected, Dr. Bahubali Shiragapur(Director), Dr. Maheshwari Biradar (HOD BCA & MCA), Mrs. Vaishali Kumar (Internship Coordinator), TPO Cell and Hon’ble Vice Chancellor, DYPIU, Akurdi, Prof. Prabhat Ranjan for permitting us to utilize all the necessary facilities of the college.

We are also thankful to all the other faculty, staff members and laboratory attendants of our department for their kind cooperation and help. Last but certainly not the least; we would like to express our deep appreciation towards our family members and batch mates for providing support and encouragement.

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**Abstract**

ECG (Electrocardiogram) is a reliable and efficient test for monitoring the activities inside the cardiovascular system. The ECG reports are used to measure the electrical activities of the heartbeat which can be useful for many important conclusions regarding the heart diseases. In the recent past, there has been a lot of attention for the classification of these heartbeats using the ECG reports. In the last few years, Artificial Intelligence and Machine Learning are serving a lot in the area of automation in the medical and health-care domain. Deep Learning techniques are really growing day-by-day and Neural Networks are one of the major advancements in it. Neural Networks are really efficient in the problems like classification and segmentation. This study proposes a Deep CNN based model for classification of heartbeat using the ECG reports in five different classes which correspond to the different types of arrhythmias that are according to the standards of AAMI-EC57. We have evaluated our model on the Physio net’s MIT-BIH and PTB Diagnostics datasets.

***Keywords: Data flow diagram, Convolutional Neural Network, Unified Modeling Language , 2D convolution layer , electrocardiogram, Streamlit***

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   1. **INTRODUCTION**

ECG was first invented in 1895 and it has gained a lot of popularity in analysis of cardiovascular system and the measurement of electrical activity of the heartbeat. An ECG report depends upon the signals generated by electrical activities of the heart during the heartbeat generation. This signal is used to predict the state of patient who is suffering from a heart disease. ECG reportsare really useful in the medical domain for revealing the facts about the heart of a human being.The data generated from this ECG report is a time series data and like other time series data it is very difficult to detect and categorize various wave-forms and morphology in the signal. Themanual analysis of these ECG reports can lead to mistakes due to lack of technical knowledgeand the complexity of the waveforms. Heart is considered as an important organ for human body. It pumps blood which transforms nutrients throughout the body. Heart diseases are verycommon since last few decades and due to hypertension and a lot of pressure on human beings,there are a lot of cases of heart related diseases everyday throughout the world and the analysisand diagnosis of types of disease is a slow procedure and will remain slow if the automationis not introduced here. Due to complexity of data and its visualization it is tough, complicated and time taking process for proper classification.

1. **Background**

The sub-domains of AI especially Deep Learning has been evolved a lot in last few years in the medical and health-care use-cases and it is also giving very good results. It provides doctors the ease to analyze the disease and treat it with great precision. This helps in providing better medical care. It also helps in discovering a new drug. It analyses a patient’s medical history and guides the doctor to provide the patient with better medical attention. It also comes handy in medical imaging like MRI scans, CT scans, ECG and all. It helps the doctor to diagnosis the dreadful disease and provides the patients with better medical attention. One of the biggest achievements of deep learning is detecting the Alzheimer’s disease as early as possible. Neural Networks are the most widely used algorithms in deep learning which has helped it a lot to grow. Computer Vision, Image Classification and Image Segmentation are some of the important applications of neural networks in various domains. These were the complex problems which was not possible to solve before deep learning. There are a lot of machines that detect heart disease by the help of machine learning and deep learning. There are a lot of methods by which a model can detect heart disease. It can detect by training on the X-Ray images of the diseased person , by taking important features like blood pressure, resting blood pressure and all. It can also predict the type of heart disease by the help of ECG signals. This paper mainly focuses on the classification of a heart disease named Arrhythmia, which is a disease related to the rate of heart beat. In this disease, the heart beats too quickly or slowly or in an irregular manner. When?

the heart beats too faster than normal range then it is called tachycardia and when it’s slower than faster than it is known as bradycardia. A very common type of arrhythmia is arterial fibrillation in which the heart beat becomes irregular and faster than normal. The main purpose of the study is to propose a methodology using a famous Deep Learning algorithm called CNN which will classify the type of heartbeat with the given ECG report data.

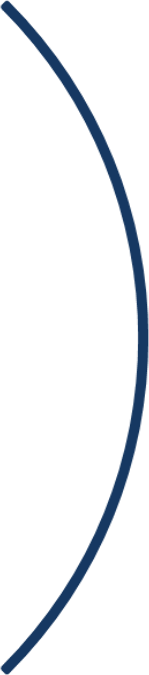
1. **Objectives**

The objective of an ECG categorization project is to develop a model that can accurately classify electrocardiogram (ECG) signals into different categories or classes. ECG signals represent the electrical activity of the heart and provide valuable information about its functioning. By categorizing ECG signals, we can diagnose various cardiac conditions or abnormalities.

The main goals of an ECG categorization project can include: 1. Classification: Develop a model that can classify ECG signals into different categories, such as normal ECG, arrhythmia, myocardial infarction, or other cardiac conditions. The model should accurately distinguish between different types of ECG patterns or abnormalities. 2. Accuracy: Achieve a high level of accuracy in ECG classification to ensure reliable and precise diagnosis. The model should be able to detect subtle changes or variations in ECG signals that might indicatespecific cardiac conditions. 3. Real-time Processing: Design an efficient model that can process ECG signals in real-time, allowing for quick analysis and diagnosis. Real-time processing is particularly important in applications such as remote monitoring or emergency situations where timely detection of cardiac abnormalities is critical. 4. Generalization: Develop a model that can generalize well to new and unseen ECG data from different patientsand sources. The model should not be overly specific to the training dataset but be able to handle variations and different ECG patterns that may arise in clinical practice. 5. Interpretability: Create a model that provides interpretable results, enabling healthcare professionals to understand the reasoning behind the classification decisions. This can aid in trust-building, decision- making, and enhancing the model’s acceptance in clinical settings.

1. **Purpose**

The purpose of ECG heart rate categorization is to accurately classify and categorize heart rates based on electrocardiogram (ECG) signals. ECG signals represent the electrical activity of the heart and provide valuable information about the heart’s functioning. By categorizing heart rates derived from ECG signals, we can gain insights into the heart’s health and identify abnormalities or conditions that may require medical attention. The main purposes of ECG heart rate categorization include:



Identification of Normal Heart Rates

Detection of Heart rate

Monitoring Heart Rate Variability

Clinical Decision Support

Remote Monitoring and Early Warning Systems.

ECG heartrate Categorization

1. **Scope**

The scope of heart rate categorization using deep learning and Streamlit is quite extensive, and it can have a significant impact on various applications in the healthcare and wellness domains. Here are some key aspects of the scope:

**Heart Rate Categorization**: Deep learning models can be trained to categorize heart rate data into different classes, such as normal, bradycardia (low heart rate), tachycardia (high heart rate), or arrhythmia (irregular heart rate). This categorization can aid in early detection and diagnosis of cardiac abnormalities, allowing for timely medical interventions.

**Remote Health Monitoring**: By integrating deep learning models for heart rate categorization with Streamlit, a web application framework, it becomes possible to create user-friendly interfaces for remote health monitoring. Patients can record their heart rate using wearable devices or smartphones, and the data can be analyzed in real-time using the deployed deep learning model via Streamlit.

**Personalized Health Insights:** Deep learning models can also be trained to recognize patterns in heart rate data and derive personalized health insights for individuals. For instance, it can identify trends in heart rate fluctuations related to stress, exercise, or sleep patterns, helping individuals understand their cardiovascular health better.

**Risk Assessment and Early Warning Systems:** A robust deep learning-based heart rate categorization system can serve as an effective risk assessment tool. By continuously monitoring and categorizing heart rate patterns, it can identify potential health risks and trigger early warning systems when anomalies are detected.

**Clinical Decision Support:** Deep learning models for heart rate categorization can complement the skills of healthcare professionals by providing additional insights and supporting clinical decision-making. Physicians can use the results to confirm or rule out specific diagnoses, leading to more accurate and efficient treatments.

**Research and Insights:** The data collected through the heart rate categorization system can be valuable for research purposes. Researchers can analyze large-scale datasets to gain insights into cardiovascular health trends, contributing to the advancement of medical knowledge and public health initiatives.

**User Interface and Accessibility:** Streamlit allows for the development of interactive and user- friendly web applications without extensive coding knowledge. It simplifies the deployment of deep learning models, making the heart rate categorization system accessible to a broader audience, including healthcare professionals, researchers, and individuals concerned about their heart health.

**Future Innovations:** The combination of deep learning and web-based frameworks like Streamlit opens up possibilities for continuous improvement and innovations in heart rate analysis. As deep learning models advance and more data becomes available, the accuracy and effectiveness of heart rate categorization systems are likely to improve further

1. **Applicability**

ECG categorization has wide applicability in various healthcare and clinical settings. Here are some areas where ECG categorization finds significant use: Cardiac Diagnosis: ECG categorization is crucial in diagnosing various cardiac conditions and abnormalities. It helps in identifying arrhythmias, myocardial infarctions, heart blocks, and other cardiac disorders. Categorizing ECG signals allows healthcare professionals to make accurate diagnoses and provide appropriate treatment plans.

**Risk Assessment:** ECG categorization aids in assessing the risk of cardiovascular events such as heart attacks or strokes. By analyzing ECG patterns and heart rate variability, the categorization process helps identify individuals at high risk and enables early intervention to prevent potential cardiac events.

**Remote Monitoring:** ECG categorization plays a significant role in remote patient monitoring systems. Wearable devices equipped with ECG sensors can continuously monitor heart activity and categorize ECG signals in real-time. This allows for early detection of abnormalities and timely medical interventions.

**Telemedicine:** ECG categorization supports telemedicine services by enabling remote ECG interpretation and diagnosis. Patients can transmit their ECG recordings to healthcare professionals electronically, who can then categorize and analyze the signals remotely, providing medical advice and recommendations.

**Personal Health Monitoring:** Individuals with cardiac conditions or those interested in monitoring their heart health can benefit from ECG categorization. Portable ECG devices or smartphone applications with ECG capabilities can categorize ECG signals on-demand, empowering individuals to track their heart health and seek medical attention if necessary.

**Fitness and Sports Performance Monitoring**: ECG categorization is relevant in the fitness and sports domain. Athletes and fitness enthusiasts can utilize ECG categorization to monitor heartrates during exercise, identify training intensity levels, track recovery, and optimize performance while ensuring cardiovascular health and safety.

**Clinical Trials and Research:** ECG categorization plays a vital role in clinical trials and researchstudies related to cardiac health. It helps in characterizing ECG patterns in different populations, evaluating the efficacy of new treatments or interventions, and identifying specific ECG markers associated with certain conditions.

**Health Screening Programs:** ECG categorization is valuable in large-scale health screening programs where a high volume of ECG data needs to be analyzed efficiently. Automated categorization enables quick screening and identification of individuals requiring further diagnostic tests or intervention

* 1. **INTERNSHIP PROJECT PLAN**
     1. **Problem Statement**

The problem is to develop an accurate and efficient ECG categorization system that can automatically classify electrocardiogram (ECG) signals into different categories for cardiac health assessment. The system aims to assist healthcare professionals in diagnosing various cardiac conditions and abnormalities, enabling timely interventions and improving patient outcomes. The goal of this project is to develop a robust and accurate ECG categorization system that can aid healthcare professionals in diagnosing cardiac conditions, monitoring patients, and providing timely interventions. The system should contribute to improving patient outcomes, reducing diagnostic errors, and enhancing the efficiency of cardiac health assessments.

* + 1. **Requirement Specification**

Hardware Requirements

Windows / linux Os

Processor with 1.7 - 2.4 Ghz speed

Minimum 8 Gb RAM

2Gb Graphic Card

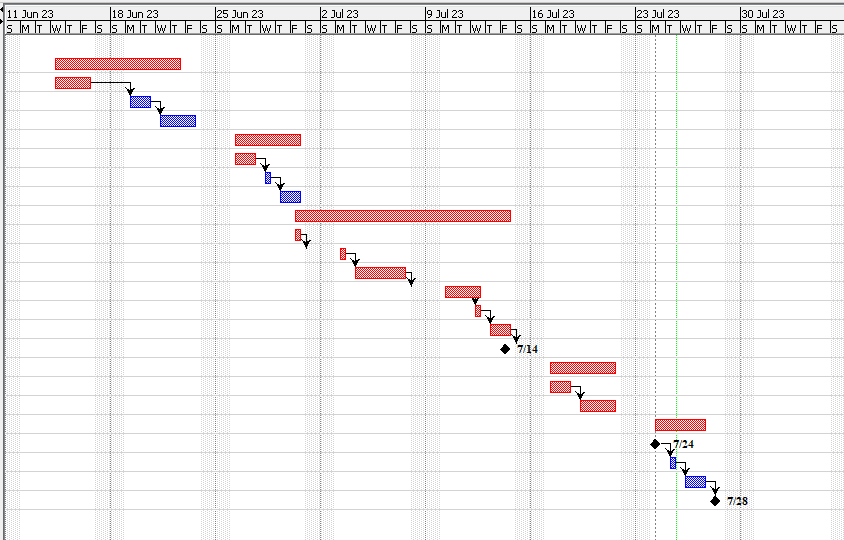
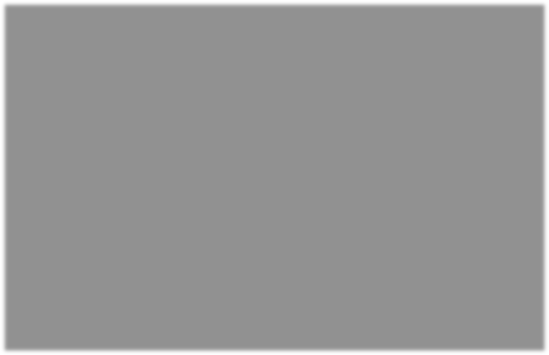
Software Requirements

Google Colab

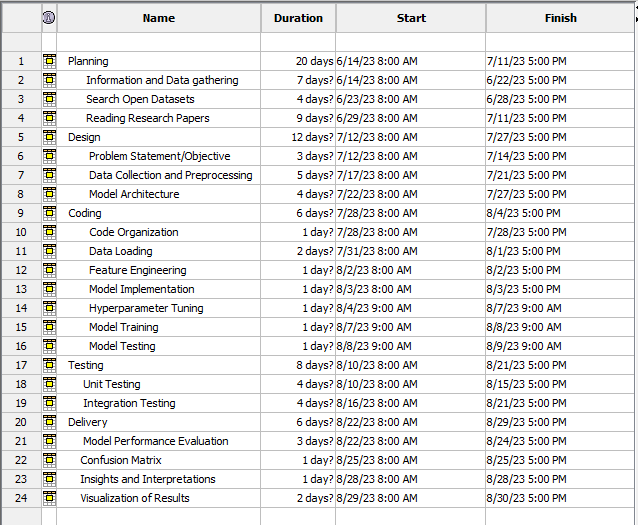
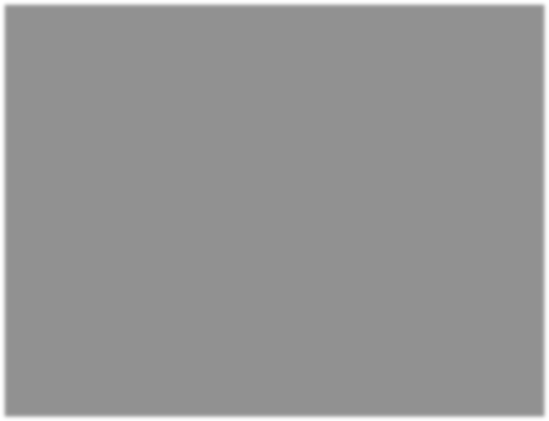
Python libraries: SKlearn, NumPy, Streamlit, TensorFlow, Keras, ngrok

Requirements Hardware & Software

* + 1. **Timeline chart**

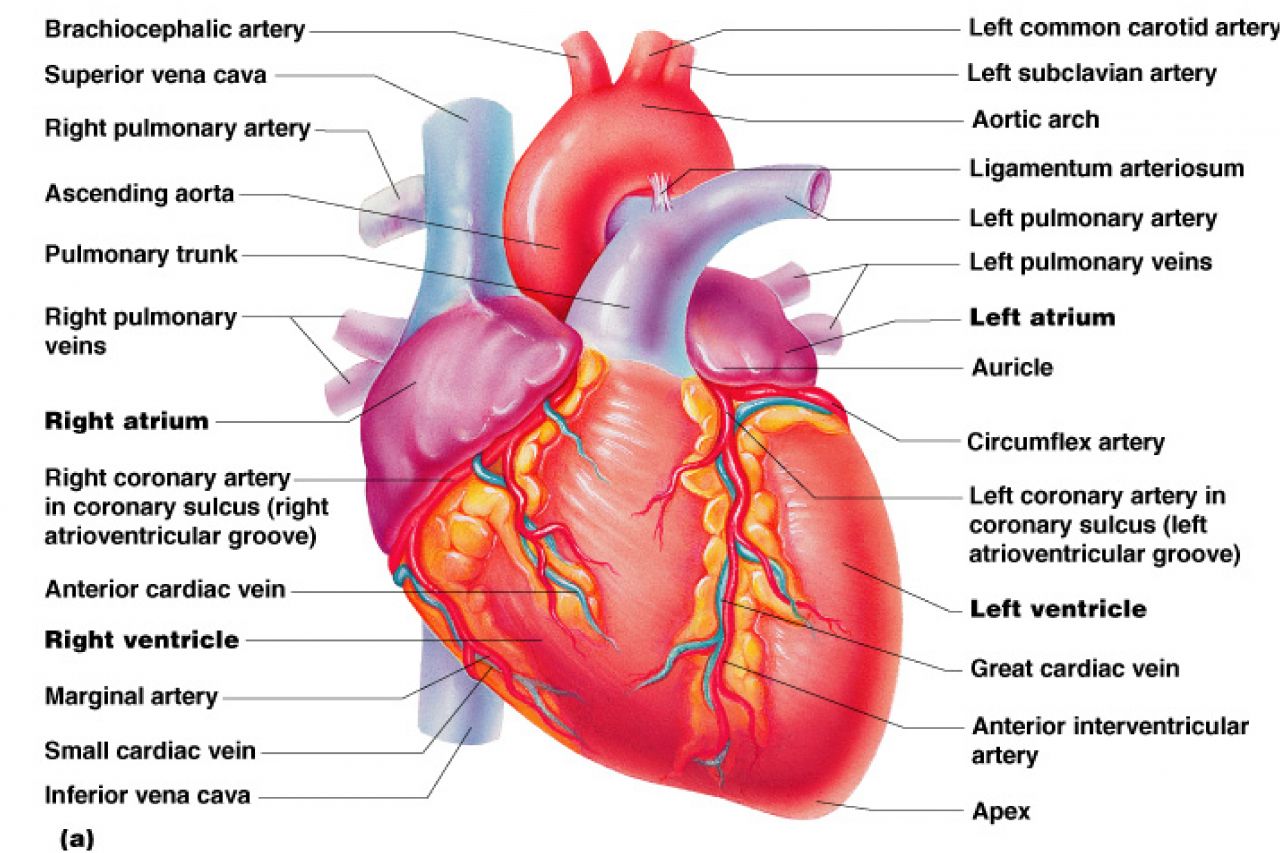


Project Timeline



Gantt Chart Details

1. **. PROPOSED SYSTEM AND METHODOLOGY**
   1. **Anatomy of heart**



Heart Anatomy

The "Anatomy of the Heart" refers to the structure and components of the human heart. The heart is a vital organ that functions as the primary pump responsible for circulating blood throughout the body. It is a muscular organ located in the chest cavity, slightly to the left of the midline. Below, I'll provide an overview of the anatomy of the heart:

Pericardium: The heart is surrounded by a double-walled sac called the pericardium. The outer layer is the fibrous pericardium, which provides protection and anchoring for the heart. The inner layer, the serous pericardium, consists of two layers: the parietal layer (lining the fibrous pericardium) and the visceral layer (also known as the epicardium, which covers the heart's surface).

* Heart Wall: The heart wall is composed of three layers:
* Epicardium: The outermost layer, forming the visceral layer of the pericardium.
* Myocardium: The middle layer, consisting of cardiac muscle tissue responsible for the heart's contraction and pumping action.
* Endocardium: The innermost layer, a smooth endothelial lining that lines the heart chambers and heart valves.
* Heart Chambers: The heart has four chambers, divided into two atria and two ventricles:
* Right Atrium: Receives deoxygenated blood from the body through the superior and inferior vena cava.
* Left Atrium: Receives oxygenated blood from the lungs through the pulmonary veins.
* Right Ventricle: Pumps deoxygenated blood to the lungs for oxygenation.
* Left Ventricle: Pumps oxygenated blood to the rest of the body.
* Heart Valves: The heart has four valves that ensure one-way blood flow through the heart:
* Tricuspid Valve: Located between the right atrium and right ventricle.
* Pulmonary Valve: Located between the right ventricle and the pulmonary artery.
* Mitral (Bicuspid) Valve: Located between the left atrium and left ventricle.
* Aortic Valve: Located between the left ventricle and the aorta.
* Blood Vessels: Blood vessels connected to the heart include:
* Superior and Inferior Vena Cava: Bring deoxygenated blood from the upper and lower body to the right atrium.
* Pulmonary Arteries: Carry deoxygenated blood from the right ventricle to the lungs for oxygenation.
* Pulmonary Veins: Return oxygenated blood from the lungs to the left atrium.
* Aorta: Carries oxygenated blood from the left ventricle to the rest of the body.
* Coronary Arteries: These arteries supply oxygenated blood to the heart muscle itself, ensuring its nourishment and function.
  1. **Difference between normal heart rate and abnormal heart rate**

The difference between a normal heart rate and an abnormal heart rate lies in the number of heart beats per minute (bpm) and the regularity of the heart's rhythm. The heart rate is the number of times the heart contracts or beats in one minute, and it can vary depending on factors like age, fitness level, emotions, and health conditions.

Normal Heart Rate: In adults, a normal resting heart rate typically ranges between 60 to 100 beats per minute. However, for well-trained athletes, it may be lower, around 40 to 60 bpm, as their hearts are more efficient at pumping blood. In newborns, the normal heart rate can be higher, ranging from 100 to 160 bpm, which gradually decreases with age.

Abnormal Heart Rate: An abnormal heart rate, also known as arrhythmia, refers to any irregularity in the heart's rhythm. It can be characterized by:

a. Bradycardia: A heart rate that is too slow, usually below 60 bpm in adults. In some cases, a slow heart rate may not cause any problems, especially in well-conditioned individuals. However, it can also be a sign of an underlying health issue or heart disease.

b. Tachycardia: A heart rate that is too fast, typically above 100 bpm in adults. This rapid heartbeat may not allow the heart enough time to fill with blood properly, compromising its ability to pump effectively. Tachycardia can be caused by various factors, such as stress, fever, stimulant use, certain medications, or heart-related conditions.

c. Arrhythmias: These are irregular patterns in the heart rate, where the heartbeat may be too fast, too slow, or erratic. There are different types of arrhythmias, and they can lead to various symptoms and health complications.

d. Flutter or Fibrillation: These are specific types of rapid and irregular heart rhythms that can significantly affect the heart's ability to pump blood efficiently. Atrial flutter and atrial fibrillation are common examples.

It's essential to note that an abnormal heart rate doesn't always indicate a severe problem, and some people may live with mild arrhythmias without any significant issues. However, if you notice persistent irregularities in your heart rate, experience symptoms like dizziness, chest pain, shortness of breath, or fainting, it's crucial to seek medical attention to assess the underlying cause and receive appropriate treatment if necessary. Only a healthcare professional can provide accurate diagnosis and advice based on an individual's specific situation.

* 1. **Orthodox method to check normal and abnormal heart rate**

The orthodox method to check normal and abnormal heart rate is through the measurement of the pulse or heartbeats per minute (bpm). There are several ways to do this:

Palpation of the Pulse: Place your index and middle fingers on the radial artery, which is located on the wrist just below the base of the thumb. Press lightly until you feel a pulsating sensation, and then count the number of beats you feel in 60 seconds. This will give you the heart rate in beats per minute.

Using a Heart Rate Monitor: Wear a heart rate monitor that tracks your heart rate continuously or use a fitness tracker with heart rate monitoring capabilities. These devices can provide real-time heart rate data and may offer additional features like tracking exercise intensity and heart rate variability.

Electrocardiogram (ECG or EKG): An ECG is a medical test that records the electrical activity of the heart. It is typically done in a medical setting, such as a doctor's office or a hospital. Electrodes are placed on the chest, arms, and legs to measure the heart's electrical signals and identify any irregularities in the heart rhythm.

Holter Monitor: A Holter monitor is a portable device that records the heart's electrical activity over an extended period, usually 24 to 48 hours. It provides a continuous ECG recording, allowing doctors to assess the heart's activity during various activities and while sleeping.

Stress Test: A stress test involves monitoring the heart's activity while the person exercises on a treadmill or stationary bike. It helps evaluate how the heart responds to physical activity and can detect abnormal heart rate patterns that may not be apparent at rest.

Remember that a single measurement of heart rate might not always provide a complete picture of your heart health. Sometimes, heart rate can vary throughout the day due to factors such as physical activity, stress, emotions, and caffeine intake. If you have concerns about your heart rate or are experiencing symptoms like palpitations, dizziness, or chest pain, it's essential to consult a healthcare professional for a thorough evaluation and appropriate diagnosis.

* 1. **System Architecture**

The system architecture for heart rate categorization using deep learning and Streamlit involves several components that work together to achieve the desired functionality. Below is a high- level overview of the architecture: Data Collection: The first step is to collect heart rate data from various sources. This data can be obtained from wearable devices, fitness trackers, mobile apps, or any other sensors capable of measuring heart rate.

**Data Preprocessing:** The collected heart rate data may require preprocessing to clean and prepare it for the deep learning model. Preprocessing steps may include data normalization, filtering, and feature extraction to represent the heart rate signals effectively.

**Deep Learning Model:** The heart rate data is fed into a deep learning model for categorization. The model can be designed using various architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), or a combination of both. The model is trained on a labeled dataset, where each heart rate sample is associated with its corresponding category (e.g., normal, bradycardia, tachycardia, arrhythmia).

**Model Training:** In this phase, the deep learning model is trained using the labeled dataset. Training involves feeding the data into the model, computing the loss (error), and updating the model’s parameters through optimization algorithms (e.g., stochastic gradient descent) to minimize the loss.

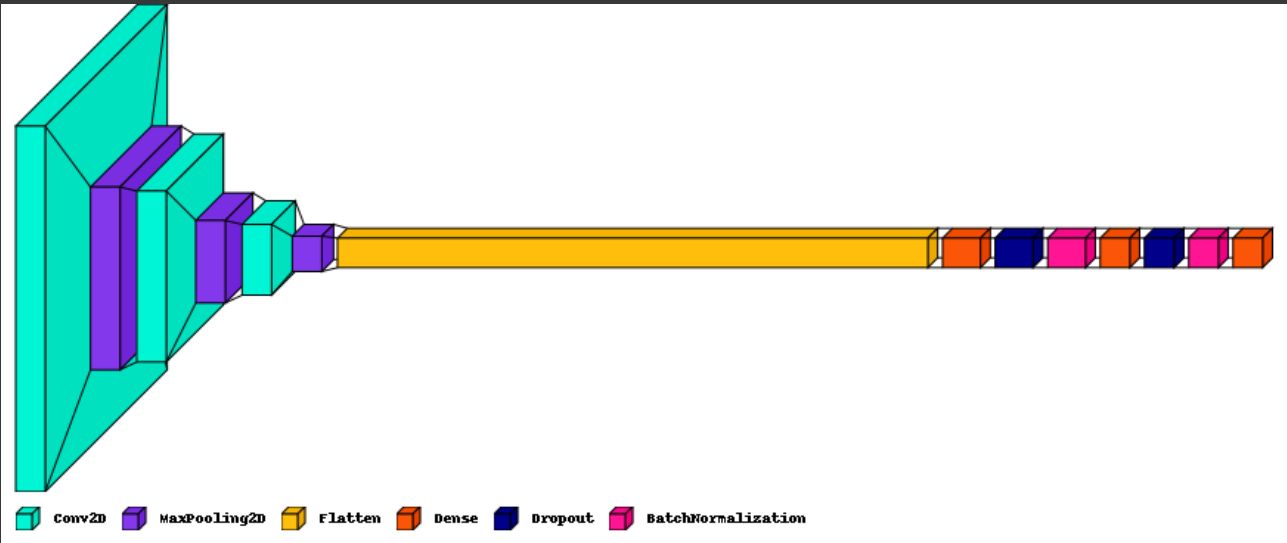
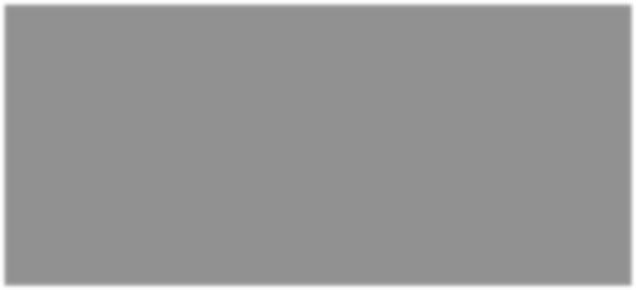
**Model Evaluation:** Once the model is trained, it is evaluated on a separate dataset (validation or test set) to assess its performance and generalization ability. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to measure the model’s effectiveness.

**Model Deployment:** The trained deep learning model is then saved and prepared for deployment. Popular deep learning frameworks like TensorFlow is commonly used for this purpose.

Streamlit Application: Streamlit is used to develop the user interface for the heart rate categorization system. It provides a simple way to create web applications using Python. The Streamlit app allows users to interact with the system, input their heart rate data, and visualize the categorization results.

* 1. **Methodology (Algorithms used)**
* **Algorithms used for model training**

A Convolutional Neural Network (CNN) is a type of deep learning model specifically designed for image recognition and computer vision tasks. CNNs are widely used in various applications, such as image classification, object detection, facial recognition, and more. They are highly effective in capturing spatial patterns and hierarchies in images, making them well-suited for tasks that involve extracting features from visual data.



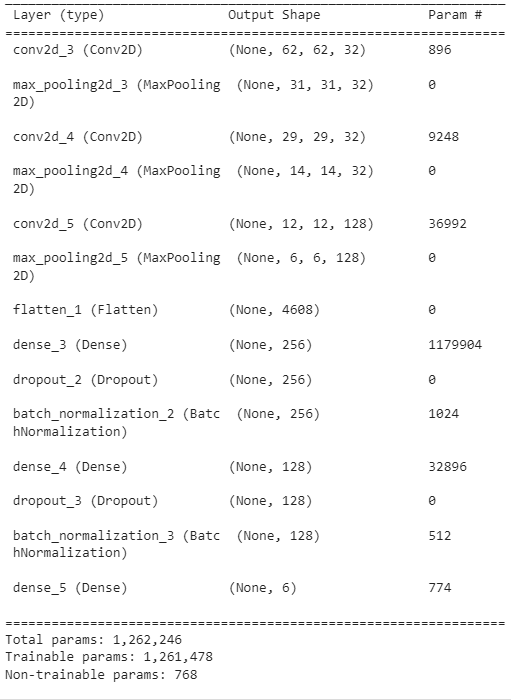
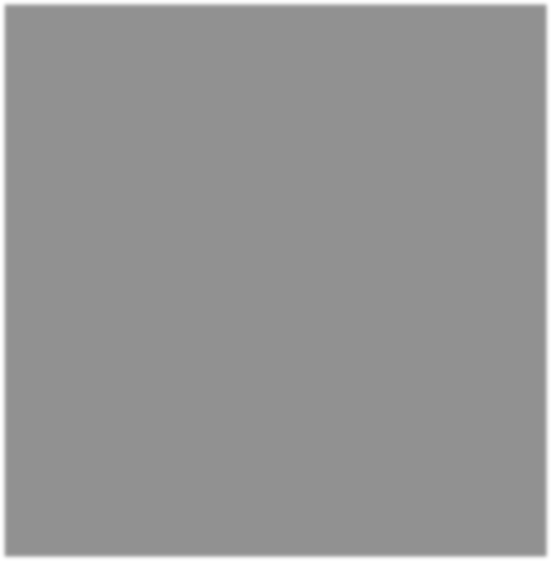
Convolutional Neural Network Architecture

1. **Input Layer:** The model takes input images of shape (height, width, channels), where the height and width are both 64 pixels (62x62), and there are 3 color channels (e.g., Red, Green, Blue). The number of channels (3) is typically used for RGB images.
2. **Convolutional Layers:**

conv2d\_**3:** This is the first convolutional layer with 32 filters (also knownas kernels) of size 3x3. It applies these filters to the input image and produces feature maps of size 62x62x32.

1. **max pooling2d\_3:** Following the convolution, this layer performs max pooling with a pool size of 2x2, which reduces the spatial dimensions by half. The output of this layer is 31x31x32.
2. **conv2d\_4:** The second convolutional layer also has 32 filters of size 3x3 and operates on the previous layer’s output, resulting in feature maps of size 29x29x32.
3. **max pooling2d\_4:** Another max pooling layer is applied, halving the spatial dimensions again, yielding an output of 14x14x32.
4. **conv2d\_5:** The third convolutional layer consists of 128 filters of size 3x3, which produces feature maps of size 12x12x128.
5. **max pooling2d\_5**: The third max pooling layer reduces the spatial dimensions to 6x6x128.
6. **Flatten Layer:** After the convolutional and max pooling layers, the Flatten layer is used to transform the 3D feature maps into a 1D vector of size 4608 (6 \* 6 \* 128).
7. **Dense Layers: dense 3**: This is a fully connected dense layer with 256 neurons. It takes the flattened input and applies weights to produce a hidden layer of size 256.
8. **dropout 2:** Dropout is applied to the output of the first dense layer to prevent overfitting by randomly setting a fraction of the neurons to zero during training.
9. **batch normalization\_2:** Batch normalization normalizes the outputs of the previous layer, aiming to stabilize and accelerate training.
10. **Dense\_4:** The second fully connected dense layer has 128 neurons.
11. **Dropout\_3:** Another dropout layer is applied to the output of the second dense. 13 **layer.batch normalization\_3:** Batch normalization is applied again.

**Output Layer:** The final dense layer consists of 6 neurons, which correspond to the number of classes the model needs to classify. The output of this layer represents the model’s predictionsfor the input images, with each neuron representing the probability of a particular class.



Convolutional Layers

* 1. **Implementation**
     1. **Data Flow Diagrams**

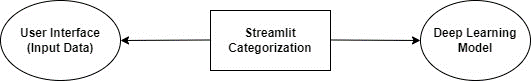
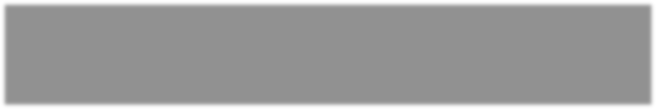


Fig 3.3.1.1 DFD LEVEL: 0

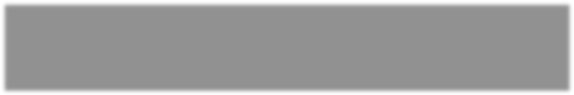


Figure 3.3.1.2 DFD LEVEL: 1

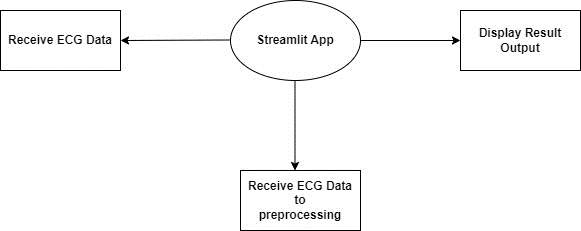
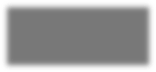


Figure 3.3.1.3 DFD LEVEL: 2

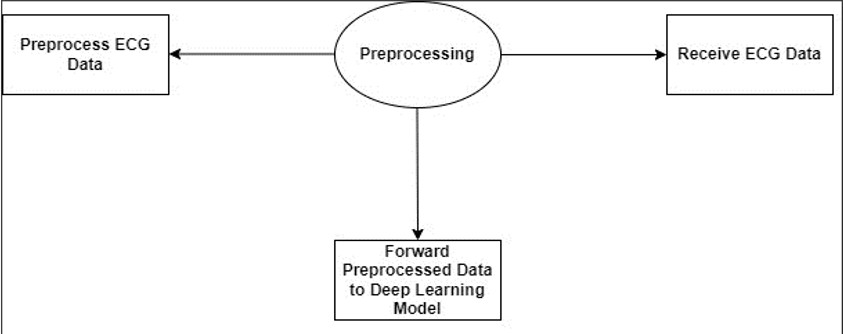


Figure 3.3.1.4 DFD LEVEL: 3

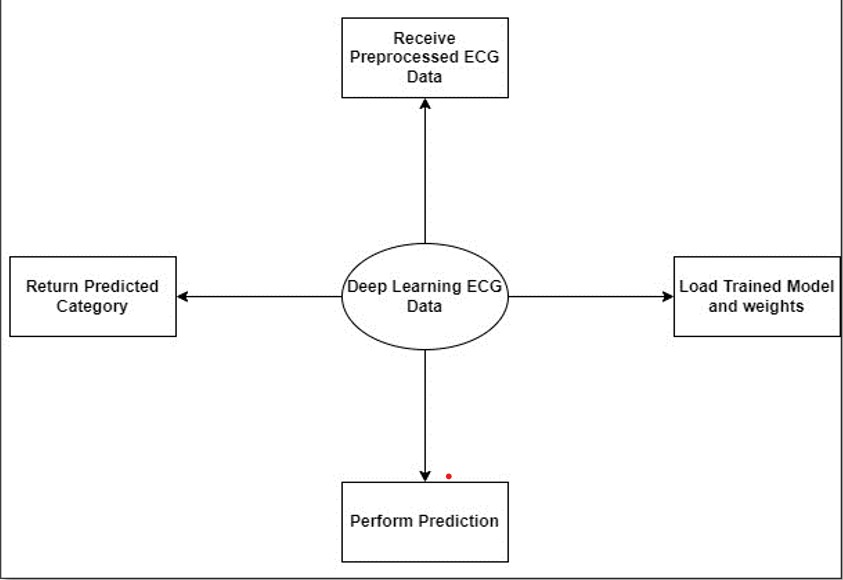


Figure 3.3.1.5 DFD LEVEL: 4

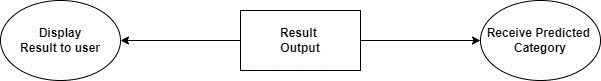


Figure 3.3.1.6 DFD LEVEL:5

* + 1. **UML Diagrams**

1. **Flow Chart Diagram**

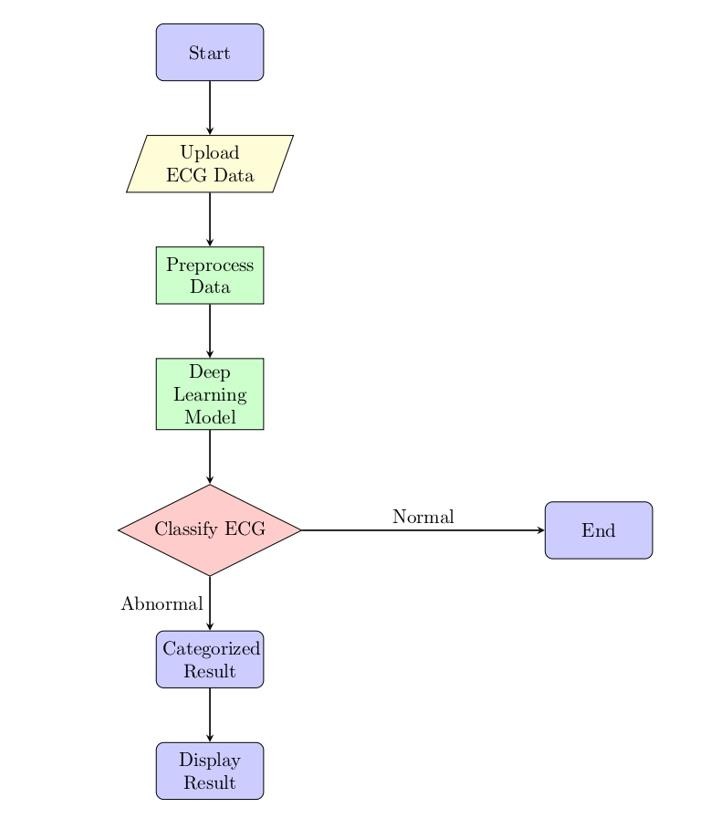
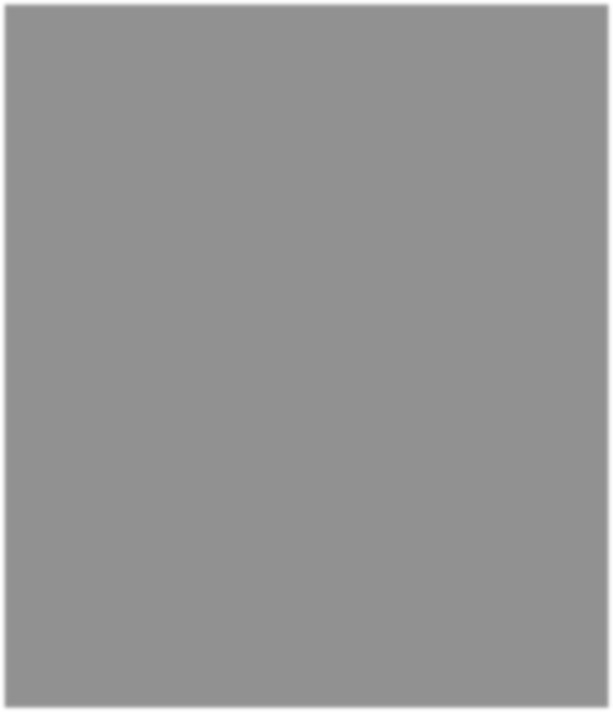


Figure 1: Flow Chart

# Use Case Diagram

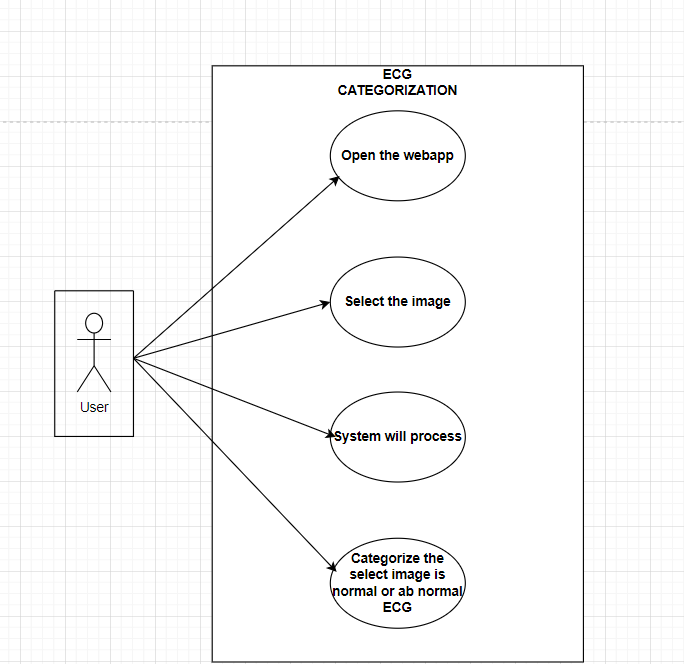
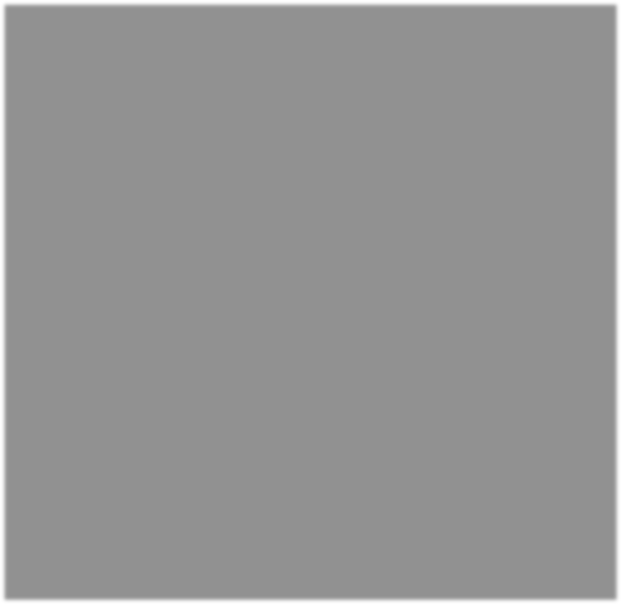


Figure 2: Use Case Diagram

# Sequence Diagram

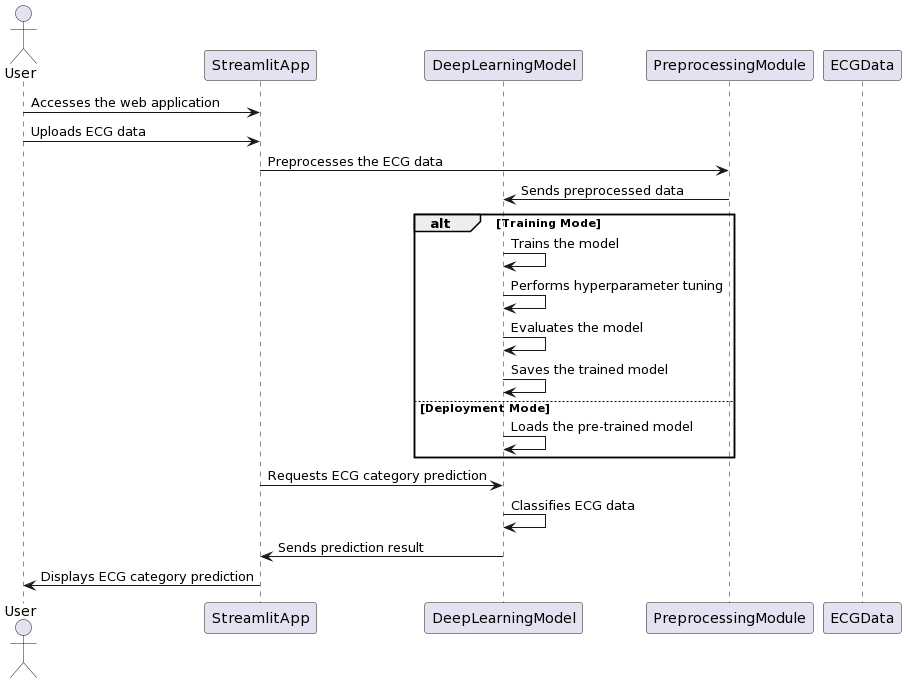
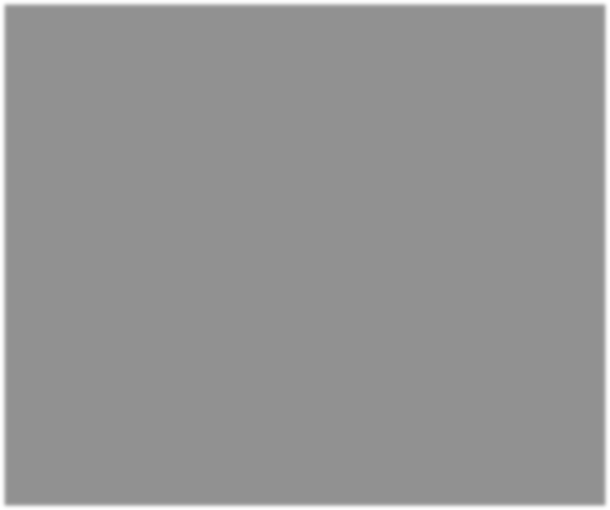


Figure 3: Sequence Diagram

# Activity Diagram

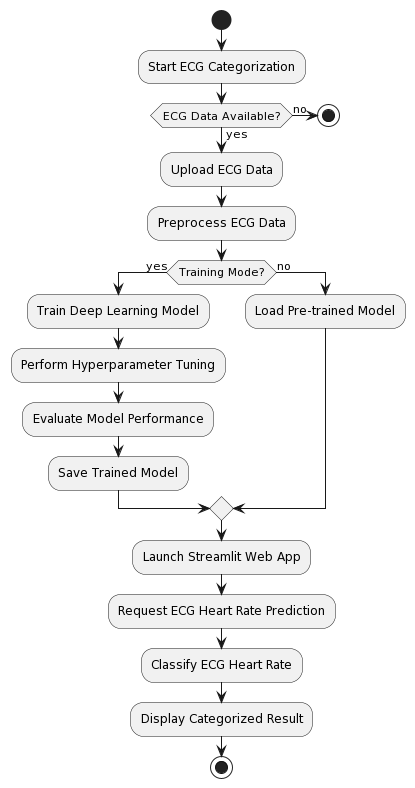
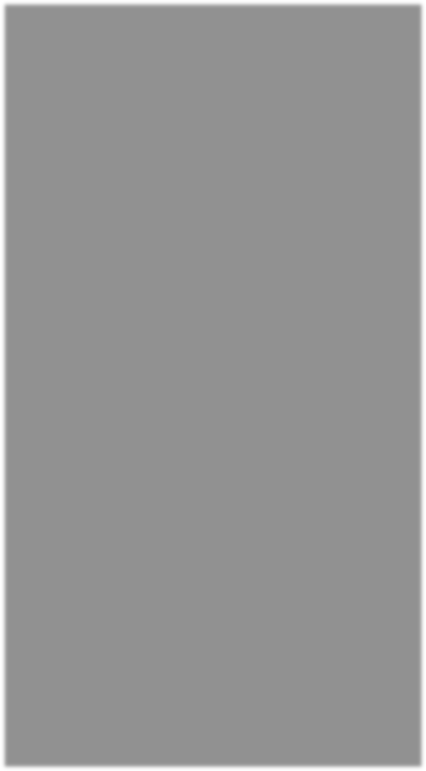


Figure 4: Activity Diagram

# Class Diagram

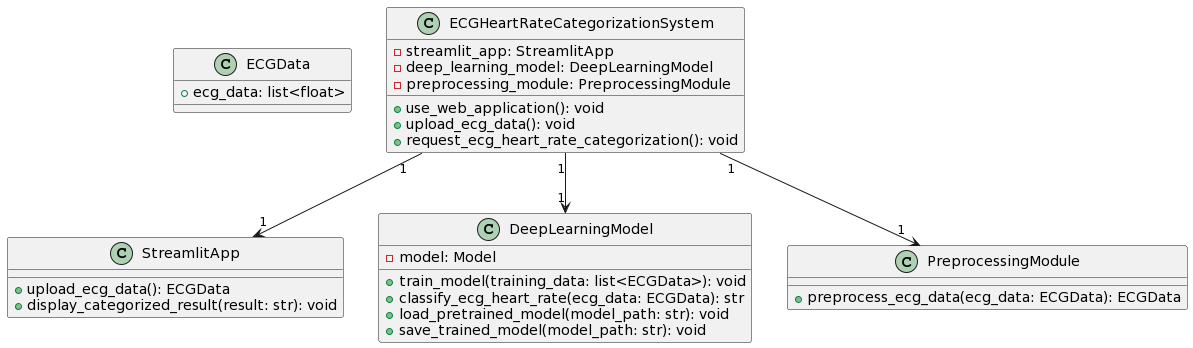
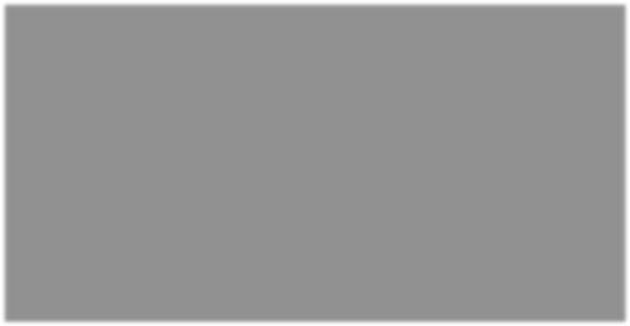


Figure 5: Class Diagram

# Component Diagram

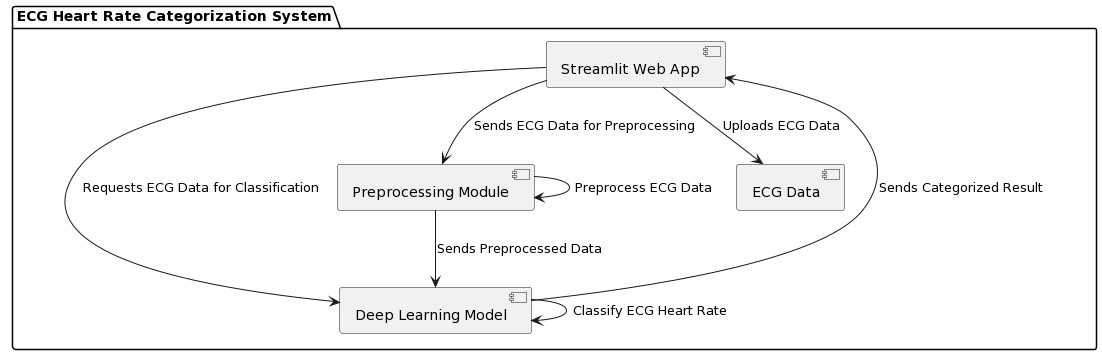
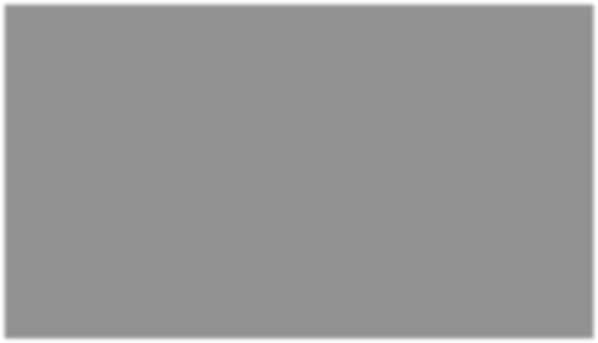


Figure 6 : Component Diagram

1. **RESULTS AND EXPLANATION**
   1. **Implementation Approaches**

**Data Collection and Preprocessing:** Gather a labeled dataset of ECG data, where each sample is associated with a heart rate category (e.g., normal, abnormal). You can source data from public datasets or collaborate with medical institutions to collect data. Preprocess the ECG data to ensure it is in a suitable format for deep learning analysis. This may involve tasks such as data normalization, denoising, filtering, and segmentation. Make sure to handle missing or noisy data appropriately.

**Deep Learning Model Development:** Choose an appropriate deep learning model architecture for heart rate categorization. Common choices include Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs). Split the dataset into training, validation, and test sets. Use the training set to train the model, the validation set to tune hyperparameters, and the test set to evaluate the model’s performance. Implement the chosen model using a deep learning framework like TensorFlow. Consider using pre-trained models or transfer learning if you have limited data.

**Model Training and Evaluation:** Train the deep learning model using the training dataset. Monitor the training process and validate the model’s performance on the validation set to avoid overfitting. Use appropriate evaluation metrics (e.g., accuracy, precision, recall, F1-score) to measure the model’s performance on the test set.

**Streamlit Web Application Development:** Set up a Streamlit development environment. Streamlit is a Python library for creating web applications with minimal effort. Create a Streamlit web application that serves as the user interface for the ECG heart rate categorization system. Implement user authentication functionality to ensure secure access to the system, especially if handling sensitive medical data.

**Integration of Deep Learning Model with Streamlit**: Load the trained deep learning model intothe Streamlit application. Implement the necessary preprocessing steps in the Streamlit app to prepare the uploaded ECG data for inference using the deep learning model.

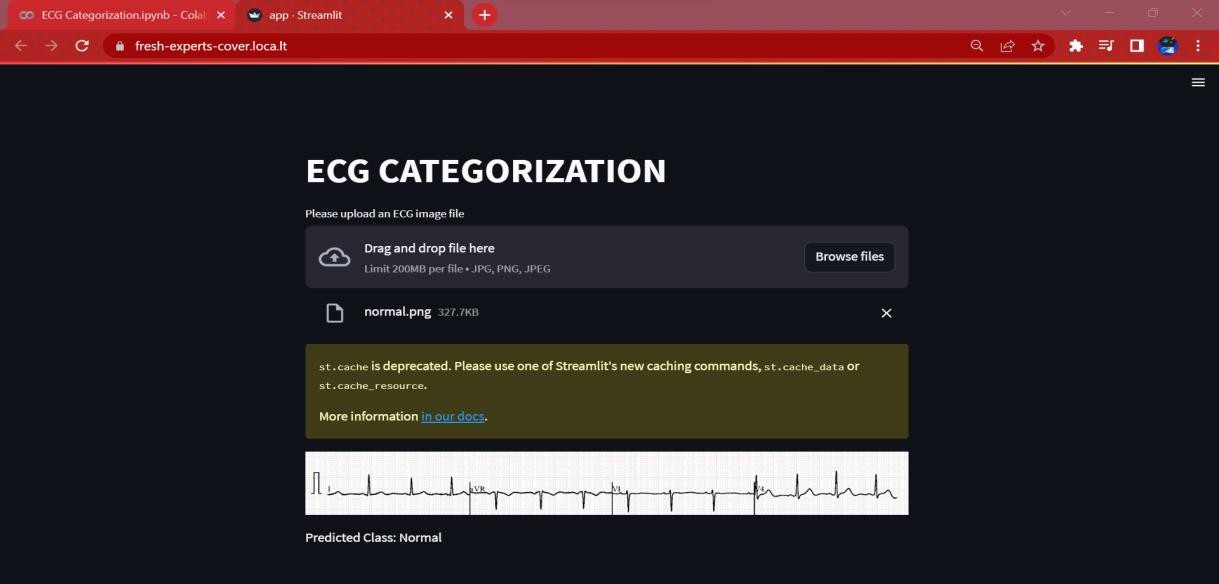
**Inference and Categorization**: Allow users to upload ECG data files through the Streamlit interface. Feed the preprocessed ECG data into the deep learning model for inference. Obtain heart rate categorization results from the model’s output. Visualize the results and heart rate categories in an interactive and informative manner using plots or graphical representations.

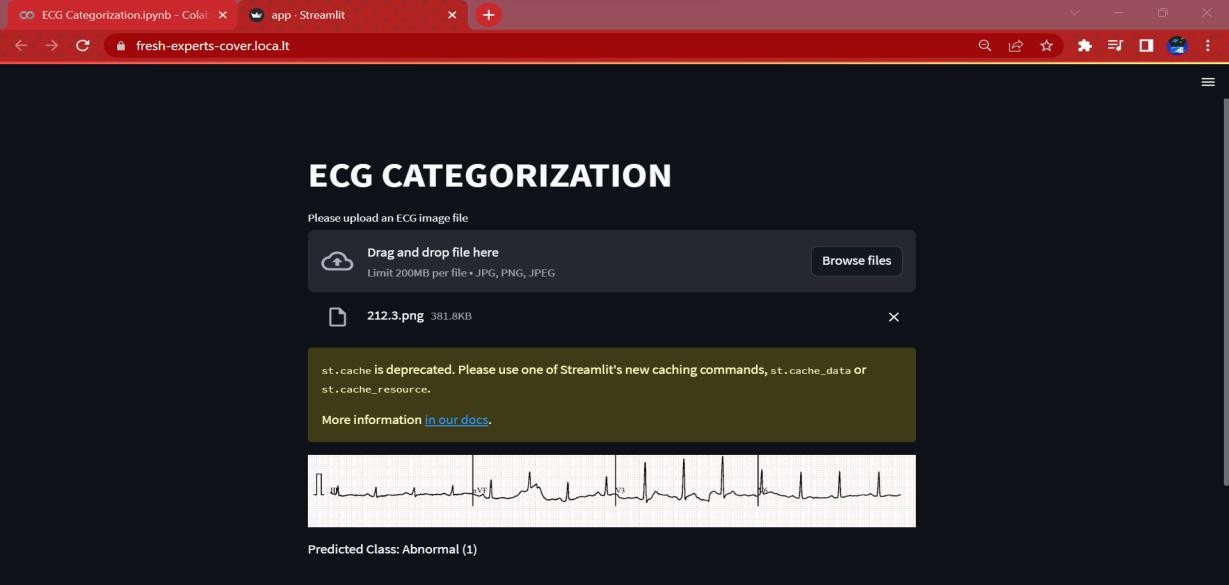
**Deployment:** Prepare the Streamlit web application for deployment on a web server or cloud platform. You can deploy the app using services like Heroku, AWS, or Azure. Ensure that the deployment environment meets the requirements for running the deep learning model and Streamlit application.

**Testing and Validation:** Conduct extensive testing of the application to ensure its functionality and accuracy. Validate the heart rate categorization results against ground truth labels to assess the model’s performance.

**Continuous Improvement and Maintenance:** Collect user feedback and iterate on the system to improve its usability and performance. Update the deep learning model periodically with new data and retrain it to enhance accuracy. Regularly maintain the application and ensure compatibility with the latest dependencies and libraries.

* **Results:**





* 1. **Coding Details**
* **Model building using deep learning**

**import** numpy **as** np

**import** pandas **as** pd

**import** tenccsorflow **as** tf

**from** PIL **import** Image**,** ImageOps

**from** IPython**.**display **import** display**,**clear\_output

**from** tensorflow**.**keras**.**models **import** Sequential

**from** tensorflow**.**keras**.**layers **import** Conv2D**,** MaxPooling2D**,** Flatten**,** Dense**,**

Dropout**,**BatchNormalization

**from** tensorflow**.**keras**.**optimizers **import** Adam

**from** tensorflow**.**keras**.**callbacks **import** LearningRateScheduler

**from** tensorflow**.**keras**.**preprocessing**.**image **import** ImageDataGenerator **from** tensorflow**.**keras**.**preprocessing**.**image **import** ImageDataGenerator train\_datagen **=** ImageDataGenerator**(**rescale **=** 1.**/**255**,**shear\_range **=** 0.2**,**zoom\_range **=** 0.2**,**horizontal\_flip **= True)**

test\_datagen **=** ImageDataGenerator**(**rescale **=** 1.**/**255**) import** matplotlib**.**pyplot **as** plt

test\_datagen **=** ImageDataGenerator**(**rescale**=**1.**/**255**)**

img **=** Image**.open(**'/content/drive/MyDrive/abnormal (1)/211.1 (1).png'**)** img\_array **=** np**.**array**(**img**)**

rescaled\_img\_array **=** test\_datagen**.**apply\_transform**(**img\_array**, {**'rescale'**:**

1.**/**255**})**

plt**.**figure**(**figsize**=(**10**,** 5**))**

plt**.**subplot**(**1**,** 2**,** 1**)** plt**.**imshow**(**img**)** plt**.**title**(**'Original Image'**)** plt**.**axis**(**'off'**)** plt**.**subplot**(**1**,** 2**,** 2**)**

plt**.**imshow**(**rescaled\_img\_array**)** plt**.**title**(**'Rescaled Image'**)** plt**.**axis**(**'off'**)**

plt**.**show**()** x\_train **=**

train\_datagen**.**flow\_from\_directory**(**"/content/drive/MyDrive/data/train"**,**target

\_size **= (**64**,**64**),**batch\_size **=** 32**,**class\_mode **=** "categorical"**)** x\_test **=**

test\_datagen**.**flow\_from\_directory**(**"/content/drive/MyDrive/data/test"**,**target\_s ize **= (**64**,**64**),**batch\_size **=** 32**,**class\_mode **=** "categorical"**)** x\_train**.**class\_indices

model **=** Sequential**()**

model**.**add**(**Conv2D**(**32**,(**3**,**3**),**input\_shape **= (**64**,**64**,**3**),**activation **=** "relu"**))** model**.**add**(**MaxPooling2D**(**pool\_size **= (**2**,**2**)))** model**.**add**(**Conv2D**(**32**,(**3**,**3**),**activation**=**'relu'**))** model**.**add**(**MaxPooling2D**(**pool\_size**=(**2**,**2**)))**

model**.**add**(**Conv2D**(**128**, (**3**,** 3**),** activation**=**'relu'**))**

model**.**add**(**MaxPooling2D**(**pool\_size**=(**2**,** 2**)))** model**.**add**(**Flatten**())** model**.**add**(**Dense**(**units**=**256**,** activation**=**'relu'**))** model**.**add**(**Dropout**(**0.5**))** model**.**add**(**BatchNormalization**())** model**.**add**(**Dense**(**units**=**128**,** activation**=**'relu'**))** model**.**add**(**Dropout**(**0.5**))** model**.**add**(**BatchNormalization**())**

model**.**add**(**Dense**(**units **=** 6**,**activation **=** "softmax"**))** model**.**summary**()** model**.compile(**optimizer**=**Adam**(**learning\_rate**=**1e-3**),** loss**=**'categorical\_crossentropy'**,** metrics**=[**'accuracy'**])**

model**.**fit\_generator**(**generator**=**x\_train**,**steps\_per\_epoch **= len(**x\_train**),**epochs

**=** 10**,** validation\_data**=**x\_test**,**validation\_steps **= len(**x\_test**))**

**Streamlit code:**

**%%**writefile app**.**py **import** streamlit **as** st **import** tensorflow **as** tf **import** cv2

**import** numpy **as** np

**from** PIL **import** Image**,** ImageOps

*@st***.**cache**(**allow\_output\_mutation**=True) def** load\_model**():**

model **=** tf**.**keras**.**models**.**load\_model**(**'/content/my\_model.hdf5'**) return** model

**def** import\_and\_predict**(**image\_data**,** model**):** size **= (**64**,** 64**)**

image **=** ImageOps**.**fit**(**image\_data**,** size**,** Image**.**ANTIALIAS**)** image **=** np**.**asarray**(**image**)**

img **=** cv2**.**cvtColor**(**image**,** cv2**.**COLOR\_BGR2RGB**)** img\_reshape **=** img**[**np**.**newaxis**, ...]** prediction **=** model**.**predict**(**img\_reshape**) return** prediction

st**.**write**(**"# ECG CATEGORIZATION"**)**

file **=** st**.**file\_uploader**(**"Please upload an ECG image file"**, type=[**"jpg"**,**

"png"**])**

**if** file **is None:**

st**.**text**(**"Please upload an image file"**) else:**

model **=** load\_model**()** image **=** Image**.open(**file**)**

st**.**image**(**image**,** use\_column\_width**=True)** predictions **=** import\_and\_predict**(**image**,** model**)** class\_names **= [**'Abnormal'**,**

'Abnormal (1)'**,**

'Abnormal (2)'**,**

'Abnormal (3)'**,**

'Abnormal (4)'**,** 'Normal'**]**

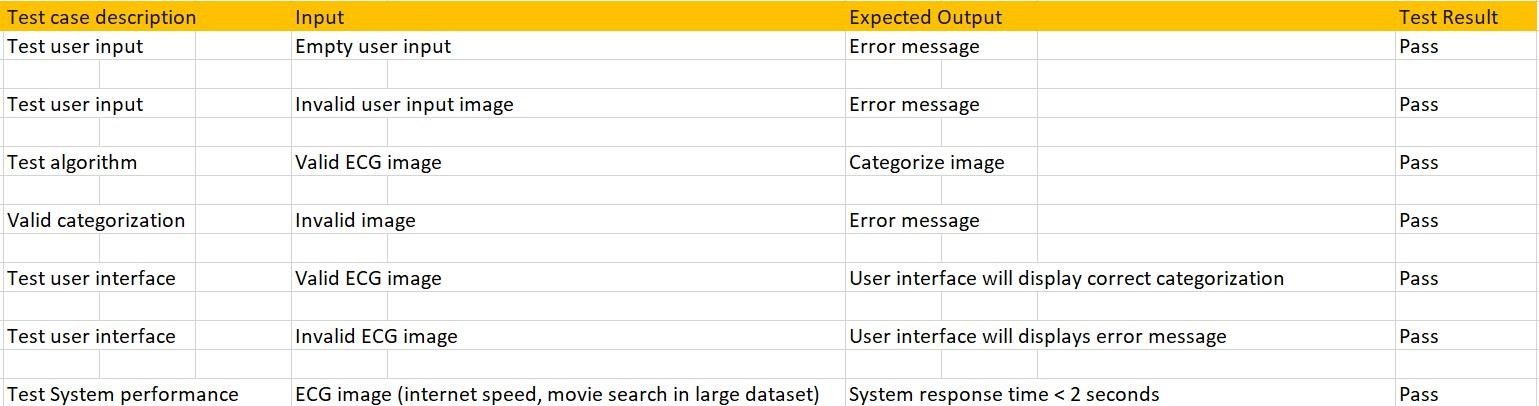
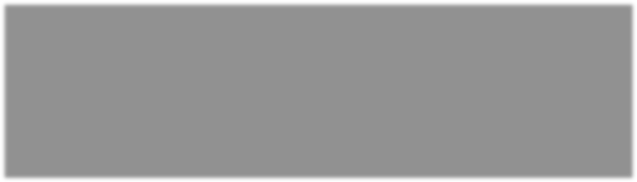
score **=** tf**.**nn**.**softmax**(**predictions**[**0**])** predicted\_class **=** np**.**argmax**(**score**)** confidence **=** 100 **\*** np**.max(**score**)**

st**.**write**(**"Predicted Class:"**,** class\_names**[**predicted\_class**])**

* 1. **Testing**

1. **Unit testing:**

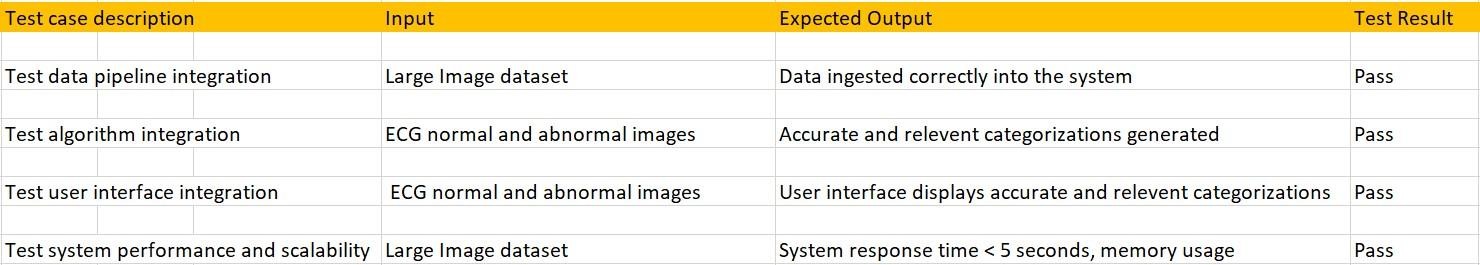
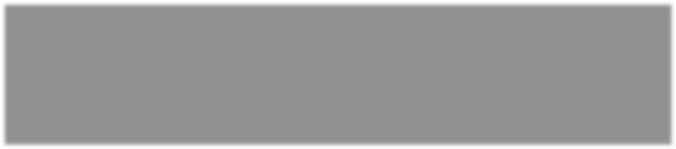
In the context of ECG (Electrocardiogram) categorization using deep learning and Streamlit, unit testing refers to the process of testing individual units or components of thesoftware in isolation to ensure that they work correctly and meet their expected functionality. Each unit is tested independently to verify its behavior, and any issues or bugs in that unitcan be identified and fixed early in the development process. Unit testing helps ensure that the individual building blocks of the application, such as data preprocessing functions, model prediction functions, and Streamlit app functions, function as intended.



Unit Test Results

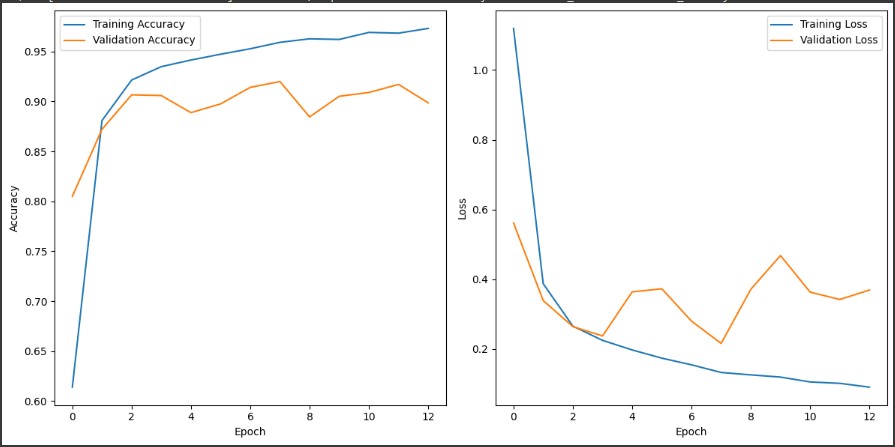
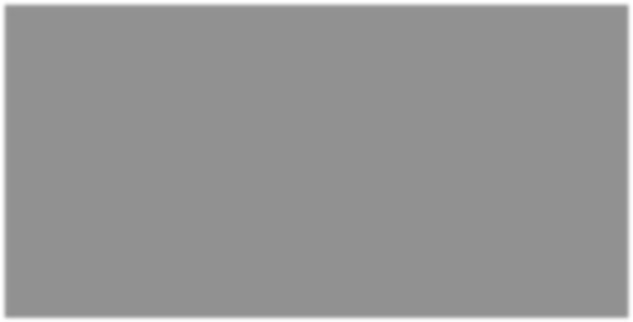
1. **Integration testing:**

In the context of ECG (Electrocardiogram) categorization using deep learning and Streamlit, integration testing refers to the process of testing the interactions and integration between different components or modules of the software to ensure that they work together as expected. Integration testing focuses on verifying that the various parts of the application function correctly when integrated as a whole.



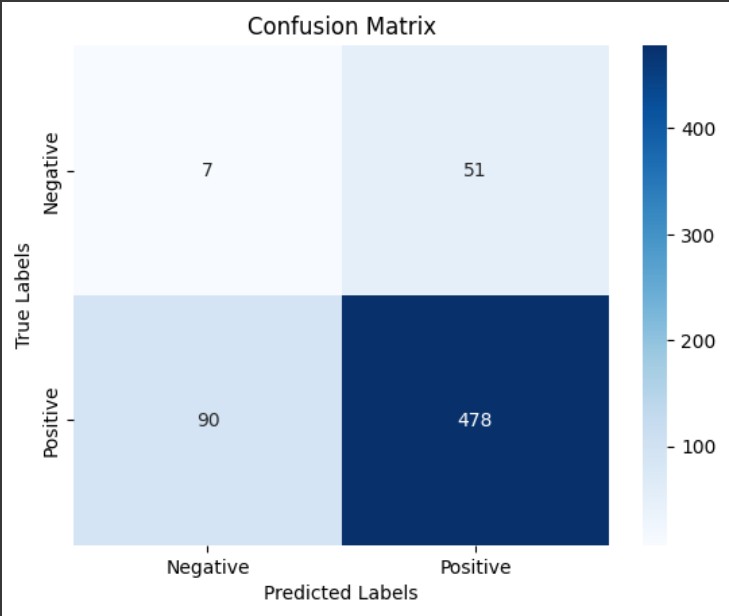
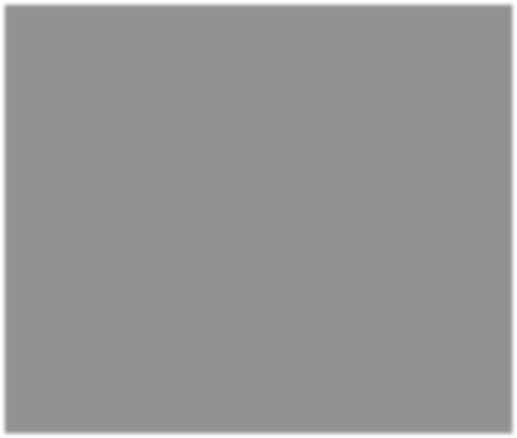
Integration Test Results

* 1. **Analysis (graphs/chart)**
     1. **Training Accuracy and Loss, Validation Accuracy and Loss**



Training and Validation (Accuracy & Loss)

* + 1. **True positive, True negative, False positive, False Negative**



Confusion Matrix

**4.4.3. F1 score, precision, recall, specificity**

* **F1 score, precision, recall, specificity of Train dataset**

|  |  |
| --- | --- |
|  |  |
|  |  |
|  |  |
|  |  |

* **F1 score, precision, recall, specificity of Test dataset**

|  |  |
| --- | --- |
| **Precision** | **0.86** |
| **Recall** | **0.85** |
| **F1 score** | **0.87** |
| **Specificity** | **1.0** |
| **Accuracy** | **0.90** |

|  |  |
| --- | --- |
| **Precision** | **0.90** |
| **Recall** | **0.91** |
| **F1 score** | **0.92** |
| **Specificity** | **1.0** |
| **Accuracy** | **0.95** |

**5. CONCLUSION**

* In conclusion, the utilization of deep learning techniques combined with Streamlit for ECG categorization has shown great promise in the field of healthcare. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated remarkable performance in analyzing ECG signals and accurately classifying various cardiac conditions.
* By leveraging the power of deep learning, these models can automatically learn and extract meaningful features from ECG data, enabling accurate categorization of different arrhythmias, heart diseases, and abnormalities. This can greatly aid healthcare professionals in diagnosing and treating patients more efficiently and effectively.
* The integration of Streamlit, a user-friendly web application framework, further enhances the accessibility and usability of these deep learning models. Streamlit allows for the creation of interactive and intuitive user interfaces, enabling healthcare practitioners to easily input ECG data, visualize predictions, and interpret the results in real-time.
* The combination of deep learning and Streamlit not only provides a reliable and automated method for ECG categorization but also enables healthcare professionals to gain insights into the model’s decision-making process. This transparency and interpretability are crucial in building trust and understanding the model’s limitations, ultimately leading to improvedpatient care.
* However, it is important to note that while deep learning and Streamlit offer significant advancements in ECG categorization, they should be considered as supportive tools rather than replacements for clinical expertise. The interpretation of ECG results should always involve consultation with trained medical professionals, who can provide comprehensive analysis and make informed decisions based on various clinical factors.
* In summary, the combination of deep learning techniques and Streamlit for ECG categorization holds tremendous potential in revolutionizing healthcare practices. The integration of these technologies can improve the accuracy and efficiency of ECG analysis, ultimately benefiting patients by enabling earlier detection, intervention, and treatment of cardiac conditions.

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